Financial Stimulus and Microfinance Institutions in Emerging Markets*

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Abstract

We study how microfinance institutions (MFIs) shape the allocation and aggregate impact of financial stimulus during recessions. We develop a stylized model showing that private lenders may deviate from the social optimum, prioritizing inframarginal clients when poaching threats are strong. This distortion is amplified when lenders are specialized in such clients. We then exploit a large-scale loan guarantee program for small firms implemented in Peru during the COVID-19 recession, combined with administrative data covering the universe of small business loans. We show that guarantees significantly reduced delinquency rates, particularly among micro-firms and those in high-contact industries, segments facing severe liquidity needs. MFIs channeled a larger share of guarantees to these high-sensitivity segments, while traditional banks prioritized inframarginal firms, consistent with our model. We extend our framework to incorporate lender specialization and heterogeneous firms and calibrate it to the data. The model shows that the program reduced defaulting debt by 30 percent relative to a counterfactual where only traditional banks distributed guarantees. Our core insight that MFI specialization shapes the aggregate impact of financial stimulus remains robust across settings where MFIs face higher distribution costs, serve riskier clients, or have weaker monitoring incentives.

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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.

We study 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.

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 a simple way to strengthen ties with valuable, stable borrowers, even if the financial aid is less important 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 to financial stimulus, which enables them to channel resources to the intended beneficiaries. However, a possible drawback lies in that MFIs' business model relies on building relationships, gathering soft information, and monitoring through costly, in-person interactions with borrowers. The safety of a government guarantee could distort these incentives, reducing monitoring and encouraging risk-taking, which could undermine the effectiveness of the program. Thus, understanding how lender incentives shape the effectiveness of loan guarantees and whether MFIs can improve the allocation of financial stimulus 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 two 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 key for 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. These features allow us to cleanly identify the causal effects of loan guarantees and quantify how MFI participation shapes the allocation and 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 city of loan origination. Firm-level characteristics include industry, age, and lender-reported risk rating. 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 to trace the allocation of guarantees for each type of lender, observing which firms are prioritized, and linking this to estimated firm-level elasticities. Thus, we can quantify how the composition of lenders shapes the allocation and aggregate effectiveness of the program.

[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`.

Our analysis proceeds in three steps. First, we develop a conceptual framework showing that private lenders may deviate from the social optimum when distributing loan guarantees. Facing poaching threats and valuing preserving lending relationships, they tend to prioritize inframarginal clients, firms that would survive even without assistance, over more sensitive borrowers. This distortion is amplified when lenders specialize in such clients. Second, we provide empirical evidence on the allocation and effectiveness of a large-scale guarantee program in Peru, showing that MFIs channeled a larger share of guarantees to the most sensitive firms, while traditional banks disproportionately served inframarginal borrowers, consistent with our framework. Third, we build and calibrate a quantitative model with lender specialization and heterogeneous firms to rationalize our findings and quantify the optimal participation of MFIs.

In the first part of the paper, we build a stylized conceptual framework to illustrate how lender incentives and specialization shape the allocation of loan guarantees. We consider a continuum of heterogeneous firms, each characterized by revenue and debt obligations that determine net cash-flow. We model the recession as a firm-specific, unexpected liquidity shock drawn from a common distribution. Firms survive if their net cash-flow, augmented by any guaranteed loan received, exceeds the shock. A social planner would maximize the total value of non-defaulting debt by ranking firms according to their treatment effect, defined as the increase in survival probability from receiving a guarantee, and allocating funds to those with the highest treatment effect until the budget of guarantees is exhausted.

Private lenders, however, face different incentives. We assume they are exposed to poaching threats that bind if they deny a guarantee to a client (Joaquim and Netto 2022). Because lenders also capture future profits from preserved relationships, their allocation rule weighs both the firm's treatment effect and its survival probability absent the program. This creates a potential inefficiency: lenders may favor inframarginal clients–firms that are likely to survive even without support–over more sensitive but ex-ante riskier borrowers. The distortion

is amplified when lenders specialize in such inframarginal firms. Thus, our framework implies that different types of financial institutions allocate guarantees differently, and consequently, the mix of lenders participating in the program matters for its aggregate effectiveness.

In the second part of the paper, we provide empirical evidence on the mechanisms highlighted by our conceptual framework. Using a difference-in-differences design that leverages cross-sectional variation in the intensity of guarantee uptake across financial institutions, we estimate the effects of the loan guarantee program on credit supply and firm performance.[2] Our specification compares 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. Third, we exploit a three-month delay in the program's implementation, which gives us a period of Covid-19 restrictions without loan guarantees, as a placebo test. Our treatment measure is uncorrelated with credit during this window. 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 uptake is uncorrelated with predetermined 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

[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).

with the program partially crowding out private credit. Thus, 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 total credit, we aggregate our data at the firm-level and construct a corresponding measure of treatment using pre-recession 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.

The program only allowed guarantees to be extended to existing lending relationships, not to new clients. However, the additional liquidity provided may have allowed banks to extend non-guaranteed credit to new borrowers. To quantify this effect, we estimate bank-level regressions, which show a 42 percent increase in lending to new borrowers among highly treated banks relative to less treated ones. Thus, the program reallocated bank credit supply, substituting guaranteed for non-guaranteed loans among existing firms, while indirectly facilitating an expansion of non-guaranteed credit to new firms.

We use a difference-in-differences instrumental variable approach to estimate the effect of the program on small firm performance, measured by delinquency rates. This approach is essential for distinguishing between marginal, sensitive firms and inframarginal borrowers. Using our firm-level treatment as an instrument for program participation, we find that receiving a guarantee reduces delinquency by 11 percentage points. We then estimate the elasticity of delinquency to credit, which measures the effectiveness of each Peruvian Sol distributed by the program. A 10 percent increase in credit reduces delinquency rates by 1.4 percentage points. These results indicate that alleviating liquidity needs played a dominant role in explaining the effect of loan guarantees on small firm performance during the crisis, outweighing potential alternative mechanisms such as risk-shifting or weakened screening incentives.

We then estimate heterogeneous effects across small firms to identify the most sensitive borrowers. 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 (Cerda et al. 2023). Our hypothesis is that the smallest firms and those in high-contact industries suffered more severe liquidity needs and would therefore be more sensitive to participating in the program. 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), compared to only 0.4 percentage points 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, versus 0.9 percentage points for the remaining firms. These findings confirm that loan guarantees helped small firms alleviate the liquidity shock from pandemic restrictions.

We complement our analysis using tax records for small firms in the formal economy. 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 the program impacted firms mainly through the extensive margin.[4] One standard deviation higher treatment reduces firm exit probability by 1 percent in 2020, and 2 percent in 2021.

Having identified the most sensitive firms, we now compare the lending patterns of MFIs and traditional banks. We document that MFIs prioritized sensitive borrowers, allocating 65 percent of their guarantees to the smallest firms, while traditional banks allocated only 29 percent. Furthermore, 60 percent of MFIs' guarantees went to firms in high-contact industries, compared to 46 percent for traditional banks. A back-of-the-envelope calculation suggests that these allocation differences had meaningful aggregate consequences. Under the actual mix of lenders, the program reduced aggregate delinquency by 12 percentage points, compared to a counterfactual reduction of 8 percentage points if only traditional banks distributed the guarantees.

[3]We consider companies within the small firm category. All comparisons are within this segment.
[4]Extensive margin is interpreted as being formal (reporting taxes) or not.

These allocation patterns closely mirror lenders' pre-recession specialization. Prior to the pandemic, traditional banks concentrated 74 percent of their small-firm lending in the largest small borrowers, while MFIs allocated only 50 percent of their portfolios to this segment. Similarly, MFIs had 64 percent of their pre-recession portfolios in high-contact industries, compared to 59 percent for traditional banks.

This specialization enabled better targeting within borrower segments: among highly sensitive firms, those that received guarantees from MFIs performed better than those attended by traditional banks. A 10 percent increase in credit reduced delinquency by 4 percentage points for smaller firms attached to MFIs, compared to only 0.3 percentage points for smaller firms attached to banks. Similarly, a 10 percent credit increase for high-contact firms attached to MFIs reduced delinquency by 4 percentage points, while the response for similar firms attached to banks was statistically insignificant. This evidence confirms that the composition of lenders critically shapes the allocation of financial stimulus and, through this channel, its aggregate impact.

In the third part of the paper, we extend our conceptual framework to endogenize firms' net cash-flow and lender specialization, allowing us to rationalize our empirical findings and conduct counterfactual analysis. Our model includes a continuum of firms that choose whether to operate as hard or soft information, and two risk-neutral intermediaries, MFIs and traditional banks, that engage in Cournot competition using different lending technologies. MFIs have a cost advantage with soft-information firms, while traditional banks have a cost advantage with hard-information firms. In equilibrium, this generates different client distributions for each lender.

Firm timing is as follows. Upon observing a productivity signal, firms pay a fixed cost to become hard-information or remain soft-information at zero cost. After choosing their type, they observe productivity and risk, then choose capital, fully financed with debt, to maximize profits operating a Cobb-Douglas technology. The benefit of becoming hard-information is

access to cheaper credit, as loan origination costs are lower for such firms.

We model the recession and guarantee allocation following our conceptual framework. Firms face an idiosyncratic liquidity shock and survive if their net cash-flow plus any guaranteed loan exceeds the shock. The aggregate program impact is measured as the share of debt saved from default. Poaching threats and relationship value create a wedge between private and social allocation: lenders weigh both treatment effects and firms' baseline survival probability, leading to potential misallocation.

Our calibrated model generates an equilibrium distribution of clients for MFIs and traditional banks that matches key empirical moments such as market shares and lender specialization. On average, MFIs' clients are smaller, soft-information, and have lower levels of cash-in-hand, making them more likely to exit without loan guarantees. Traditional bank clients, by contrast, are larger, hard-information, and have more cash-in-hand, making them more likely to survive the recession even without assistance.

Indeed, the distribution of treatment effects among MFI clients is concentrated at higher values than that of traditional banks. This difference is even more pronounced among program recipients. Thus, by redirecting loan guarantees away from inframarginal firms and toward highly sensitive ones, MFI participation amplifies the aggregate impact of the program. Our calibrated model shows that, under the observed MFI participation rate, the program saved 32 percent of debt at risk of default. In a counterfactual where only traditional banks distributed guarantees, this ratio would have been just 22 percent.

However, our results caution against over-relying on MFIs. Beyond a certain point, additional guarantees flow to riskier, less-responsive firms within MFI portfolios–borrowers who may fail even with support. Our analysis finds the optimal MFI participation rate is 57 percent, at which the program would have saved 43 percent of at-risk debt. Moving to an MFI-only scenario reduces effectiveness to 29 percent, illustrating the trade-off between leveraging MFIs targeting advantages and exhausting their pool of hightreatment-effect clients.

Finally, we extend our baseline model to broaden its applicability to other settings. First, we introduce distribution inefficiencies, allowing MFIs to face higher costs when administering guarantees. In this extension, the optimal MFI participation rate remains constant for low inefficiency levels, reflecting that the gains from better targeting initially offset the additional costs, and declines when inefficiency is sufficiently high. Second, we allow MFIs to specialize in riskier borrowers by making soft-information firms inherently riskier. This reduces the optimal MFI share, as their clients become more likely to default regardless of the guarantee. Third, we consider the possibility that loan guarantees weaken monitoring incentives. Since monitoring is particularly important for soft-information firms, a reduction in these incentives disproportionately affects MFIs, leading to a lower optimal participation rate. The core insight that lender specialization shapes the aggregate impact of financial stimulus remains robust across these extensions.

