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Loan Guarantees and Bank Incentives: Evidence from Covid-19 Relief Funds in Peru

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Abstract

We estimate the effects of loan guarantees on delinquency rates during economic downturns and explore how the allocation of such guarantees shapes its aggregate effect. We do so by studying a large program of loan guarantees implemented by the Central Reserve Bank of Peru and the Peruvian government, aimed at providing liquidity to the financial system in order to prevent disruptions in the supply chain. We find that the program expanded credit supply and reduced delinquency rates. A 10 percent increase in credit is associated with a 1.4 percentage points decline in the probability of experiencing repayment delays for the average firm. This elasticity is significantly bigger among small firms operating in highly exposed industries. However, these firms obtain less credit when participating in the program, due to their reduced operating scale and borrowing capacity (relative to bigger firms) and financial institutions' own credit assessment. Our results suggest that targeting more sensitive firms matter for the aggregate impact of the program. Thus, by implementing auctions for different segments of the credit market, which increased competition among financial institutions, the Central Bank improved the effectiveness of the program in terms of delinquency rates and financial stability.

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1 Introduction

Loan guarantees are a key policy tool used to promote economic development by helping young and small firms with low collateral to obtain bank credit. They have been also implemented to preserve jobs and financial stability in recessions by providing liquidity to firms in need of external financing. These programs are usually implemented through private banks to avoid public banks political incentives that might conflict with social goals. In this paper, we estimate the effects of loan guarantees on delinquency rates during economic downturns and explore how the allocation of such guarantees shapes its aggregate effects.

The response of delinquency rates and financial stability is a priori unclear. Risk-shifting incentives associated with an expansion of firms debt may lead to an increase in delinquency rates and a deterioration of financial stability. Moreover, banks providing loans that are collateralized by the government may have low incentives to screening borrowers, increasing aggregate risk. On the other hand, firms exposed to liquidity shocks during economic downturns may need external financing to survive and repay their debt. Thus, whether loan guarantees weakens or strengthens financial stability in recessions is an empirical question. Bank incentives might also play a role in shaping the effects of loan guarantees. Banks might prefer to attend bigger clients that represent a bigger share of their portfolio and, since bigger clients have better access to external financing, they may be less sensitive to the program in terms of delinquency rates. Banks might also prefer to attend more profitable firms, which are not necessarily the most sensitive ones, in particular during recessions driven by shocks that are not evenly distributed across industries or regions. Thus, whether the allocation of guarantees matters for the aggregate impact of the program is also an empirical question.

We address these questions in the context of *Reactiva Perú*. This was a macro program initially designed by the Central Bank of Peru to provide liquidity to the financial system and prevent supply chain disruptions. The central bank provided liquidity through repos and received loans backed by government guarantees as collateral. The government guarantees were given through separate auctions depending on the size of the firm, to improve the distributions of the relief funds and foster the competition among financial institutions.

We use loan-level data covering the universe of lending relationships that firms have with each bank established in Peru in a quarterly frequency between 2019 and 2021. For each lending relationship we observe the balance of loans, the number of days of repayment delay, and the city where the loan was originated. On the firm side, we observe the industry where firms operate, a measure of firm risk, and age.

We estimate the effects of the program using a difference-in-differences strategy that exploits variation in banks takeover of loan guarantees. We construct a continuum measure of treatment in the spirit of the "reimbursement shock" proposed by Granja et al. (2022) and identify the effect of loan guarantees on credit supply by comparing the balance of loans that firms have with more treated banks relative to less treated ones, before and after the program. Our identifying assumption is that absent the program, credit provided by more and less treated banks would have followed parallel trends. We provide evidence supporting our identification in two ways. First, we plot event study graphs showing that our measure of treatment had null effects on credit before the program, consistent with the parallel trends assumption. Second, even though our identification does not require for banks to be similar in levels, we include high dimensionality fixed effects to control for unobserved time-varying shocks taking place at different quartiles of the bank size distribution. By comparing similar banks, we deal with concerns related to a potential sorting of *better banks* with *better firms* that might be better prepared to face Covid-19 restrictions.

The first part of the paper estimates the average effect of the program. We start by analyzing the response of credit supply. We do so by using our bank-firm level data to estimate a within regression where we control for any time-varying demand shock at the firm level. We find that banks with one standard deviation higher treatment expand credit supply by 14% after the program. We also find that these banks reduce the supply of non-Covid loans[1] by 35%, which we interpret as evidence of public guarantees partially crowding out the normal activity of banks. Then, we estimate the role of lending relationships in shaping firm access to the program. We do so by aggregating our data at the firm level and computing a measure of treatment that indicates how well connected firms are to treated banks. This measure is equal to the weighted average bank treatment, where weights are based on the outstanding debt that firms had with each bank before Covid-19. We find that firms that are one standard deviation better connected to treated banks experience a 12% increase in total loans after the program, despite of a 29% reduction in non-Covid loans, suggesting an important role of lending relationships for the allocation of guaranteed loans. Finally, we estimate the effect of the program on delinquency rates using a difference-in-differences instrumental variable approach. We use our firm-level

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

treatment to instrument total loans and estimate the elasticity of delinquency to credit. We find that a 10% increase in credit leads to a 1.4 ppts decline in the probability of experiencing repayment delays. Our findings indicate that the need of external financing associated with Covid-19 restrictions played a more important role than risk-shifting and weak screening in shaping the response of delinquency for the average firm.

The second part of the paper studies the heterogeneous effects of the program and the allocation of guaranteed loans. We first rely on the following characteristic of the Peruvian market of corporate loans. Corporate loans are divided in five segments: loans to micro-firms, small firms, medium-size firms, large firms, and corporations. Firms are assigned to each of these segments depending on their sales and outstanding debt in the banking sector. We find that micro and small firms exhibit a bigger elasticity of delinquency to credit, consistent with smaller clients facing stronger needs of external financing in recessions. However, these firms receive less credit when participating in the program, due to their relative smaller scale and their consequent lower borrowing capacity, and due to financial entities' own credit assessment. This suggest that, by implementing separate auctions for different segments of the market of corporate loans, the Central Bank strengthened the effectiveness of the program.