Our paper shows that microfinance institutions can significantly enhance the aggregate impact of financial stimulus in emerging markets by channeling resources to more responsive borrowers.

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 study the role of lender specialization and focus on the optimal policy design to ensure financial stimulus reaches the most sensitive 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; Griffin et al. 2023). 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), by providing evidence that the pre-existing expertise 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 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 tar-

get 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 our main results in section 5. Section 6 presents our model and 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 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. This dataset contains firm-level tax records from 2018 to 2022, including annual sales, capital stock, and employment. It also includes 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[5] (MFIs). Loans are categorized into five segments based on firm sales and outstanding debt: micro-credit, small-firm credit, and loans to medium-size firms, large firms, and corporations. For example, micro-credit is defined as loans to firms whose total debt in the banking sector is below $6 thousand. On the other hand, loans to corporations are defined as credit to firms 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 that 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 hold 80 percent of total credit. MFIs account for 13 percent of aggregate lending but play a predominant role in small business loans—they originate 68 percent of micro-credit and 47 percent of small firm credit. 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 financial institutions 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.

[5]Micro-finance institutions as all lenders that are regulated by the Peruvian Bank Supervisor but are not classified as banks. They include saving and loan institutions, financial enterprises, and enterprises for the development of small and micro firms.

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)	(5)
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).

2.3 Traditional Banks and Micro-Finance Institutions

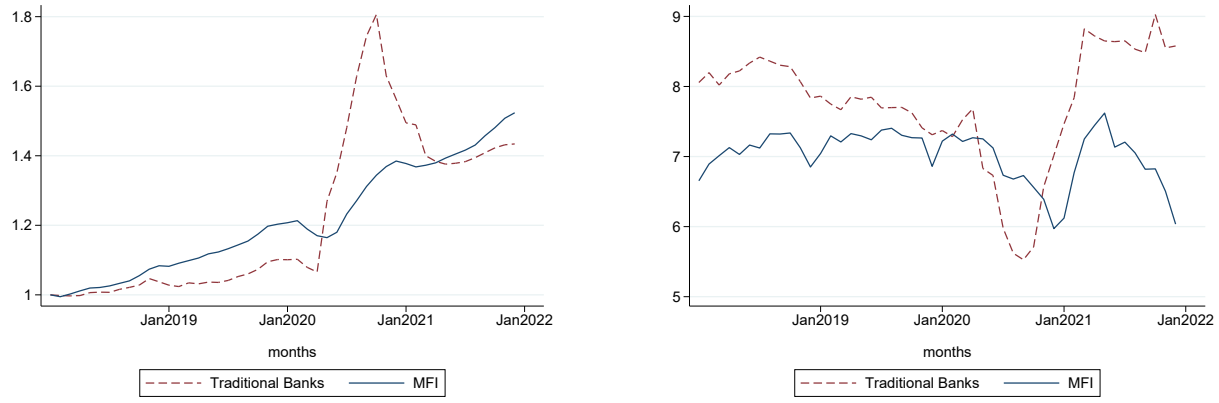
MFIs expanded significantly in Peru over the past two decades, driven by deep deregulations. The industry is mature and plays a key role in the segment of small business loans nowadays. Figure 1 plots credit growth and delinquency rates for small business loans between 2018 and 2022. Panel (a) shows 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%, slightly below traditional banks' delinquency.

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.[6].

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. Considering only small business loans, the average top 10 MFI provides $360 million in loans, while the average traditional bank provides $420 million.

Figure 1: Small Business Credit Growth and Delinquency by Type of Lender



(a) Total Loans

(b) Delinquency Rates

This figure plots the evolution of small business 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 2018. Panel (b) plots delinquency rates measured by the share of outstanding debt with more than 30 days of repayment delay.

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

Figure A1 highlights cities where traditional banks and micro-finance institutions have active branches in December 2019.[7] 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. 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.[8] Thus, MFIs play a key role in expanding geographical credit access.

2.4 The Program of Loan Guarantees

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

Guarantees covered between 80 and 98 percent of loan value (higher for smaller loans), and were allocated via first-price auctions where lenders bid on interest rates. There were separate auctions for each type of business loans. Private lenders were in charge of screening borrowers and allocating loan guarantees. These loans had an average duration of 36 months and were 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 in 2019, were not allowed to participate.

Table 2 provides summary statistics on the program's scale for different types of credit. Column (1) shows the value of guarantees distributed, and column (2) shows the ratio of this value relative to total credit in December 2019, before the recession. Similarly, column (3)

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

[8]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.

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.

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.

We conclude this subsection by describing how different lenders behave around the program implementation date. 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 made 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.

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 net cash-flow 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. We model the recession as 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. Firm i survives the recession if and only if its net cash-flow $y_i - rb_i$ plus the amount received from

the program is bigger than the liquidity shock:

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

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

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

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

The first implication of our conceptual framework is that T_i depends on the severity of the shock and the net cash-flow of the firm $y_i - rb_i$. In a soft recession, where the distribution of liquidity shocks is concentrated over lower values, the effect is bigger across firms with low net cash-flow, and negligible among firms with high cash who will survive even without guarantees. On the other hand, in a deeper recession, the effect is bigger among firms with high net cash-flows, and insignificant across firms with low cash that will not survive even if they receive loan guarantees.

3.2 Social Planner's Allocation

We define the social planner's optimal allocation as the one that maximizes non-defaulting debt, since the goal of the program was preserving financial stability.

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

where M represents the total value of guaranteed loans.

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 social planner implements this solution by ranking firms based on treatment effect T_i and distributing guarantees from the highest value until the total amount M is distributed.

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 $\psi_F b$, capturing bank 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 client i is:

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

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:

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

3.4 Loan Guarantee Misallocation

The second implication of our framework 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. We measure this channel in our quantitative analysis.

To illustrate qualitatively the role of lender incentives, we consider a relationship lending parameter equal to 0.1/0.04, meaning that banks make 10% returns every year, on expectation, upon preserving a client, and assuming a discount rate of 4%. Additionally, we assume that poaching threats realize with 10% probability.[9]

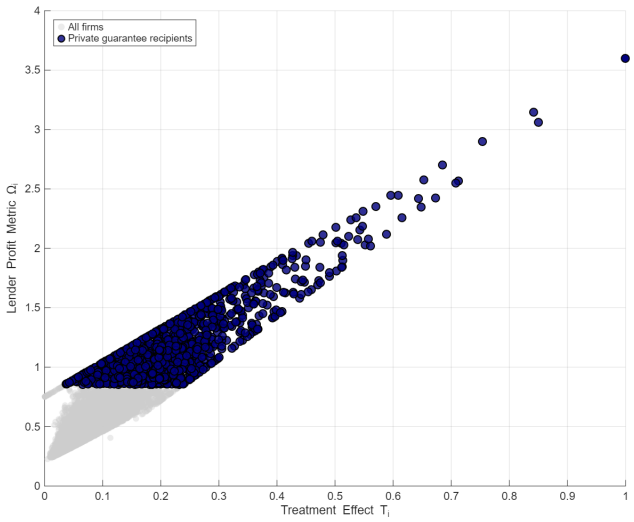
Figure 2 plots the relationship between treatment effect T_i and lender profit function Ω_i for a simulated set of borrowers using the parametrization described above. The figure highlights the firms that are selected by the private lender to get a guaranteed loan. We observe that the allocation departs 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.

Our conceptual framework shows the potential misallocation in the private distribution of loan guarantees when lenders face poaching threats and value preserving lending rela-

[9]We set the recovery rate to 10%. We model sales as a Pareto with shape parameter 1.6 over the support $[1,\infty)$ and assume that debt follows $b = 0.15y \times u$, where u is distributed as a log-normal with mean zero and variance 0.5. We can think of a revenue function $y = k^{0.3}$ with interest rate of 20%. 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 $[0,5]$.

tionships. Next sections provide empirical evidence on loan guarantee misallocation and quantifies how different mix of lenders can improve the aggregate efficiency of the program.

Figure 2: 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 guarantee in the private equilibrium.

4 Empirical Framework

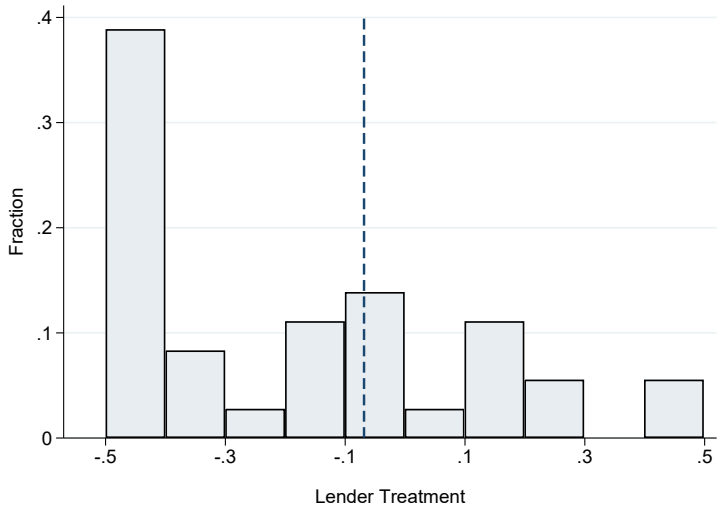
We exploit differences in lenders uptake of loans guarantees to estimate the effect of the program on credit supply. We compute the difference between the share of loan guarantees distributed by lender j relative to its pre-existing share of small business loans as follows:

$$\text{Treatment}_j = \frac{\text{Share of Guaranteed Loans}_{j,2020} - \text{Share of Total Loans}_{j,2019}}{\text{Share of Guaranteed Loans}_{j,2020} + \text{Share of Total Loans}_{j,2019}} \times 0.5 \qquad (2)$$

This continuum measure of treatment captures lender-specific reimbursement shocks (Granja et al. (2022)) that guarantee repayment for new small business loans. Figure 3 plots the distribution of Treatment_j across lenders. We can see large heterogeneity in take-

up. The dashed line indicates the median of bank treatment, weighted by pre-recession market share.

Figure 3: Distribution of Bank Treatment



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

Before presenting our estimable equation, we split financial institutions into two groups based on the median exposure and plot the corresponding evolution of credit and delinquency rates in Figure A2. Panel (a) shows that treatment was uncorrelated with aggregate credit growth before the program. Furthermore, high-treatment predicts a rapid and persistent expansion of credit for traditional banks and MFIs. Panel (b) shows that treatment is also uncorrelated with delinquency before the program. Finally, while highly treated MFIs exhibit a strong and persistent reduction in delinquency rates, traditional banks' delinquency remains constant during the recession and deteriorates after the grace period. It is worth noting that the 3 percentage points difference in delinquency rate among highly treated MFIs and traditional banks after the recession is economically meaningful since small business loans' aggregate delinquency was around 7 percent before the recession.

Bank-firm level specification. We identify the credit supply effect of loan guarantees using a difference-in-differences approach that compares the outstanding debt that firms hold with more treated banks relative to less treated ones, before and after the program. We estimate the following equation:

$$Y_{ijt} = \theta \times \text{Treatment}_j \times \text{Post}_t + \delta_{ij} + \delta_{it} + u_{ijt} \tag{3}$$

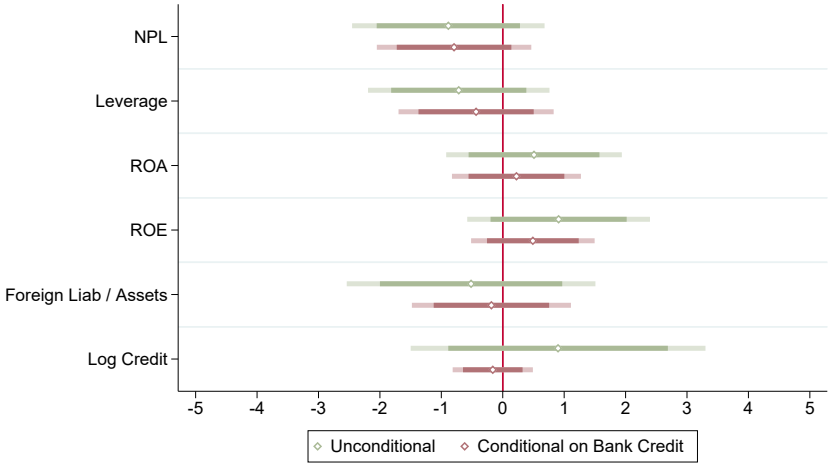
where Y_{ijt} denotes the balance of total loans (in logs) that firm i has with lender j in period t, and Treatment_j is the standardized treatment defined by equation (2). We include firm-bank fixed effects δ_{ij} to control for match-specific time-invariant characteristics such as lender specialization in a given industry. δ_{it} denote firm-by-period fixed effects and remove any time-varying shock at the firm level. Our parameter of interest θ measures the impact of one standard-deviation higher treatment on bank lending to the same firm. Standard errors are clustered at the bank level.

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. Even though we plot event-study graphs showing no evidence of pre-trends for multiple outcomes, a remaining concern is that bigger lenders might be more likely to serve bigger firms that are better prepared to deal with COVID-19 restrictions. We deal with this potential source of bias by including time-varying fixed effects for interaction of bank and firm size-bins $\delta_{g(i),g(b),t}$, which allows us to compare credit obtained from more versus less treated banks within the same bin.

While our identification strategy does not require that more and less treated banks be similar in levels, such similarity makes the parallel trend assumption more plausible. We conduct a covariate balance test regressing multiple bank-level pre-determined characteristics, separately, on our measure of treatment. Figure 4 shows the estimated coefficients

and corresponding confidence intervals indicating that treatment is statistically uncorrelated with the share of non-performing loans, leverage ratio, ROA and ROE, and foreign liabilities.

Figure 4: Balance of covariates



Note: This figure reports the resuls of a covariate balance test. It shows coefficient estimates along with 95% confidence intervals (darker bars) and 99% confidence intervals (lighter bars) for the impact of a one standard deviation increase in bank treatment across different variables. All variables are standardized to have zero mean and a standard deviation of one. The conditional regressions include fixed effects for each bank size quartile.

Firm level specification. We aggregate our dataset at the firm level to estimate the impact of the program on small firm performance. To do so, we construct the following measure of treatment:

$$\text{Treatment}_i = \sum_j \frac{L_{ij}}{L_i} \times \text{Treatment}_j \tag{4}$$

where L_{ij} denotes the outstanding debt that firm i holds with lender j in December 2019 and Treatment_j is defined in equation (2). Then we quantify the impact of the program on small firm performance by estimating the following equation:

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

where Y_{it} can denote the balance of credit (in logs) or 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. Standard errors are clustered at the main-lender level.

5 Results

5.1 Loan Guarantees 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 3 of Table 3. We find that one standard deviation higher treatment leads to a 10% increase in credit supply in our benchmark specification reported in column 2. Our results are robust to using different sets of fixed effects as reported in columns 1 and 3.

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, our estimated coefficients are statistically zero up to the first quarter of the policy, already two quarters in a recession, and when a negligible amount of guarantees were distributed. Even though our identifying assumption is not testable by definition, this evidence provides critical support to our identification because it indicates that treatment

[10]We define delinquency rate as an indicator variable equal to one for firms that experience more than 30 days of repayment delay on any loan at a given point in time.

was orthogonal to factors affecting firm credit demand when the shutdowns were already in place for two quarters. The balance of loans experience a significant and persistent increase since the third quarter of 2020.

Table 3: Effect of Loan Guarantees on Bank Credit Supply

	Total Loans			Non-Guaranteed Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_j \times \text{Post}_t$	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

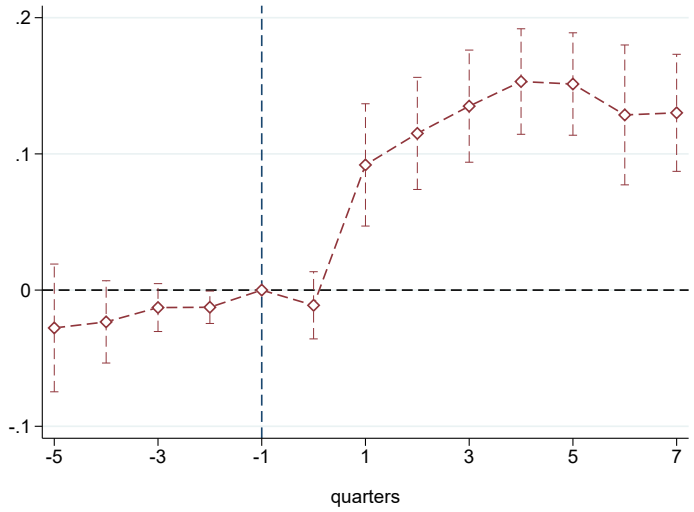
This table shows the effect of the program on the balance of total loans and non-Covid-19 loans at the bank-firm level. Treatment is standardized. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the bank level. Observations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

We study how loan guarantees expanded total credit. An important question for policymakers is whether government-backed guarantees crowd out the normal activity of banks or not (Stiglitz (1993), La Porta, Lopez-de-Silanes, and Shleifer (2002), Ru (2018)). We estimate equation (3) using the log of normal loans, those that are not collateralized by the government, as our dependent variable. We report our results in columns 4 to 6 of Table 3. We estimate that one standard deviation higher treatment leads to a decline of 30% in the supply of normal loans in our benchmark specification reported in column 5.

Figure A3 plots the event study graph associated with our benchmark spcification showing no evidence of pre-trends. The balance of normal loans exhibit a steady decline after the program, indicating that loan guarantees partially crowded out the normal activity of banks. Thus, the program of guarantees fully explains the expansion of total credit during

the recession.

Figure 5: Effect of the Program on Total Credit



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%.

5.2 Loans Guarantees and Small Firm Performance

To study the impact of loan guarantees on small firm performance, we aggregate our data at the firm level and calculate a corresponding measure of treatment as described in equation (4), which captures how well connected small firms were with more treated banks before the program. 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 would easily switch to highly treated lenders and obtain guaranteed loans even if they were not linked before the recession. Otherwise, if lending relationships were sticky, better connected firms would experience an expansion in credit relative to worse connected ones.

We estimate equation (5) using total loans as our dependent variable and report our results in columns 1 to 3 of Table 4. We find that one standard deviation better connected firms experience a 14% increase in total loans after the program.[11] We report quarterly treatment effects in panel (a) of Figure A4 showing no pre-trends. Similar to our bank-firm estimation, our treatment effects are statistically null up to the first quarter of the program, where COVID-19 shutdowns were in place for two periods but only a negligible part of guarantees was distributed. We find that better connected firms have more credit, and this effect is persistent. Our results indicate that lending relationships play a key role in shaping the ability of firms to obtain guaranteed loans.

Table 4: Effect of Loan Guarantees on Small Firm Borrowing

	Total Loans			Non-Guaranteed Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_i \times \text{Post}_t$	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 report our estimation of the response of normal loans in columns 4 to 6 of Table 4. Firms with one standard deviation higher treatment have a 36% lower balance of non-guaranteed loans relative to worse connected firms. Panel (b) of Figure A4 reports quarterly treatment effects, showing no evidence of pre-trends.

[11] Since we cannot include firm-time fixed effects in this specification, the corresponding bank-firm level estimation is reported in column (1) of Table 3. Thus, a smaller coefficient in our firm-level specification means that firms have positive but limited ability to switch lenders.

We now explore the response of delinquency rates, our measure of small firm performance. We define delinquency as an indicator variable equal to one if the firm experience more than 30 days of repayment delay in a given quarter. Our results are reported in columns 1 to 3 of Table 5. We find that highly treated firms perform better after the program. One standard deviation higher treatment reduces the probability of experiencing repayment delays by 2 ppts. Figure A5 plots the event-study graph associated with our benchmark specification and shows no evidence of pre-trends. Furthermore, the decline in delinquency among highly treated firms persists after the end of the grace period.

We then estimate two elasticities that provide policy-relevant information. First, we estimate the response of firm delinquency rates to participating in the program of loan guarantees. Second, we measure the response of delinquency to the amount of credit received from the program. These elasticities are crucial to identify which firms are more sensitive and which are infra-marginal. By estimating these elasticities, we can study to what extent reallocating loan guarantees across firms can increase the aggregate effectiveness of the program and what is the role of MFIs in achieving a better allocation. We estimate the following IV difference-in-differences specification:

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

where X_{it} can be either being a program recipient or total loans. In each case, we instrument this variable with our firm-level measure of treatment. Our coefficient of interest γ measures the elasticity of delinquency to participating in the program or to the liquidity received from the program.

We report our results in columns 4 and 5 of Table 5. We find that program recipients are 11 percentage points less likely to exhibit repayment delays compared to non-participants.

Furthermore, a 10 percent increase in credit reduces the probability of delinquency in 1.4 percentage points.

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

	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Treatment$_i$× Post$_t$	-0.020***	-0.019***	-0.020***		
	(0.004)	(0.004)	(0.005)		
Receipient$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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.

Overall, our results show that the program was effective in expanding credit supply during the recession, and by doing so, it improved small firm performance. Highly treated firms, i.e., those better connected to highly treated banks, receive more credit and are less likely to be delinquent after the program. The lower delinquency is consistent with the unprecedented need of external financing generated by COVID-19 restrictions, which offsets potential firm risk-shifting incentives and lower lender screening.

5.3 Heterogeneous Effects and Loan Guarantees' Allocation

In this subsection, we estimate the heterogeneous effects of the program and study the role of MFIs in allocating loan guarantees towards more sensitive firms. First, we split firms into

two groups based on their outstanding debt in 2019. We define firms in the top decile of the debt distribution as large and those at the bottom deciles as small borrowers.[12] Large firms account for 60 percent of small-firm debt in the pre-recession period.

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$_i$× Post$_t$	-0.020***			-0.008*		
	(0.004)			(0.004)		
Treated$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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.