Since these segments differ in many dimensions related to both, banks and firms characteristics, we focus on small and micro firms, more comparable segments and the most sensitive ones, to explore the role of bank incentives. We split firms in three groups based on their balance of loans before Covid-19. We find that borrowers in the bottom tercile exhibit an elasticity of delinquency that is twice as large as the elasticity in the top tercile. Still, we find that these firms receive less credit when participating in the program. We interpret this finding as evidence that financial institutions prefer to attend bigger clients despite of being less sensitive in terms of delinquency. We then study a second margin of heterogeneity motivated by the nature of the Covid-19 shock, whose effects differ substantially across sectors. We find a significant heterogeneity in the elasticity of delinquency across industries. For example, a 10% increase in credit for the average firm in the sector of hotels and restaurants reduces delinquency in 1.7 ppts while the reduction is only 0.1 ppts in the mining industry. However, we find that firms operating in more sensitive industries receive less credit when participating in the program. We interpret our findings as evidence that financial institutions prefer to attend bigger clients in industries that are less exposed to Covid-19 restrictions despite of their lower sensitivity in terms of delinquency rates.

Overall, our paper shows that government guarantees are effective in expanding credit supply and reducing delinquency rates. Even though the decline in delinquency rates is bigger among small firms operating in highly exposed industries, they obtain less credit when participating in the program. Our results indicate that targeting more sensitive firms is critical to improve the aggregate effect of loan guarantees on delinquency rates and financial stability. Thus, by implementing segment-specific auctions, the Central Bank improved the effectiveness of the program.

Literature Our paper is related to four main strands of the literature. First, we contribute to the literature studying the effects of loan guarantees (Lelarge et al. (2010), Brown and Earle (2017), Mullins and Toro (2018), Ru (2018), Cong et al. (2019), Bachas et al. (2021), Barrot et al. (2020), Haas-Ornelas et al. (2021), González-Uribe and Wang (2021), Bonfim et al. (2022)). We contribute to this literature in two ways. First, we study the effects of loan guarantees on delinquency rates in recessions. We find that this program is effective in reducing repayment delays. Our findings contrast with those documented by Lelarge et al. (2010) in France. We interpret this discrepancy as evidence that the Covid-19 shock generated an unprecedented need of external financing that offset risk-shifting effects associated with loan guarantees. Our second contribution is to focus on the role of private bank incentives in shaping the effectiveness of loan guarantees. We document that even though small borrowers operating in highly exposed industries are more sensitive in terms of delinquency rates, they are less likely to participate in the program and receive less credit when participating. We discuss the role of targeting more sensitive clients to improve the effectiveness of the program. Our results are in line with those reported by Haas-Ornelas et al. (2021) who find that private banks tend to allocate public guarantees to bigger clients in Brazil.

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

We also contribute to the literature that studies political incentives in banking (La Porta et al. (2003), Sapienza (2004), Dinç (2005), Khwaja and Mian (2005), Claessens et al. (2008), Agarwal et al. (2016)). This literature has extensively documented that political connections distort the allocation of public bank credit. We show that private banks incentives can also conflict with social goals in recessions. Our paper indicates that targeting more sensitive firms might improve the allocation of private bank lending. Finally, we contribute to the broad literature that studies the role of public policy in recessions (House and Shapiro (2008), Mian and Sufi (2012), Lucas (2016), Kelly et al. (2016), Zwick and Mahon (2017)). We contribute by studying the effects of loan guarantees, the most common policy worldwide during the Covid-19 crisis.

The remaining of this paper is organized as follows. Section 2 describes our data and the institutional background, and section 3 presents our empirical framework. We report the average effect of loan guarantees in section 4 and explore the heterogeneous effects of the program and the role of targeting in section 5. Section 6 concludes with a brief discussion of our current work.

2 Data and Institutional Background

2.1 Data

We use loan-level data from the *Reporte Crediticio de Deudores* provided by the Central Bank of Peru to estimate the effects of government guarantees on credit and delinquency rates. This is a quarterly panel going from 2019 to 2021 where we observe the balance of loans that firms hold with each bank established in Peru. Our dataset also includes the number of days of repayment delay, type of loan[2], and the city where loans are originated. On the firm side, we observe the industry where firms operate, credit rating (4 categories), and the year when firms obtained their first loan.

2.2 Institutional Background

Reactiva Perú is the loan guarantees program originally designed by the Central Bank of Peru and implemented in May 2020 in coordination with the government. The program consisted on guarantees allocated through first-price sealed-bid auctions where private banks bid on the average interest rate they would charge on these loans. The government provided the guarantees and the Central Bank the funding for these loans. The objective of adopting this auction mechanism was to ensure low interest rates on Covid-19 loans, and, in that sense, to accelerate the pass-through of the reduction in the policy rate to the market rates[3].

There were separate auctions for each of the five types of corporate loans: loans to micro firms, small firms, medium-size firms, large firms, and corporations. This classification is based on firms' sales and balance of credit, and is determined by the Peruvian Bank Supervisor. For example, loans to corporations are those granted to firms whose total sales in the past two years is above USD 60 million, while loans to micro firms are those provided to firms whose total debt in the banking sector is below USD 6 thousand. The guarantees ranged from 80 to 98% of the loan value. Higher guarantees were allocated towards micro and small firms loans. The average Covid-19 loan guarantee was 97% and the loan-size weighted average was 90%. Government guarantees were allocated through separate auctions for different segments of the market of corporate loans to improve the distributions of relief funds among firms with different size.

Private banks were responsible of screening borrowers and allocating Covid-19 loans. These loans were granted between May and December 2020, with an average duration of 36 months. The repayment period started 12 months after the loan was granted, and firms were allowed to repay before if they wanted so. Out of the 52 financial institutions established in Peru, 28

[2]Corporate loans are classified in five groups, as we describe in the Subsection 2.2.

[3]In Peru, the Central Bank implements an explicit inflation target scheme. For that reason, was interested on enhancing the effects of the changes in policy rate during Covid-19 crisis.

participated in the program providing USD 16 billion of Covid-19 loans, which represented 29% of the outstanding debt that firms had by December 2019 and 8% of Peruvian GDP.

2.3 Descriptive statistics

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

Table 1: Peruvian Banking Sector

	Total Loans		Number of	Share Top 5
	Mean	Median	Banks	Banks
	(1)	(2)	(3)	(4)
Total	1 106	169	49	77
Loans to:				
Micro-credit	77	28	42	58
Small firms	190	50	45	56
Medium-size firms	263	13	48	86
Large firms	491	8	27	87
Corporations	1 272	166	13	94

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

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

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

Table 2: Characteristics of Borrowers

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

This table reports summary statistics for borrowers in December 2019. We report the mean and median of the distribution of total loans and age across firms. Repayment delay is an indicator variable such that the average value indicates the share of firms exhibiting repayment delays. Total loans is expressed in USD thousand. Age is equal to the number of years since firms receive their first loan. Number of firms is expressed in thousand.

Table 3: Guaranteed Loans by Type of Credit

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

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

3 Empirical Framework

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

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

where the shares are based on the value of credit. The share of total loans is defined in December 2019 and the share of Covid-19 loans is calculated with data of 2020. Figure 1 plots the distribution of bank treatment in the segment of micro-credit. We can observe a large heterogeneity in banks takeover of public guarantees. The dashed line indicates the median of bank treatment, weighted by pre-Covid market share. We split banks in two groups based on this value and plot the aggregate credit and delinquency rates in each group, high and low-treated banks, in Figure 2. We can observe a bigger expansion of credit among highly treated banks relative to less treated ones together with a decline in delinquency rates.

Figure 1: Distribution of Bank Treatment in Micro-credit

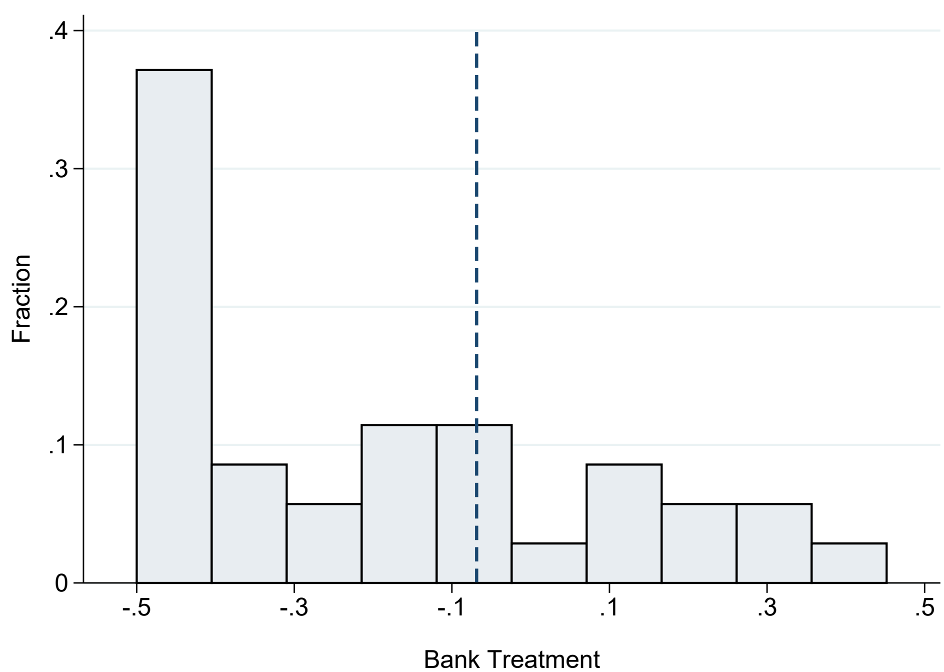
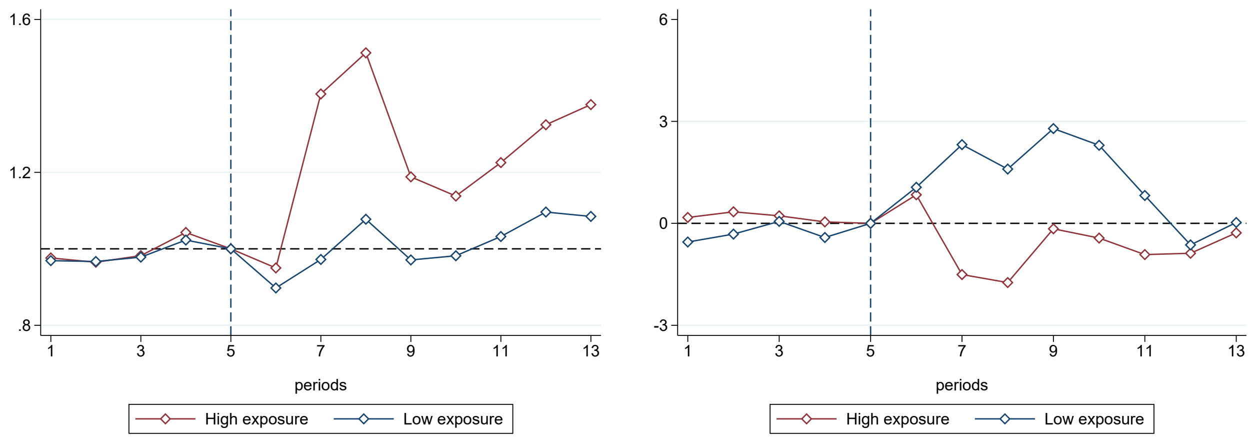


Figure 2: Credit, Delinquency and Bank Treatment



(a) Total Loans

(b) Delinquency Rates

We identify the effect of loan guarantees by comparing the outstanding debt that firms hold with more treated banks relative to less treated ones, before and after the program, using a difference-in-differences approach. Our identifying assumption is that absent the program, credit provided by more and less treated banks would have followed parallel trends, i.e., treatment should have null effects absent the policy.