Then, we estimate equation (6) for each group of firms. Our key hypothesis is that liquidity needs are bigger among small firms. Since large firms typically exhibit higher levels of cash-flows and liquidity buffers, they will be more likely to survive the recession even without the program.[13] Our estimation results are reported in columns (1) to (6) of Table 6. Consistent with our hypothesis, the elasticity of delinquency rates to credit among smaller

[12]It is worth noting that we split firms within the segment of small-firm credit. Thus, all firms in our sample are small.

[13]The alternative hypothesis discussed in our conceptual framework is that, in a deeper recession, large firms can be more sensitive to the program. This is because, given the size of the shock, small firms with low levels of cash will not survive even if they receive liquidity from the program.

firms is four times that of large borrowers. While a 10 percent increase in liquidity reduces the probability of delinquency by 1.5 percentage points among smaller borrowers, the response is only 0.4 percentage points among large clients.

Second, we split firms based on the industry where they operate. We define high-contact industries as those with high levels of interaction with customers (e.g., retail, restaurants, transportation, etc.), and low-contact industries as those where interactions are less common (e.g., manufacturing), following Cerda et al. 2023. In this case, our hypothesis is that high-contact industries faced a bigger liquidity shock because they were more affected by COVID-19 restrictions.

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$_i$× Post$_t$	-0.021***			-0.016***		
	(0.003)			(0.005)		
Treated$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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.

Our estimation results are reported in columns (1) to (6) of Table 7. Consistent with our hypothesis, the elasticity of delinquency to credit is bigger in high-contact industries. While

a 10 percent increase in liquidity reduces the probability of delinquency by 1.6 percentage points in high-contact industries, the effect is 0.9 percentage points in low-contact sectors.

Having identified the most sensitive borrowers, smaller in high-contact sectors, we now study the allocation of guarantees implemented by each type of lender. The top panel of Table 8 reports the participation of small and large borrowers in the portfolios of loan guarantees and pre-recession small business loans for traditional banks and micro-finance institutions.

Table 8: Share of Credit and Loan Guarantees by Type of Bank and Firm

	Loan Guarantees		Pre-Recession Loans	
	Banks (1)	MFIs (2)	Banks (3)	MFIs (4)
Size (pre-Covid Debt):				
Small	0.29	0.65	0.26	0.50
Large	0.71	0.35	0.74	0.50
Industries:				
High-Contact	0.46	0.60	0.59	0.64
Less- and Non-Contact	0.54	0.40	0.41	0.36
Lender share:	0.75	0.25	0.48	0.52

This table reports the composition of MFI and traditional bank portfolios. Columns (1) and (2) show the distribution of loan guarantees across firm types, while columns (3) and (4) show the distribution of pre-recession loans as of December 2019. Small firms are defined as those in the bottom nine deciles of the pre-Covid debt distribution among small businesses; large firms are in the top decile. High-contact industries include corner stores, restaurants and bars, hotels, bus passenger, clothing stores, and others as defined in Cerda et al. 2023. All figures represent shares within each lender type.

We can observe that traditional banks' portfolios are more concentrated towards large borrowers who represent 74 percent of bank small-firm credit before the recession. In contrast, large firms represent 50 percent of MFIs' portfolios. The allocation of guarantees

implemented by traditional banks exhibits a similar pattern with 71 percent of guaranteed credit received by their large, low-sensitive clients. On the other hand, MFIs provide 65 percent of guarantees to smaller, high-sensitive borrowers.

Similarly, we observe that traditional banks provided more guarantees to low-contact industries, while MFIs attended mainly high-contact sectors. These allocation patterns indicate that MFIs were more likely to provide guarantees to high-sensitive borrowers such as smaller firms in high-contact industries, mirroring their pre-recession specialization.

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.

6 Quantitative Analysis

We extend our conceptual framework in two key directions that allow us to rationalize our findings and perform counterfactual analysis. First, we endogenize firm heterogeneity: a continuum of firms chooses whether to operate as a soft- or hard-information type and decides on its optimal level of debt-financed capital. Second, we include two lenders, traditional banks and MFIs, with different comparative advantages across firm types. Our model equilibrium yields endogenous distributions of clients for each lender.

6.1 Firms

We model the timing of firm decisions following Ulyssea (2018). First, each firm receives a private signal ν about its future productivity potential. This signal is drawn from a Pareto

distribution with shape parameter ξ over the support $[\nu_0, \infty)$, where we normalize $\nu_0 = 1$. Based on this signal, the firm chooses its type, $f \in \{s, h\}$. It can pay a fixed cost c_e to become a hard-information firm ($f = h$), or operate at zero cost as an opaque, soft-information firm ($f = s$). After this choice, the firm's actual productivity z is realized as $z = \epsilon \times \nu$, where ϵ is an idiosyncratic shock drawn from a log-normal distribution with mean zero and variance V.

Firms also face an idiosyncratic probability of failure σ, drawn from a Beta distribution $\sigma \sim \text{Beta}(\alpha_\sigma, \beta_\sigma)$ over $[0, 0.5]$.[14] Firms have access to a Cobb-Douglas production technology, $y = zk^\alpha$, where k denotes capital. After choosing their type f, and observe their productivity z and failure risk σ, firms choose their capital level, which is fully financed with debt. Firms maximize profits taking the interest rate r as given, leading to the following capital demand function:

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

6.2 Banking Sector

The banking sector includes two lender types: a representative traditional bank and a representative microfinance institution (MFI), each employing distinct lending technologies and competing à la Cournot. This technological difference is captured by their marginal costs of loan origination. The traditional bank has a comparative advantage in serving hard-information firms, reflected in a lower marginal cost $c_h^T < c_h^M$ in that segment. Conversely, the MFI specializes in relationship lending, granting it a cost advantage with opaque, soft-information firms, where $c_s^M < c_s^T$. The traditional bank face higher costs in the soft-information segment due to their reliance on standardized, hard-information techniques.

[14] 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.

Taking the competitor's quantity as given, lender j chooses its loan supply k_j to solve:

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

where $k = \sum_j k_j =$ is the total credit extended to the firm. The inverse demand function for loans, derived from the firm's optimal capital choice, is $r(k) = \alpha z k^{\alpha-1}$. Then, Lender j's first order condition is:

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

Let $s_j = k_j/k$ denote lender j's market share in lending to a given firm. In a symmetric equilibrium, where all lenders charge the same interest rate r to a firm of type f with risk σ, we obtain the following equilibrium interest rate:

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

where $c_f = \sum_j c_f^j \times s_j$ is the weighted average marginal cost and $\mathrm{HHI}_f = \sum_j s_j^2$ is the Herfindahl-Hirschman Index for the segment of firms (σ, f). This expression captures how firm risk, technological specialization, and lender competition shape credit costs. The rate increases with the firm's default risk σ and with the segment's average origination cost c_f, and decreases as the market becomes more competitive–lower HHI_f. Firms formulate expectations over this pricing schedule when deciding whether to operate as a soft- or hard-information entity.

6.3 Equilibrium

After observing their productivity signal ν, firms choose their type by maximizing expected profits. A firm chooses to become a hard-information entity if the benefit of better financing

terms outweighs the fixed cost c_e:

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

where $\Lambda_f = (1-\alpha)\left(\alpha[1+(\alpha-1)\text{HHI}_f]/c_f\right)^{\frac{\alpha}{1-\alpha}}$ is a profit shifter that incorporates the equilibrium lending terms for type f, and F denotes the joint distribution of (ϵ, σ). This problem yields a cutoff equilibrium: firms with signals $\nu \geq \nu^*$ pay c_e and become hard-information, while those with $\nu < \nu^*$ remain as opaque, soft-information firms. This endogenous sorting based on expected productivity generates overlapping productivity distributions across the two segments–a key feature for our counterfactual analysis.

6.4 Loan Guarantee Program

We model the recession as an unexpected liquidity shock and the program as a liquidity injection, as described in the conceptual framework. The total volume of guaranteed loans is M, with an exogenous fraction γ_{M} channeled through MFIs. Lender $j \in \{\text{TB}, \text{MFI}\}$ solves:

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

Thus, the allocation's efficiency hinges on lender-specific client distributions G^j and budget allocations γ_j. The social planner, by contrast, faces the aggregate firm distribution $G(y, k)$ and maximizes the aggregate treatment effect, following the same objective as in Section 4.

6.5 Calibration

Our calibration is structured in two blocks, each targeting distinct empirical moments. The first block calibrates parameters governing the pre-recession credit market equilibrium. We

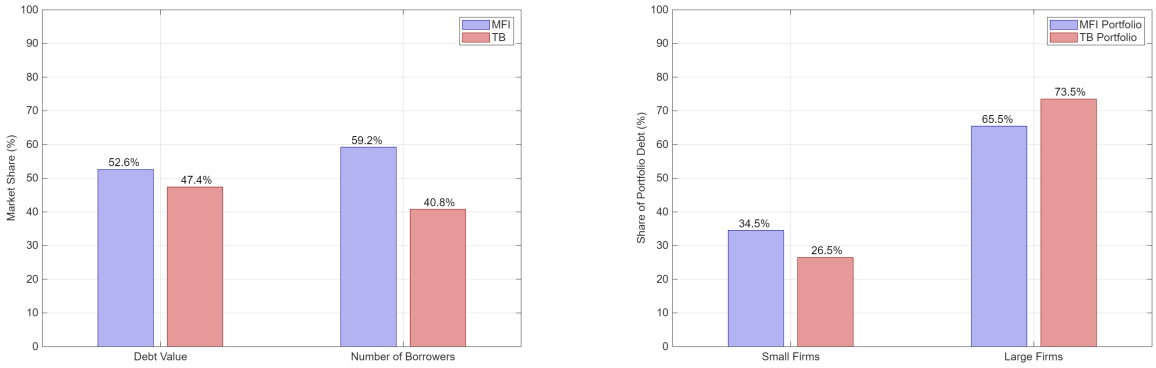
set the capital share $\alpha = 0.6$ to match the aggregate debt-to-sales ratio. The fixed cost of becoming a hard-information firm, c_e, is chosen to replicate the share of informal borrowers in the economy, where informality is proxied by the tax category "natural person with business". The parameters of the truncated Pareto signal (ξ and the upper bound) are calibrated to match the share of total debt held by large borrowers, while the risk-distribution parameters α_σ and β_σ target the average delinquency rate. The lender cost parameters $\{c_f^j\}$ are chosen to match the average interest rates paid by informal versus formal borrowers. Finally, we set the recovery rate $\delta = 0.1$ based on regulatory estimates, and the relationship value $\psi_F = 2.5$, consistent with a 10% profit margin on a perpetuity discounted at 4%. These parameters and their targets are summarized in the top panel of Table A11 in the Appendix.

Second, we calibrate the parameters governing the loan guarantee program and the recession shock. The total program size M is set to 25% of aggregate outstanding debt. The MFI participation share γ_{MFI} is set to 20%, matching its observed share in the data. The poaching probability ψ_C is calibrated to 0.1 to match the coefficient from an OLS regression of lender switching on guaranteed loan receipt. The credit injection parameter φ is chosen to replicate the estimated average debt increase among program recipients. Finally, we parameterize the liquidity shock distribution $\widetilde{\Phi}(\nu;\eta) = (\nu/c_0)^\eta$ over $[0, c_0]$, where η controls shock severity. The parameters c_0 and η are jointly calibrated to match our empirical estimates of treatment effects by firm size. The bottom panel of Table A11 summarizes these program-related parameters and their targets.