Bank-firm level specification. We quantify the effect of the program on total loans and non-Covid-19 loans by estimating the following equation:

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

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

$\delta_{q(b)t}$, we compare banks of similar size and deal with this potential concern. Finally, standard errors are clustered at the bank level.

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

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

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

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

where Y_{ikt} denotes the balance of total loans and non-Covid-19 loans (in logs), and delinquency rate[4] of firm i participating in segment k in period t. We include firm-specific fixed effects δ_i to control for any time-invariant heterogeneity across firms. $\delta_{x(i)kt}$ denotes time-varying fixed effects for each segment of the credit market interacted with city, industry, riskiness, age, and pre-Covid debt to account for multiple shocks taking place at such levels. Finally, we cluster standard errors at the firm level.

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

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

4 Average Effects

4.1 Bank-firm level effects

We start by estimating the effect of the program on credit supply. We estimate equation (2) using the log of total loans as the dependent variable. Our results are reported in columns 1-3 in Table 4. We find that one standard deviation higher treatment leads to a 14% increase in credit supply in our benchmark specification reported in column 3. Our results are robust to different specifications that exclude fixed effects as reported in columns 1 and 2.

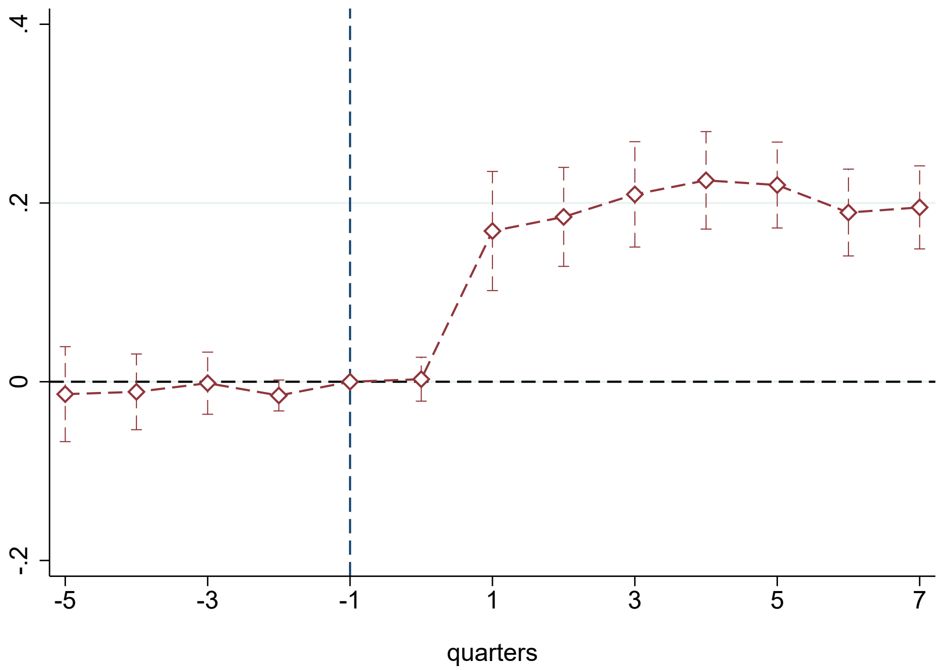
Figure 3 plots event study graphs for the response of credit supply. We show the estimated quarterly treatment effect before and after the program, including the same fixed effects used in our benchmark specification. We normalize the quarter before the program implementation to zero. Treatment had null effects before the policy, which is consistent with our identifying assumption. Moreover, treatment has null effects in the first quarter after the policy when an insignificant number of Covid-19 loans were granted. The balance of loans experience a significant and persistent increase since the third quarter of 2020. Figure A1 in the Appendix plots event-study graphs for the other specifications reported in Table 4, showing no evidence of pre-trends. Our results indicate that the program was effective in increasing credit supply.

Table 4: Effect of the Program on Credit Supply

	Total Loans			Non-Covid-19 Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_{bk}$ × Post$_t$	0.151***	0.108***	0.135***	-0.463***	-0.262**	-0.351***
	(0.041)	(0.041)	(0.016)	(0.133)	(0.117)	(0.088)
Fixed Effects						
Bank	✓	✗	✗	✓	✗	✗
Firm	✓	✗	✗	✓	✗	✗
Quarter	✓	✗	✗	✓	✗	✗
Bank-Firm	✗	✓	✓	✗	✓	✓
Firm-Quarter	✗	✓	✓	✗	✓	✓
Bank size-Quarter	✗	✗	✓	✗	✗	✓
Observations	35,913,552	21,098,394	21,098,391	2,354,898	1,154,385	20,490,615

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.

Figure 3: Effect of the Program on Total Loans

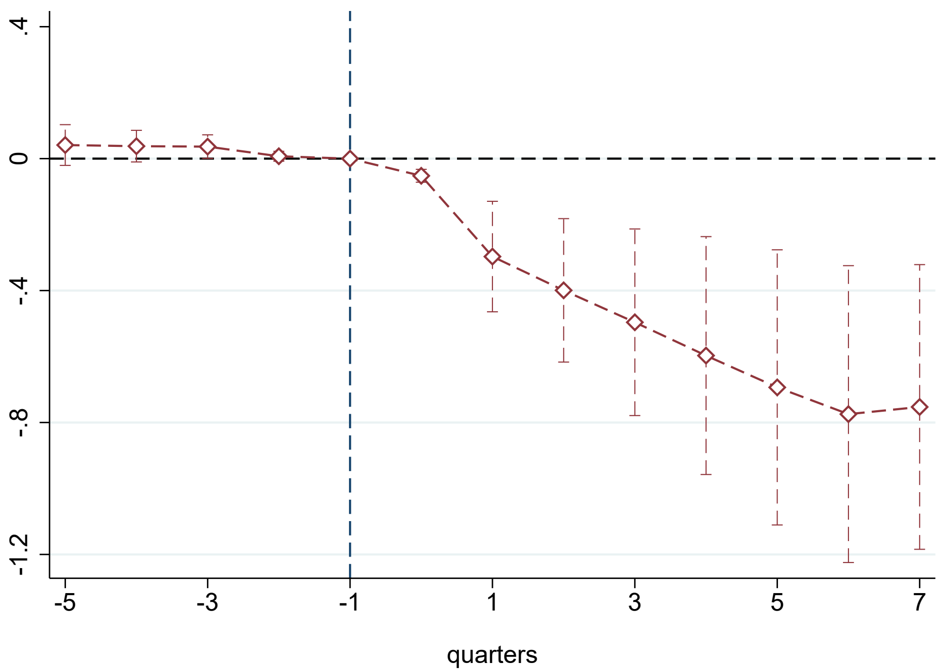


This figure plots the quarterly effects of the program on total credit at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. We normalize the treatment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

A critical question is whether loan guarantees crowd out the normal activity of banks or not (Stiglitz (1993), La Porta, Lopez-de-Silanes, and Shleifer (2002), Ru (2018)). We use our detailed administrative data to evaluate the impact of the program on non-Covid-19 loans. We estimate equation (2) using the log of non-Covid-19 loans as our dependent variable. We report our results in columns 4-6 of Table 4. We estimate that one standard deviation higher treatment leads to a decline of 35% in the supply of non-Covid-19 loans.

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

Figure 4: Effect of the Program on Non-Covid-19 Loans



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

4.2 Firm-level effects

To study how this program affected firms' access to credit and delinquency rates, we aggregate our data at the firm level and calculate treatment as dscribed in equation (3). This is simply a weighted average bank treatment, where weights are based on the outstanding debt that firms have with each bank in December 2019. This variable indicates how well connected firms are with more treated banks. Notice that while the program led to an expansion of credit provided by highly treated banks, it does not mean that better connected firms will receive more credit. If lending relationships were fully flexible, firms that are not well connected will easily switch towards highly treated banks and obtain more credit. Otherwise, if lending relationships were sticky, better connected firms will experience an expansion in credit relative to worse connected ones. To explore the relevance of this first layer of *general equilibrium effects* taking place at the firm level and test the role of lending relationships, we estimate equation (4) using total loans as our dependent variable. Our results are reported in column 1 of Table 5. We find that one standard deviation better connected firms experience a 12% increase in total loans after the program. We report quarterly treatment effects in panel (a) of Figure 5. We observe null effects in the pre-Covid-19 period. We find that better connected firms have more credit, and this effect is significant up to two years after the program implementation. This result indicates that lending relationships play a key role in shaping the ability of firms to obtain Covid-19 loans.

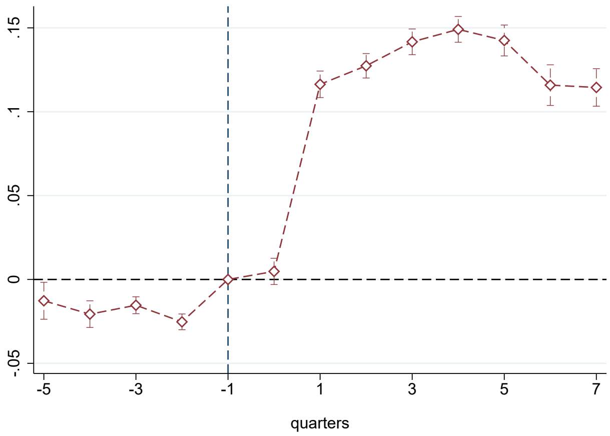
While this result shows that better connected firms obtain more credit, it does not tell us whether non-Covid-19 loans can partially help worse connected firms or not. We address this question by estimating equation (4) using the balance of non-Covid-19 loans as our dependent variable. We report our results in column 2 of Table 5. One standard deviation better connected firms have a 29% lower balance of non-Covid-19 loans relative to worse connected firms after the program. As we discussed in the previous subsection, this result is consistent with public guarantees crowding out the normal activities of private banks. Even though worse connected firms receive more non-Covid-19 loans, it is not enough to offset the response of public guarantees. Panel (b) of Figure 5 reports the quarterly effect of the program.

Table 5: Lending Relationships, Credit, and Delinquency Rates

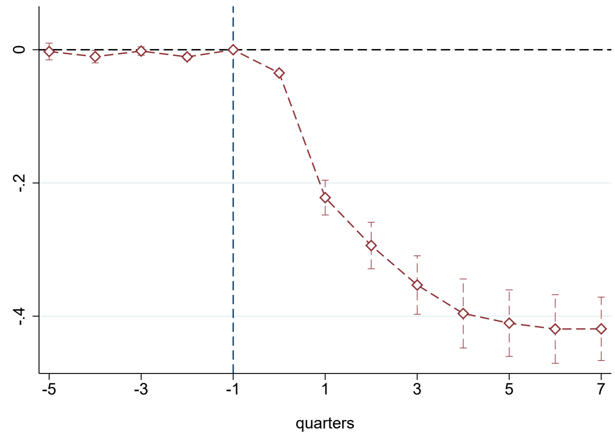
	Total (1)	Non-Covid-19 (2)	Delinquency (3)
$\text{Treatment}_i \times \text{Post}_t$	0.122***	-0.286***	-0.017***
	(0.005)	(0.019)	(0.001)
Fixed Effects			
Firm	✓	✓	✓
City-Segment-Quarter	✓	✓	✓
Industry-Segment-Quarter	✓	✓	✓
Riskiness-Segment-Quarter	✓	✓	✓
Age group-Segment-Quarter	✓	✓	✓
Debt decile-Segment-Quarter	✓	✓	✓
Observations	13,067,434	12,951,125	13,067,434