Figure 6 evaluates how well the calibrated model matches key stylized facts of the Peruvian credit market. Panel (a) displays market shares by lender type. Consistent with the descriptive statistics in Section 2, MFIs account for approximately 53% of total debt and, given their specialization in smaller clients, serve about 60% of all borrowers. Panel (b) shows portfolio composition by firm size, where small firms are defined as those in the bottom nine deciles of the debt distribution–similar to our empirical classification. The model

successfully reproduces the lender specialization documented earlier: traditional banks allocate 74% of their lending to large firms, whereas MFIs allocate only 66% of their portfolio to this segment, reflecting their greater focus on smaller borrowers.

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



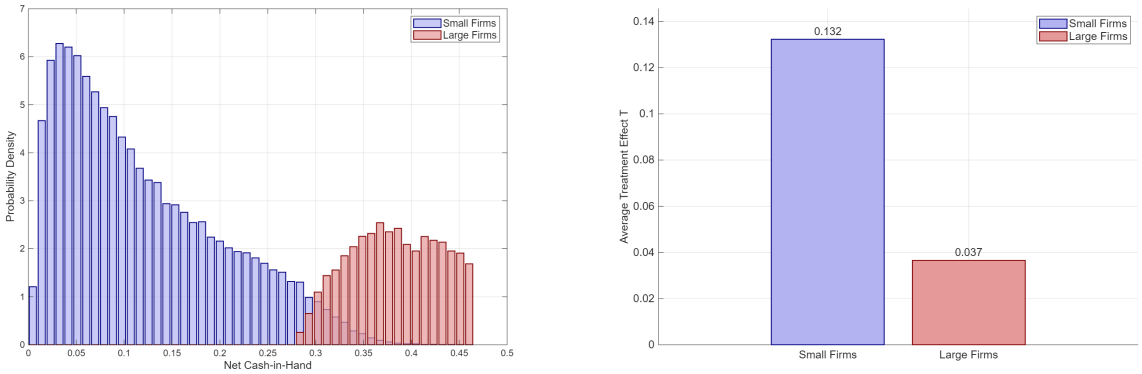
(a) Lender Market Shares **(b)** Portfolio Composition by Lender

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 presents equilibrium outcomes by firm size. Panel (a) displays the distribution of net cash-in-hand, defined as $y - rk$, separately for small (blue bars) and large (red bars) firms. Two key patterns emerge. First, small firms are concentrated at lower net-cash values, making them more vulnerable to liquidity shocks. The effect of loan guarantees is non-linear over this distribution: firms at the very bottom may fail even with a guarantee, while those in the middle experience the largest survival probability gains. Second, large firms are predominantly located at higher net-cash levels, implying they are more likely to survive a shock even without government support. Panel (b) plots the average treatment effect T_i by size group. Consistent with our empirical estimates, the treatment effect is approximately

four times bigger for smaller firms.

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.

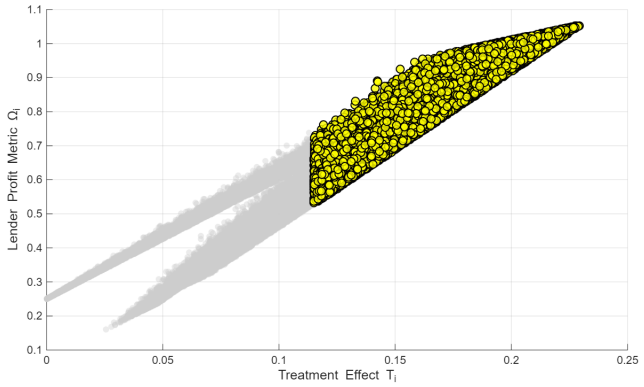
6.6 Equilibrium and Counterfactual Analysis

We use our calibrated model to quantify how MFIs shape the allocation and aggregate effectiveness of loan guarantees during recessions. We begin by comparing the social planner's guarantee allocation with that in the decentralized market equilibrium. We then compute the optimal MFI participation rate, defined as the one that minimizes the proportion of debt in default.

Allocation of Guarantees. We compare the allocation of guarantees implemented by the social planner with that emerging in the decentralized market equilibrium. Figure 8 illustrates the social planner's allocation by plotting firms in the space of two characteristics: the lender's private profit metric Ω_i and the treatment effect T_i. Because the social planner maximizes the total value of non-defaulting debt, the optimal allocation follows a simple

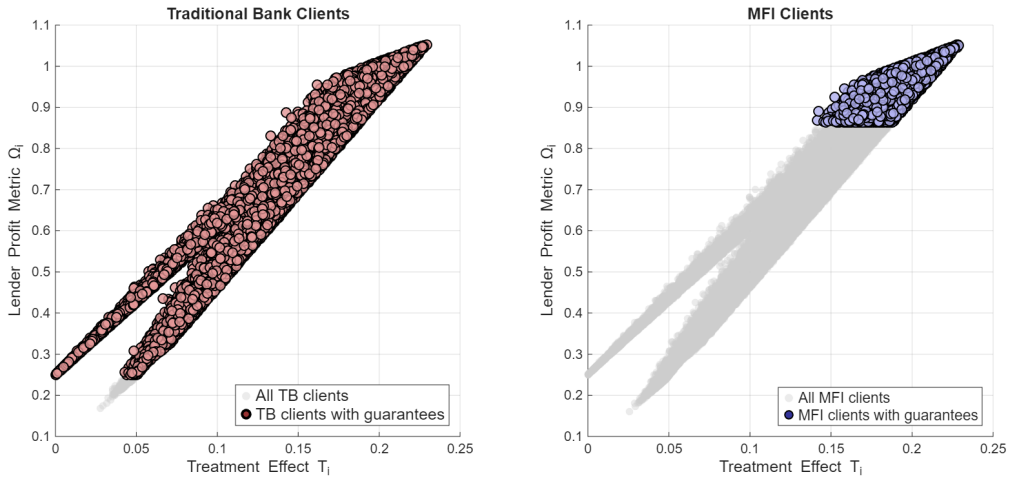
priority rule: rank firms by T_i and allocate guarantees in descending order until the budget constraint binds.

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: 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.

Figure 9 plots the decentralized allocation and illustrates the key trade-off faced by private

lenders. In the left panel, we plot the allocation by traditional banks, who distribute 75% of the guarantee funds, consistent with the data. Banks allocate guarantees by ranking clients according to the private profit metric Ω, selecting those with the highest values. Red dots represent firms that receive a guarantee; gray dots represent those that do not. The right panel shows the corresponding allocation by MFIs, who follow the same Ω-based ranking rule but, with a smaller budget share (25%), reach a more limited set of clients. The figure illustrates that reallocating a portion of the guarantee budget from traditional banks to MFIs would shift guarantees toward clients with higher treatment effects T, thereby increasing the program's overall effectiveness.

Optimal MFIs' Participation. We conduct a counterfactual analysis that varies the share of guarantees distributed by MFIs to identify their optimal participation rate. We define the effectiveness of the program, Δ, as the share of debt at risk of default that is saved by the program:

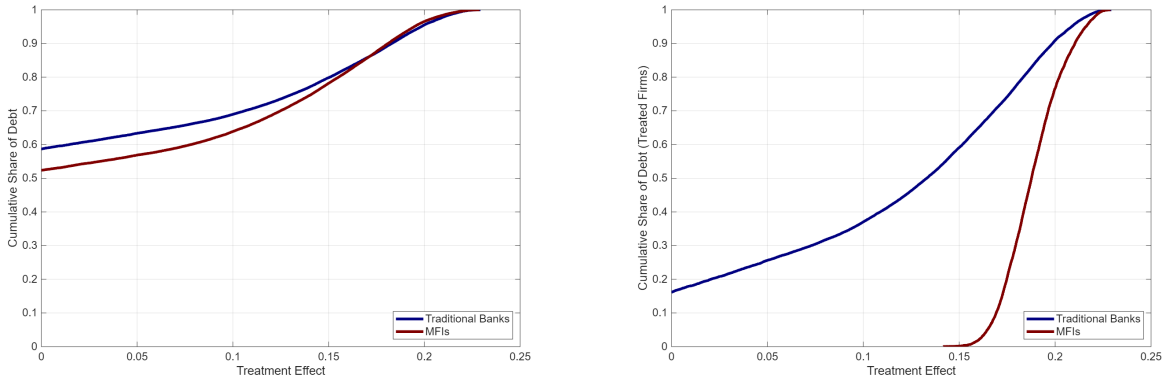
$$\Delta \equiv \frac{\int \ell_i^{\text{TB}}(\Phi_i(1) - \Phi_i(0))(1-\sigma_i)b_i di + \int \ell_i^{\text{MFI}}(\Phi_i(1) - \Phi_i(0))(1-\sigma_i)b_i di}{\int (1 - \Phi_i(0))(1-\sigma_i)b_i di} \tag{10}$$

To understand what drives the optimal MFI participation rate, we first examine how treatment effects vary across each lender's client pool. Panel (a) of Figure 10 plots the debt-weighted cumulative distribution of treatment effects for traditional bank clients (dashed blue line) and MFI clients (solid red line), and shows that a larger share of traditional banks' portfolio consists of low-treatment-effect firms. This implies that banks face greater distortionary pressure toward inframarginal lending–allocating guarantees to firms that would survive even without assistance–compared to MFIs.

Panel (b) shows the same distribution restricted to firms that actually received guarantees under the observed MFI participation rate. The marginal MFI client–the last firm to receive

a guarantee–has a treatment effect exceeding that of approximately 40% of firms served by traditional banks. Moreover, about 20% of traditional bank clients are inframarginal, with treatment effects near zero. These patterns illustrate the core mechanism: reallocating guarantee funds from traditional banks to MFIs shifts resources toward firms with higher marginal benefits, thereby increasing the program's aggregate effectiveness.

Figure 10: Distribution of Treatment Effect by Lender Type



(a) All Clients **(b)** Treated Clients

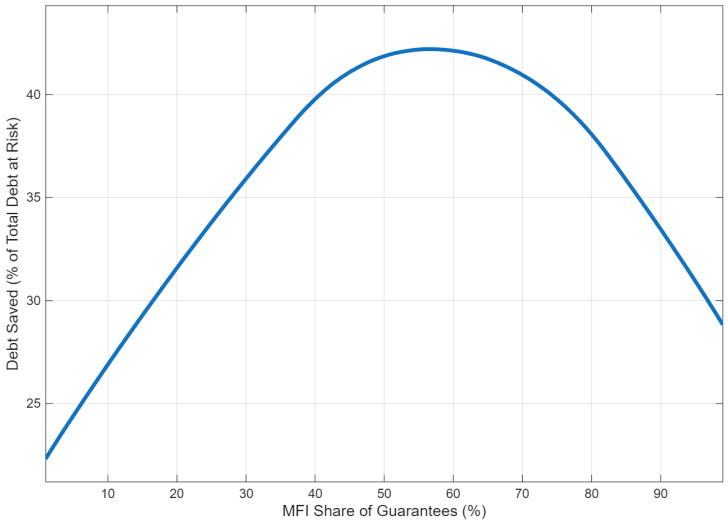
This figure shows the distribution of treatment effects across lender clienteles. Panel (a) plots the debt-weighted cumulative distribution of treatment effects T_i for all clients of traditional banks (dashed blue line) and MFIs (solid red line). Panel (b) restricts the sample to firms that received guarantees under the observed MFI participation rate of 25%.

Figure 11 confirms this intuition, plotting the program effectiveness Δ against the MFI participation rate γ_{MFI}. The function peaks at $\gamma_{\text{MFI}} = 54\%$, where the program saves approximately 45% of debt at-risk. In contrast, exclusive reliance on traditional banks saves only 22%, while exclusive reliance on MFIs saves 28%. The observed equilibrium ($\gamma_{\text{MFI}} = 0.25$) saves 34%–a substantial improvement over the bank-only counterfactual, but still below the optimum.

Two opposing forces shape this relationship. First, MFIs' comparative advantage in relationship lending means their client pool contains more high-treatment-effect firms. Consequently, in the observed equilibrium, where MFIs receive a small guarantee share, a marginal

dollar allocated through an MFI reaches a firm with a higher treatment effect than a marginal dollar channeled through a traditional bank, which serves more infra-marginal borrowers likely to survive even without assistance. Second, as MFIs distribute more guarantees, they must extend loans to firms with progressively lower treatment effects, such as very small firms that would not survive even with assistance, diluting their marginal effectiveness. The optimal participation rate balances these two margins.

Figure 11: Debt Saved by the Program and 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 yields three key insights. First, the decentralized market allocation deviates from the constrained first-best because private lenders overweight firms' probability of survival absent the program. Second, incorporating MFIs into the program mitigates this distortion: their specialization in smaller, opaque firms allows them to channel guarantees toward more responsive borrowers. Third, optimal program design involves balancing the marginal benefits of MFI specialization against the marginal costs of extending guarantees

to smaller firms that would not survive even with assistance.

6.7 Extensions

Our quantitative findings are informative for settings where MFIs exhibit low delinquency rates and can distribute guarantees as efficiently as traditional banks. However, these characteristics vary across contexts and may alter the results. To broaden the applicability of our analysis, we extend our model in three directions that capture relevant dimensions of cross-country heterogeneity in MFI development.

First, we introduce an additional cost for MFIs when distributing loan guarantees, capturing constraints such as limited digital infrastructure or scalability that may hinder their effectiveness. Second, we allow MFIs to specialize in riskier borrowers relative to traditional banks. Third, we incorporate lender monitoring incentives that weaken when loans are guaranteed by the government.

MFIs inefficiency in distributing loan guarantees. A potential concern with channeling guarantees through MFIs is that their less sophisticated infrastructure may lead to higher distribution costs, potentially dampening the program's aggregate effectiveness. To capture this, we introduce a parameter $\tau \in [0, 1]$ that measures the inefficiency of MFI distribution. When $\tau = 0.5$, for example, every *Sol* of guaranteed credit reaching a firm requires the government to provide 1.5 *Soles* to the MFI. We then compute the optimal MFI participation rate for each level of inefficiency.

This extension speaks directly to a key feature of our setting: higher distribution costs led to uncompetitive interest rate bids, limiting MFI participation at the beginning of the program. In response, the Peruvian government launched MFI-specific auctions, offering guaranteed credit at interest rates above those prevailing for traditional banks. By mapping inefficiency to optimal participation, our analysis reveals a key trade-off inherent in such

policies: expanding MFI participation may improve allocation but at the cost of higher program expenditure. This enables us to quantify how distribution costs shape optimal program design.

Higher distribution costs reduce the effective loan volume that reaches firms for a given government expenditure through MFIs. This creates a tension in optimal program design: redirecting guarantees toward traditional banks increases the total value of credit effectively distributed–since banks face lower costs–but at the expense of moving funds away from MFI clients, who tend to have higher treatment effects. The optimal MFI participation rate balances these margins, trading off the efficiency gain from larger effective loan volume against the loss from worse targeting.

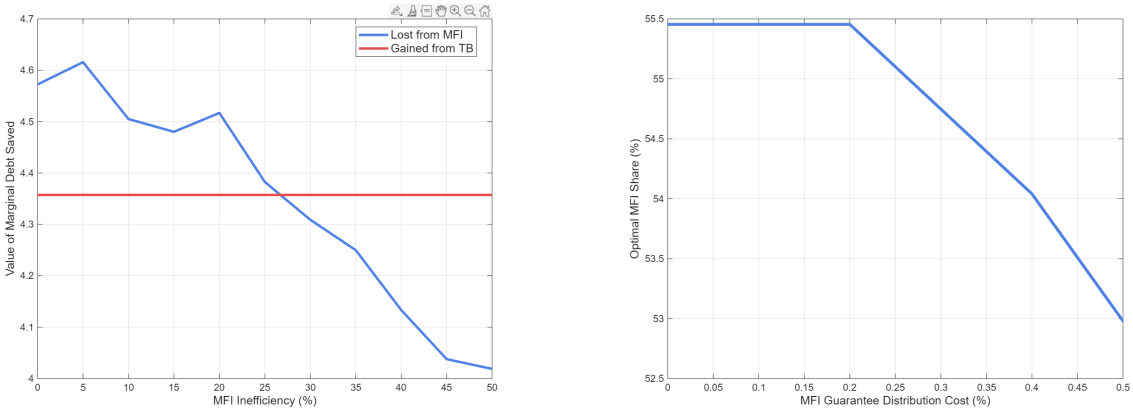
To illustrate how distribution costs reshape optimal MFI participation, we start from the frictionless optimum and consider a marginal reallocation: we shift 1% of the guarantee budget from MFIs to traditional banks. This reallocation has two effects. First, some former MFI clients–specifically, those with the lowest Ω among treated firms–lose access to guarantees, reducing the total debt saved from default. Second, new traditional bank clients gain access, increasing debt saved.

Panel (a) of Figure 12 plots these gains and losses across different levels of MFI distribution costs. The gains from reallocating guarantees to traditional banks are constant, as they depend only on the treatment effects of the marginal bank clients. The losses from withdrawing guarantees from MFI clients, however, decline with inefficiency. At low inefficiency levels, below 25%, the losses exceed the gains, making it optimal to maintain MFI participation. Once inefficiency rises above 25%, the losses become smaller than the gains, tilting the optimal allocation toward traditional banks.

Larger losses from a marginal reduction in MFI participation do not imply that increasing their share would be beneficial. The relevant test for an expansion requires comparing the marginal benefit of directing more guarantees through MFIs against the marginal cost

of shifting those guarantees away from traditional banks. Panel (b) of Figure 12 plots the optimal MFI share across inefficiency levels. For inefficiency below 25%, the optimal share remains constant at the frictionless level. In this region, the marginal gains from reallocating guarantees toward MFIs are offset by the distribution costs they incur, while the marginal gains from reallocating toward traditional banks are offset by their poorer targeting of high-treatment-effect firms. Above 25%, rising inefficiency makes further MFI participation increasingly costly, and the optimal share declines monotonically. Given the observed interest rate differential on MFI guarantees relative to traditional banks, the optimal MFI participation rate remains within the constant region.

Figure 12: Distribution Costs and Optimal MFI Participation



(a) Marginal Gains and Losses from Reallocation **(b)** Optimal MFI Participation Rate

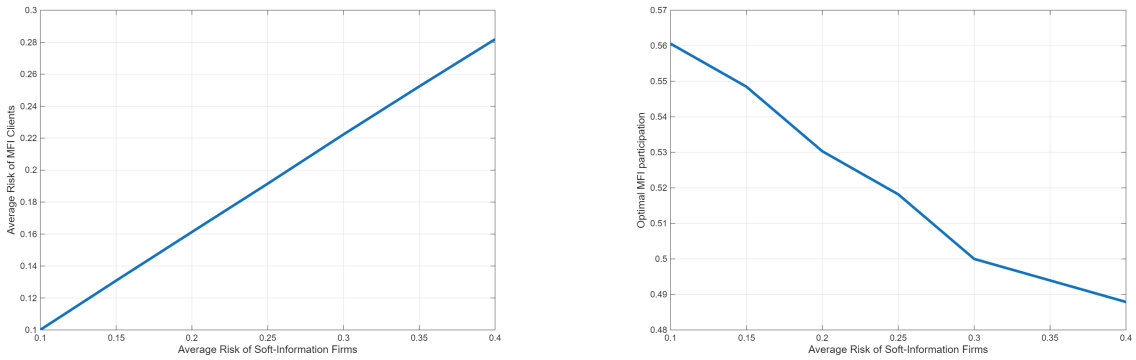
This figure shows how distribution costs shape optimal MFI participation. Panel (a) plots the marginal impact of reallocating 1% of guarantees from MFIs to traditional banks for different levels of distribution inefficiency τ. Panel (b) plots the resulting optimal MFI participation rate.

MFIs specialization in risky borrowers. In our baseline equilibrium, MFI and traditional bank clients exhibit similar levels of risk, consistent with the Peruvian financial sector. However, in other contexts, MFIs may serve riskier borrowers than traditional banks, which could affect their optimal participation in government programs, as their clients are more likely to default regardless of whether they receive guarantees.

We extend our framework to capture these differences in risk across lenders. We depart from the baseline assumption that the risk distributions of soft- and hard-information firms are equivalent and instead assume that soft-information firms are riskier. We do so by shifting the Beta distribution parameter α_s from 2 to 8 while holding the sum $\alpha_s + \beta_s$ constant, generating variation in the risk profile of soft-information clients. For example, $\alpha_s = 2$ implies an expected default probability of 0.1 for soft-information firms, while $\alpha_s = 8$ raises this expectation to 0.4.

Panel (a) of Figure 13 plots the average risk of MFI clients for different levels of soft-information risk. Given their specialization in soft-information firms, the average default probability of MFI clients rises from 0.10 to 0.28 as soft-information firms become riskier. Consequently, the optimal MFI participation rate declines from 56% to 49%, as shown in Panel (b). This is because riskier clients are more likely to default regardless of guarantee receipt, reducing the marginal benefit of increasing MFI participation.

Figure 13: Optimal MFI Participation with Riskier Borrowers



(a) Average Risk of MFI Clients **(b)** Optimal MFI Participation Rate

This figure shows how borrower risk shapes optimal MFI participation. Panel (a) plots the average default probability of MFI clients as we shift α_s, making soft-information firms riskier. Panel (b) plots the resulting optimal MFI participation rate. The parameter α_s governs the risk distribution of soft-information firms; higher values imply riskier borrowers. We hold $\alpha_s + \beta_s$ constant to isolate the shift in the distribution's mean. The x-axis reports $\frac{\alpha_s}{\alpha_s+\beta_s} \times 0.5$, which maps to the implied expected default probability of soft-information firms.

We conduct a second extension in which MFI risk exposure arises endogenously from their comparative advantage in serving risky firms. Specifically, we allow traditional banks' loan origination costs for soft-information firms to increase with borrower risk, capturing their limited capacity for relationship lending–a technology better suited to mitigating information frictions with riskier clients. In our model, this cost structure generates a higher equilibrium market share for MFIs among risky, soft-information borrowers.