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

Figure 5: Lending Relationships and Credit



(a) Total Loans



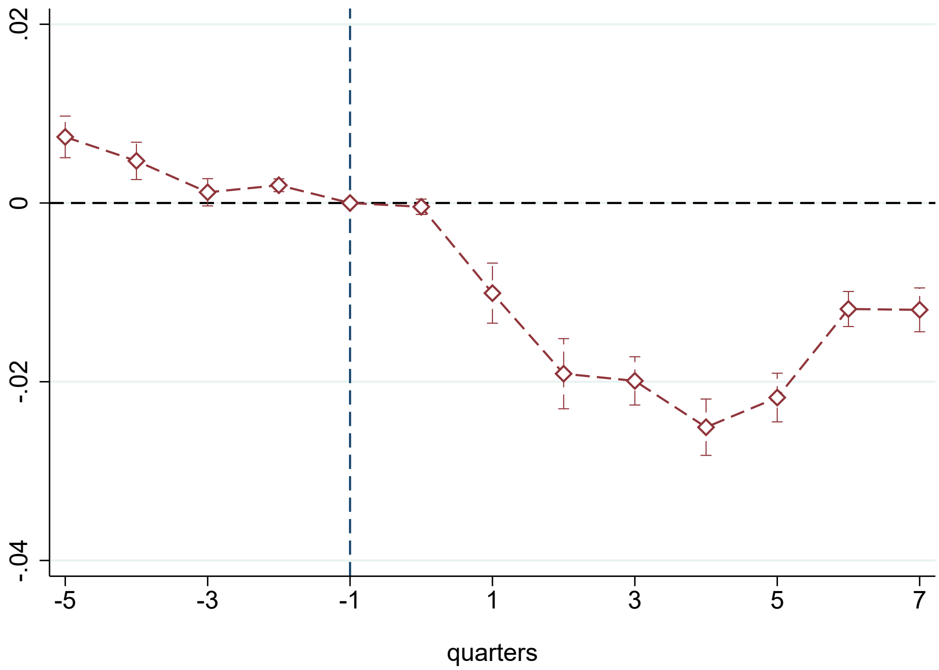
(b) Non-Covid-19 Loans

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

We now explore the response of delinquency rates defined as an indicator variable equal to one if the firm experience repayment delays in a given quarter. We then estimate equation (4) using this measure as a dependent variable. Our results are reported in column 3 of Table 5. We find that firms connected with highly treated banks perform better after the program. One standard deviation higher treatment reduces in 1.7 ppts the probability of experiencing repayment delays. Figure 6 plots the quarterly effect of the program on delinquency rates. Better connected firms experience a persistent and significant decline in repayment delays after the program and there is no evidence of pre-trends.

Overall, our results show that lending relationship play a crucial role in shaping access to credit and delinquency rates. Better connected firms receive more credit and are less likely to face repayment delays after the program. Worse connected firms obtain more non-Covid-19 loans, although this effect is not enough to offset the expansion of guaranteed loans. We are interested in exploring the effects of the program. To do so, we estimate the response of credit and delinquency to participating in the program. Then, we will estimate the elasticity of delinquency to credit and address whether more sensitive firms, i.e., those with a bigger elasticity, receive more credit or not.

Figure 6: Lending Relationships and Delinquency Rates



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

Effects of the program. We estimate the effect of the program using an difference-in-differences instrumental variable approach where we instrument firm access to the program using our treatment measure defined in equation (3). Then we use the predicted values to estimate the effect of the program on credit and delinquency rates. We estimate the following equation:

$$\begin{aligned} Y_{ikt} &= \gamma \times \text{Access}_{ikt} + \delta_i + \delta_{x(i)kt} + u_{ikt} \\ \text{Access}_{ikt} &= \rho_1 \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{x(i)kt} + u_{ikt} \end{aligned} \tag{5}$$

We define firm access to the program as an indicator variable equal to one, after the program implementation, for firms receiving a Covid-19 loan. The parameter of interest γ measures the average effect of obtaining a Covid-19 loan on credit and delinquency rates. Our results are reported in Table 6. We find that firms participating in the program exhibit an expansion of 89% in total loans, while firms that do not participate in the program obtain more non-Covid-19 loans. The program reduced the probability of experiencing repayment delays in 12 ppts for the average firm.

Table 6: IV Estimates of the Effect of the Program on Credit and Delinquency Rates

	Total (1)	Non-Covid-19 (2)	Delinquency (3)
Access$_i$ × Post$_t$	0.891***	-2.144***	-0.121***
	(0.006)	(0.016)	(0.002)
Fixed Effects			
Firm	✓	✓	✓
City-Segment-Quarter	✓	✓	✓
Industry-Segment-Quarter	✓	✓	✓
Riskiness-Segment-Quarter	✓	✓	✓
Age group-Segment-Quarter	✓	✓	✓
Debt decile-Segment-Quarter	✓	✓	✓
Observations	13,067,434	12,951,125	13,067,434

This table shows the effect of the program on the balance of total loans, non-Covid-19 loans, and delinquency rates at the firm level. Firms access to the program is instrumented by the treatment measure defined in equation (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Our results indicate that firms participating in the program receive more credit and are less likely to experience repayment delays. This evidence is consistent with the unprecedented need of external financing firms faced due to Covid-19 restrictions, which offsets risk-shifting incentives and potential weakening in bank screening associated with public guarantees. In the next section, we explore in more detail the role of needs of external financing and study the allocation of guaranteed loans.

5 Heterogeneity and allocation of Covid-19 loans

In this section we estimate the heterogeneous effects of the program and explore whether banks allocated Covid-19 loans towards more sensitive firms or not. We start by estimating the effects in different segments of the credit market. Then, we focus on small-firm lending, which is the most sensitive segment in terms of delinquency rates, and explore the role of firms' size measured by their outstanding debt before Covid-19. Finally, we study the heterogeneous effects across industries, motivated by the nature of the shock, whose effects vary substantially across sectors.

5.1 Heterogeneity across segments

We start by estimating the response of credit and delinquency across three groups: micro and small, medium-size, and large firms and corporations. Columns 1 to 3 in Table 7 report our results. We find that lending relationships play a more important role in shaping large firms' access to credit. One standard deviation better connections led to a 18% expansion in credit among large firms and 11% among micro-firms. We then estimate the response of delinquency rates and report our results in columns 5 to 6 of Table 7. Despite of the lower expansion of credit, lending relationships are more important for small firms to avoid repayment delays. Micro-firms that are better connected experience a contraction of 1.7 ppts in the probability of experiencing repayment delays, while this effect is null among large firms.