Figure A7 in the Appendix plots the optimal MFI participation rate against θ, which governs the convexity of traditional banks' cost function with respect to borrower risk. As θ increases, traditional banks become less competitive in the risky segment, and MFIs gain market share among these borrowers. Consequently, the marginal benefit of allocating additional guarantees through MFIs declines because their clients are more likely to default regardless of whether they receive a guarantee. Unlike the previous extension where we exogenously shifted the risk distribution, here risk exposure emerges endogenously from lender competition.

Monitoring incentives. A potential concern with government guarantees is that they may weaken lenders incentives to monitor borrowers. To explore this channel, we develop an extension in the online appendix following Holmstrom and Tirole (1997). In this setting, lenders commit to costly monitoring before the recession, which enhances repayment probabilities. The unexpected liquidity shock increases default risk, while the guarantee program reduces firms' net debt obligations. Lenders therefore allocate guarantees and adjust monitoring simultaneously.

Although MFIs continue to target high-treatment-effect firms, the reduction in monitoring increases default risk even for firms who receive guaranteed loans. This effect is most pronounced for soft-information borrowers, where relationship-based monitoring is most valuable. Since MFIs specialize in this segment, the decline in monitoring incentives dispropor-

tionately affects them, leading to a lower optimal participation rate.

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 during economic crises. By developing a theoretical framework that highlights the role of lender specialization and testing its predictions using a large-scale loan guarantee program in Peru, we provide evidence on how MFIs shape the effectiveness of financial stimulus during economic downturns in developing countries.

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, segments facing the most severe liquidity needs. MFIs played a central role in channeling guarantees to these high-sensitivity segments, reflecting their pre-recession specialization in relationship-based lending. We develop and calibrate a model in which lenders specialize in different client types. The model reveals that distributing guarantees solely through traditional banks would have saved only 22 percent of debt at risk of default, whereas the actual allocation, which included MFIs, raised this ratio to 34 percent.

Our results have important policy implications. Specialized lenders such as MFIs are relevant 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 inevitably serve clients with lower treatment effects, reducing the aggregate effectiveness of guarantees.

References

Angelucci, M., Karlan, D., and Zinman, J. (2015). Microcredit impacts: Evidence from a randomized microcredit program placement experiment by compartamos banco. *American Economic Journal: Applied Economics*, 7(1):151–82.

Attanasio, O., Augsburg, B., De Haas, R., Fitzsimons, E., and Harmgart, H. (2015). The impacts of microfinance: Evidence from joint-liability lending in mongolia. *American Economic Journal: Applied Economics*, 7(1):90–122.

Augsburg, B., De Haas, R., Harmgart, H., and Meghir, C. (2015). The impacts of microcredit: Evidence from bosnia and herzegovina. *American Economic Journal: Applied Economics*, 7(1):183–203.

Bach, L. (2014). Are Small Businesses Worthy of Financial Aid? Evidence from a French Targeted Credit Program. *Review of Finance*, 18(3):877–919.

Bachas, N., Kim, O. S., and Yannelis, C. (2021). Loan guarantees and credit supply. *Journal of Financial Economics*, 139(3):872–894.

Balyuk, T., Prabhala, N., and Puri, M. (2021). Small Bank Financing and Funding Hesitancy in a Crisis: Evidence from the Paycheck Protection Program. Working paper.

Barrot, J.-N., Martin, T., Sauvagnat, J., and Vallée, B. (2024). The Labor Market Effects of Loan Guarantee Programs. *The Review of Financial Studies*, 37(8):2315–2354.

Blickle, K., Parlatore, C., and Saunders, A. (2023). Specialization in Banking. Working Paper 31077, NBER Working Paper Series.

Bonfim, D., Custódio, C., and Raposo, C. (2023). Supporting small firms through recessions and recoveries. *Journal of Financial Economics*, 147(3):658–688.

Breza, E. and Kinnan, C. (2021). Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis. *The Quarterly Journal of Economics*, 136(3):1447–1497.

Brown, J. D. and Earle, J. S. (2017). Finance and Growth at the Firm Level: Evidence from SBA Loans. *The Journal of Finance*, 72(3):1039–1080.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2020). The Macroeconomics of Microfinance. *The Review of Economic Studies*, 88(1):126–161.

Cerda, M., Gertler, P., Higgins, S., Montoya, A. M., Parrado, E., and Undurraga, R. (2023). The Causal Impact of Covid-19 Government-backed Loans on MSMEs Liquidity and Earnings.

Core, F. and De Marco, F. (2024). Information Technology and Credit: Evidence from Public Guarantees. *Management Science*, 70(9):6202–6219.

González-Uribe, J. and Wang, S. (2022). The Real Effects of Small-Firm Credit Guarantees during Recessions. Working paper.

Granja, J., Makridis, C., Yannelis, C., and Zwick, E. (2022). Did the paycheck protection program hit the target? *Journal of Financial Economics*, 145(3):725–761.

Griffin, J., Kruger, S., and Mahajan, P. (2023). Did FinTech Lenders Facilitate PPP Fraud? *The Journal of Finance*, 78(3):1777–1827.

Haas-Ornelas, J., Pedraza, A., Ruiz-Ortega, C., and Silva, T. (2021). Credit Allocation When Private Banks Distribute Government Loans. Working paper, Central Bank of Brazil.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector*. *The Quarterly Journal of Economics*, 112(3):663–691.

Joaquim, G. and Netto, F. (2022). Bank Incentives and the Effect of the Paycheck Protection Program.

Kaboski, J. P. and Townsend, R. M. (2011). A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica*, 79(5):1357–1406.

Lelarge, C., Sraer, D., and Thesmar, D. (2010). Entrepreneurship and Credit Constraints: Evidence from a French Loan Guarantee Program. *International Differences in Entrepreneurship*, pages 243–273.

Mullins, W. and Toro, P. (2018). Credit Guarantees and New Bank Relationships. Working Paper 820, Central Bank of Chile.

Paravisini, D., Rappoport, V., and Schnabl, P. (2023). Specialization in bank lending: Evidence from exporting firms. *The Journal of Finance*, 78(4):2049–2085.

Ru, H. (2018). Government Credit, a Double-Edged Sword: Evidence from the China Development Bank. *The Journal of Finance*, 73(1):275–316.

Tarozzi, A., Desai, J., and Johnson, K. (2015). The impacts of microcredit: Evidence from ethiopia. *American Economic Journal: Applied Economics*, 7(1):54–89.

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: $\sum_c \left(L_{cb}/L_b\right)^2$

Table A3: Effect of Loan Guarantees on New Lending Relationships

	Value of New loans		Share of New Loans	
	(1)	(2)	(3)	(4)
$\text{Exposure}_b \times \text{Post}_t$	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)
Exposure$_i$× Post$_t$	-0.021***			-0.009*		
	(0.004)			(0.005)		
Treated$_i$× Post$_t$		-0.122***			-0.039*	
		(0.024)			(0.021)	
ln 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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)
$\text{Exposure}_i \times \text{Post}_t$	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)
Exposure$_i$× Post$_t$	-0.022***			-0.016***		
	(0.004)			(0.005)		
Treated$_i$× Post$_t$		-0.130***			-0.099***	
		(0.021)			(0.031)	
ln 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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: 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$_i$× Post$_t$	-0.028***			-0.024**		
	(0.008)			(0.009)		
Treated$_i$× 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$_i$× Post$_t$	-0.021***			-0.009***		
	(0.001)			(0.002)		
Treated$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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 A9: 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$_i$× Post$_t$	-0.024***			-0.021**		
	(0.008)			(0.009)		
Treated$_i$× 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$_i$× Post$_t$	-0.022***			-0.009***		
	(0.001)			(0.002)		
Treated$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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 - High-Contact

Panel A						
	MFI share = 1			MFI share $\in (1, 0.5]$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure$_i$× Post$_t$	-0.027***			-0.022**		
	(0.008)			(0.010)		
Treated$_i$× 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$_i$× Post$_t$	-0.010			-0.001		
	(0.007)			(0.003)		
Treated$_i$× 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
$x^{\text{Real}}(f)$ × Quarter	Yes	Yes	Yes	Yes	Yes	Yes
$x^{\text{Fin.}}(f)$ × 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.

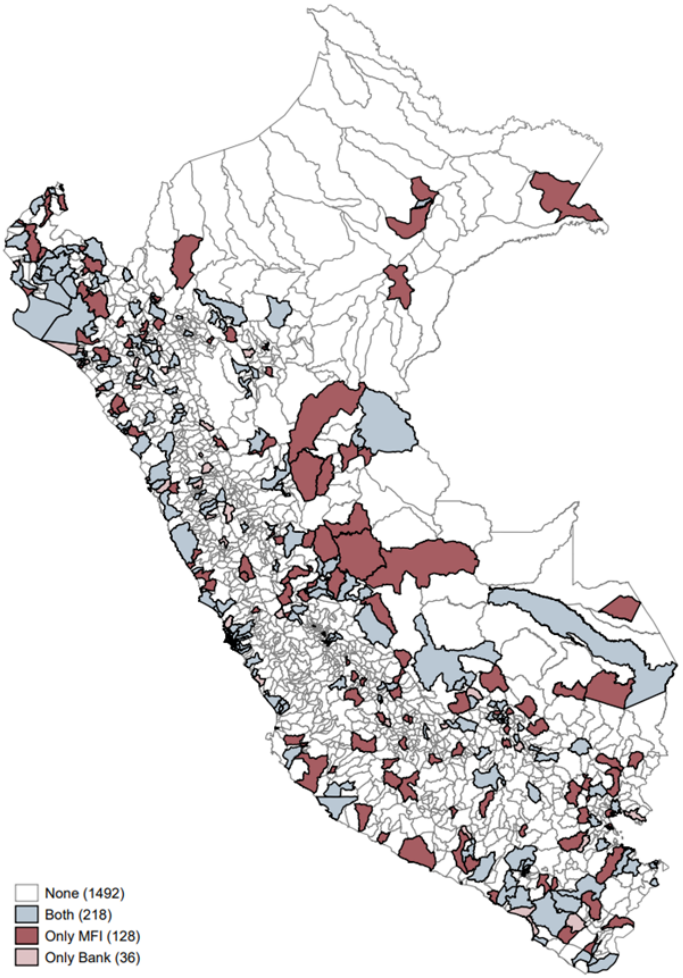
Table A11: Model Calibration

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.

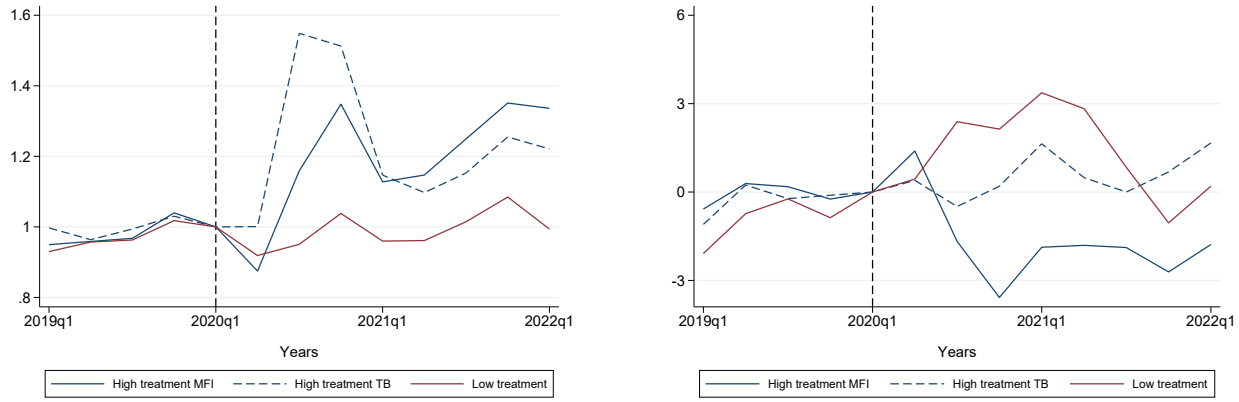
Appendix B: Additional Figures

Figure A1: Geographical Distribution of Financial Institutions



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. The confidence interval is at the 95% level.