Table 7: Lending Relationships, Credit, and Delinquency Rates across Firms

	Total Loans			Delinquency		
	Micro	Small & Medium	Large	Micro	Small & Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_i$ × Post$_t$	0.114***	0.172***	0.179***	-0.017***	-0.014***	0.001
	(0.004)	(0.003)	(0.063)	(0.001)	(0.001)	(0.014)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
City-Segment-Quarter	✓	✓	✓	✓	✓	✓
Industry-Segment-Quarter	✓	✓	✓	✓	✓	✓
Riskiness-Segment-Quarter	✓	✓	✓	✓	✓	✓
Age group-Segment-Quarter	✓	✓	✓	✓	✓	✓
Debt decile-Segment-Quarter	✓	✓	✓	✓	✓	✓
Observations	10,149,626	2,888,268	25,261	10,149,626	2,888,268	25,261

This table shows the effects of being better connected to treated banks on the balance of total loans and delinquency rates among firms in different segments of the credit market. Treatment is standardized. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Our estimates indicate that a 10% increase in credit leads to a 1.5 ppts decline in delinquency rates in the segment of micro-credit, and does not affect delinquency of large firms. This is evidence that the unprecedented needs of external financing associated with Covid-19 restrictions play a crucial role shaping the effects of the program, as we expect them to me more important among small firms.

Notice that the policy implications of this heterogeneity in the response of delinquency rates depends on whether banks allocate more guarantees to more sensitive small clients or not. If they did so, then the program should expand towards small clients to improve the aggregate response of delinquency rates. If they did not, then the government could target small firms to improve the allocation of guaranteed loans. We address this question by estimating equation (5) for the different segments of the credit market. Our results are reported in Table 8. Micro-firms participating in the program experience an 88% increase in credit, while large firms more than tripled their debt. We show in the appendix that an important part of this credit expansion is due to an increase in normal, non-guaranteed loans.

Table 8: IV Estimates of the Effect of the Program on Credit across Firms

	Micro (1)	Small & Medium (2)	Large (3)
$\text{Access}_i \times \text{Post}_t$	0.883***	0.920***	2.445*
	(0.007)	(0.013)	(1.284)
Fixed Effects			
Firm	✓	✓	✓
City-Segment-Quarter	✓	✓	✓
Industry-Segment-Quarter	✓	✓	✓
Riskiness-Segment-Quarter	✓	✓	✓
Age group-Segment-Quarter	✓	✓	✓
Debt decile-Segment-Quarter	✓	✓	✓
Observations	10,149,626	2,888,268	25,261

This table shows the effect of the program on the balance of total loans across firms with different levels of debt in December 2019. Firms access to the program is instrumented by the treatment measure defined in equation (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm level.

Our findings indicate that small firms receive less credit than large firms when participating in the program, despite their bigger elasticity of delinquency rates. This is suggestive evidence that governments can improve the effectiveness of loan guarantees by targeting small firms. However, it is important to notice that these segments are quite different in multiple dimensions related to both, banks and firms' characteristics, so comparing the sensitivity and allocation between micro-credit and large-firm loans could be misleading. To have better evidence on the role of the allocation of Covid-19 loans, we focus on micro and small-firm lending, more comparable segments and the most sensitive ones.

5.2 Heterogeneity in small-firm lending

We explore the role of bank incentives by focusing on small and micro-firms. We estimate the elasticity of delinquency rates to credit as follows:

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

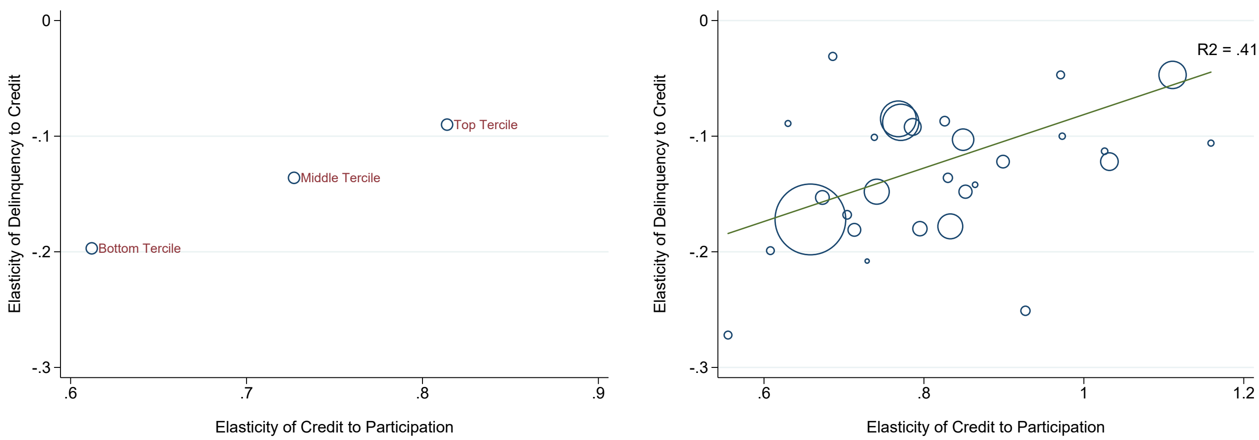
Then we ask whether banks allocated loans to more sensitive firms by plotting the estimated sensitivity δ against γ, from equation (5), which measures the expansion of credit to firms participating in the program. We interpret less sensitive firms receiving more credit as evidence that the allocation of Covid-19 loans could be improved to maximize the effect of the program on delinquency rates and financial stability. Reallocating loans from less to more sensitive borrowers would lead to a bigger reduction in aggregate delinquency.