Figure A2: Credit, Delinquency and Bank Treatment

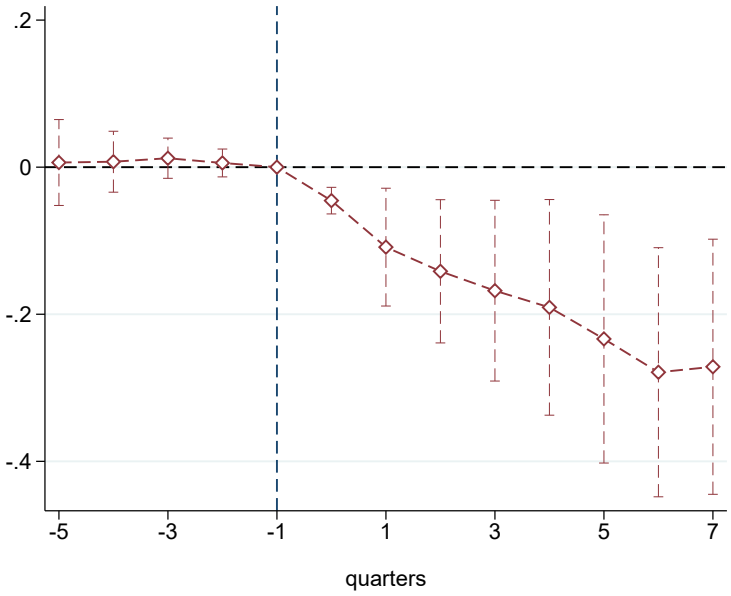


(a) Total Loans

(b) Delinquency Rates

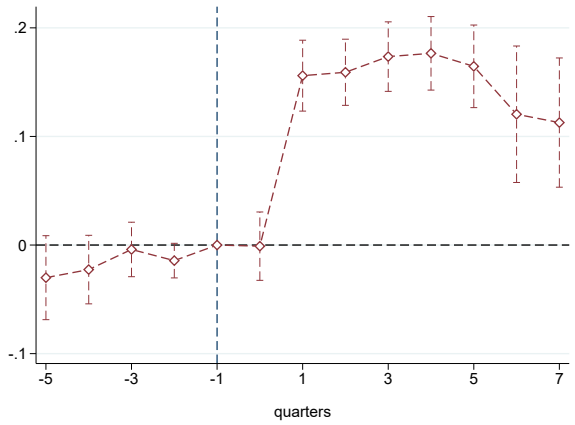
This figure plots the evolution of credit and delinquency rates for high and low treated banks according to our measure of treatment defined by equation (2). Panel (a) plots credit growth rate measured by the value of credit in a given point in time relative to the corresponding value in 2019q4. Panel (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: Effect of the Program on Non-Guaranteed Loans

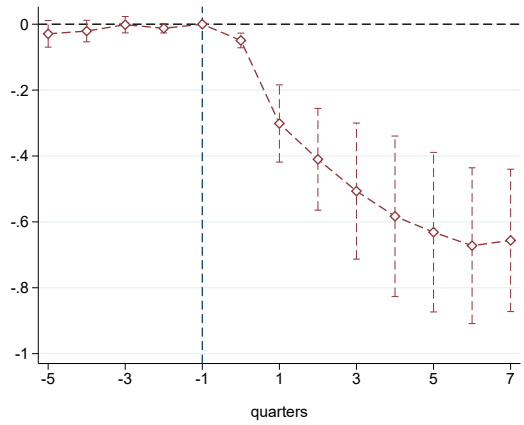


This figure plots the quarterly effects of the program on total credit and non-Covid loans at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. We normalize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

Figure A4: Lending Relationships and Credit



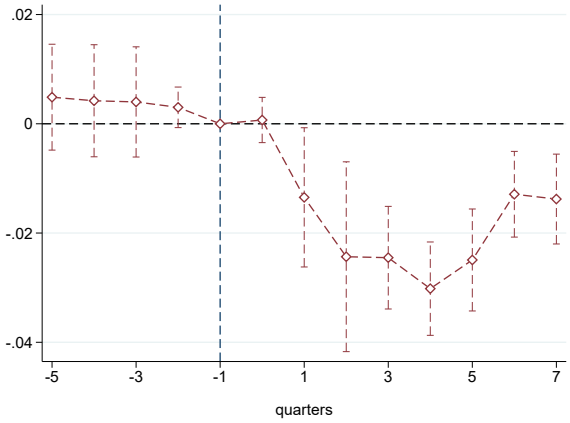
(a) Total Loans



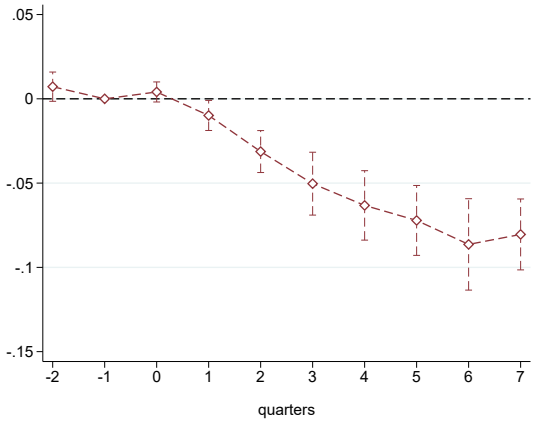
(b) Non-Guaranteed Loans

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



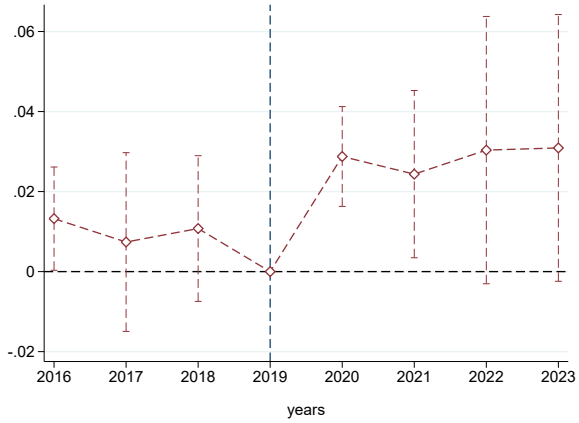
(a) Delinquency Rates



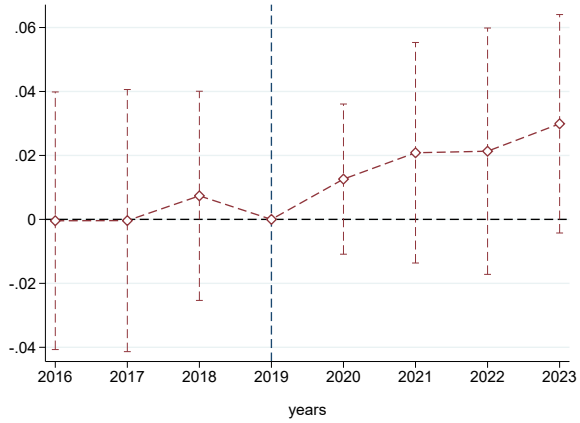
(b) Exit Rate

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.

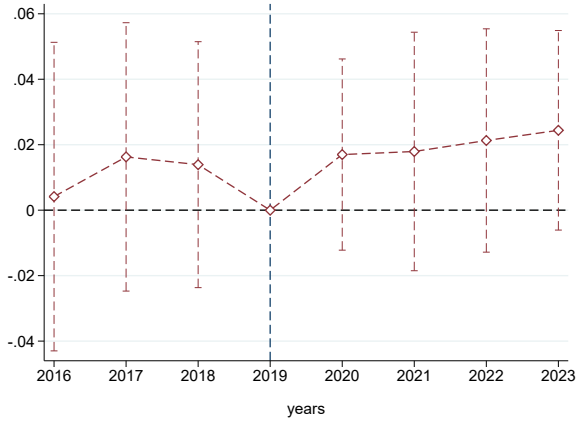
Figure A6: Lending Relationships and Real Outcomes



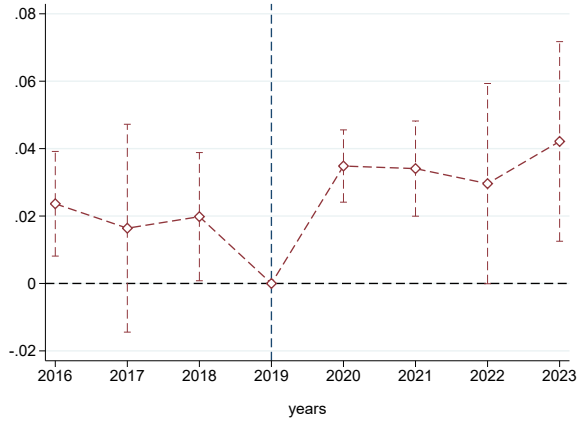
(a) Capital



(b) Wage-bill



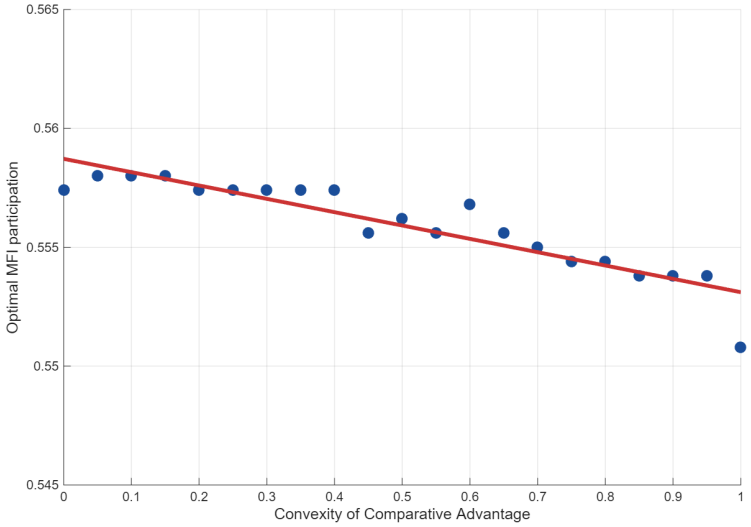
(c) Num. Workers



(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.

Figure A7: Optimal MFI participation rate with convexity of TB cost function



Appendix C: Back-of-the-Envelope Calculation

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

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

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

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

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

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

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

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

Thus, the program saved the following share of debt from default:[15]

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

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:

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

Finally, we have:

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

[15] 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.