Outstanding debt. We start by splitting firms in terciles based on their outstanding debt in 2019. Then, we estimate equations (5) and (6). We plot our estimates in the left panel (a) of Figure 7. We can see that the elasticity of delinquency to credit across firms in the bottom tercile is twice as large as the elasticity of firms in the top tercile. This is again consistent with the needs of external financing that we expect to be more important for smaller clients. However, we can see that firms in the bottom tercile receive less credit when participating in the program. This evidence suggests that banks prefer to provide loans to firms that represent a bigger share of their portfolio.

Industry heterogeneity. Now we estimate the elasticity of delinquency to credit for different industries defined at the 2-digit ISIC. We show our results in panel (b) of Figure 7. We can observe substantial heterogeneity, from 0 to 2.8 ppts decline in delinquency rates for a 10% increase in credit. For example, hotels and restaurants, a sector that was hardly hit by Covid-19 restrictions experience a 1.7 ppts decline in delinquency, while this reduction is only 0.1 ppts in mining. However, the former group receive less credit when participating in the program.

We can see in this figure that this pattern is more general, and sectors that receive more credit are less sensitive in terms of delinquency rates, suggesting that a reallocation of Covid-19 loans from less to more sensitive industries would have improved the effectiveness of the program in terms of delinquency rates and financial stability.

Figure 7: Heterogeneous Effects and Allocation of Covid-19 loans



(a) Size heterogeneity

(b) Industry heterogeneity

6 Conclusions

Loan guarantees are a key financial policy tool used by governments to promote economic growth and deal with recessions. They are usually implemented through private banks to avoid political incentives of public banks that might not be aligned with social goals. In this paper we estimate the effect of loan guarantees on delinquency rates during economic downturns and explore how the allocation of such guarantees shapes its aggregate effect. We study a large program of loan guarantees implemented in Peru during the Covid-19 recession providing guarantees for loans that represented 25% of the outstanding debt before Covid-19 and 8% of the Peruvian GDP.

We find that loan guarantees are effective in expanding credit supply and reducing delinquency rates for the average firm in the economy. Consistent with the need of external financing, we document that smaller firms in highly exposed industries exhibit a bigger elasticity of delinquency to credit. However, these firms obtain less credit when participating in the program due to financial institutions' credit assessments. Our results indicate that, by implementing separate auctions for different segments of the market of corporate loans, which foster competition among financial institutions, the Central Bank improved the effectiveness of the program in terms of delinquency rates.

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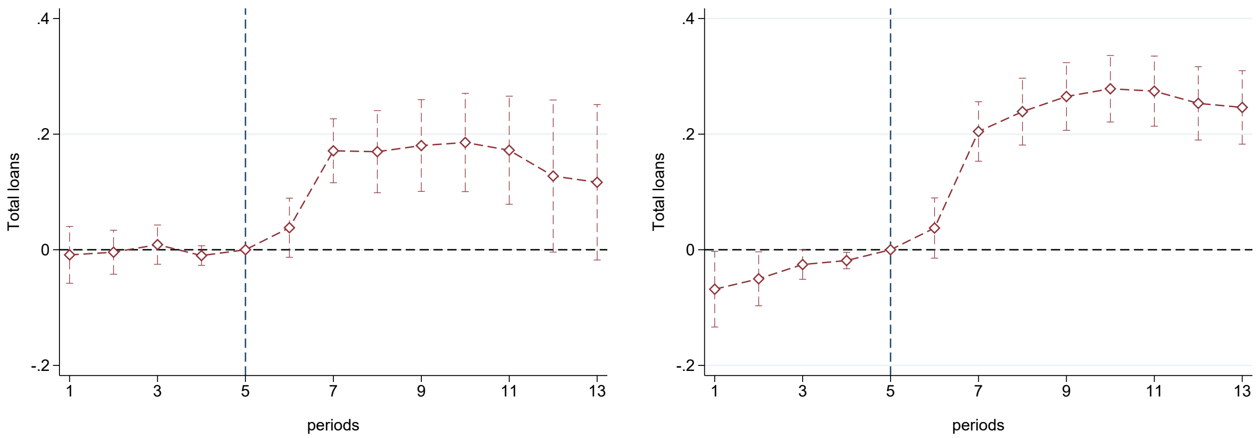
Appendix

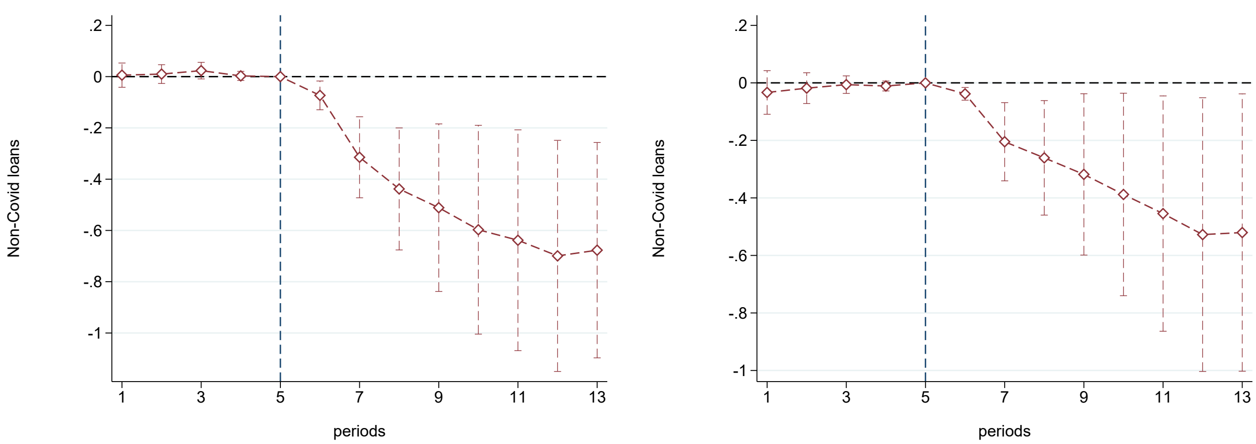
Figure A1: Effect of the Program on Total Loans



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

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

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



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

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