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

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Abstract

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1 Introduction

Government guarantees/credit as a main policy tool to promote economic development (references in Ru,2018) and deal with recessions (references on Covid papers). They have been usually implemented through private banks to avoid political incentives, however private banks might also have objectives that are not aligned with maximizing social welfare. This paper: effects of government guarantees to deal with recessions and role of private bank incentives in shaping effectiveness of this type of programs.

We do so by studying Covid-19 relief funds in Peru named Reactiva Perú. Implemented through private banks. Main goal. Size and relevance of the policy.

Data used in the paper

Estimation approach. Granja reimbursement shock. Bank-firm and firm level outcomes. Supporting evidence for identification.

First part of the paper estimates effects. First, bank-firm level, supply shock, re-balancing bank portfolio. Second, firm-level, lending relationships, treatment effect of the program on firm delinquency rate. Heterogeneous treatment effects on firms with different size, age, debt pre-Covid.

Second part of the paper explores allocation. Whether firms whose delinquency rates are more sensitive to the program receive more loans or not. Simple OLS at the bank-firm and firm levels. Discuss role of targeting. Back of the envelope calculations with and without targeting.

Brief conclusion.

Next steps (in order of priority): firm-level data, industry heterogeneity (we already have something on ISIC 5252 "Retail sale via stalls and markets" which is super sensitive - makes sense), aggregate effects at the local level, modelling bank decision and welfare effects of allocation.

Literature Guarantees and public loans. Ru (2018), Haas Ornelas et al. (2020), Joaquim and Netto (2022), Lelarge et al. (2010), Bachas et al. (2021), Mullins and Toro (2018), Barrot et al. (2020), Sauvagnat and Vallée (2021), González-Uribe and Wang (2019). Contribution: focus on the role of private bank incentives, look at business cycle, use micro-data to estimate effects.

Covid-19. Granja et al. (2020), Li and Strahan (2020), Faulkender et al. (2020), Autor et al. (2022), Bartik et al. (2020), Joaquim and Netto. Contrubution: focus on bank incentives. Use micro-data.

Government policy to deal with recessions. Mian and Sufi (2012), Zwick and Mahon (2017), Lucas (2016), Kelly et al. (2016), House and Shapiro (2008).

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, the type of loan[1], and the city where the loan was originated. On the firm side, we observe the industry, credit rating (4 categories), and the year when the firm obtained its first loan.

2.2 Institutional Background

Reactiva Perú is the program of loan guarantees introduced by the Peruvian government to help firms dealing with Covid-19 restrictions. The program was implemented by the Central Bank in May 2020 and 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[2]. There were different 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 of loans is based on firms' sales and balance of credit. For example, loans to corporations are those issued to firms whose total sales in the past two years is above USD 60 million, while loans to micro firms are those issued 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. The average Covid-19 loan guarantee was 90.1% and the loan-size weighted average was XX%.

Private banks were responsible of screening borrowers and allocating Covid-19 loans. These loans were issued between May and December 2020, with an average maturity of 36 months. The repayment period started 12 months (if this period was extended let's put here the longest period) 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 participated in the program issuing USD 16 billion, which represented 17% of the balance of loans that firms had by December 2019.

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

[2]Throughout the text we will call these guaranteed loans as Covid-19 loans.

2.3 Descriptive statistics

The Peruvian banking sector is composed of 52 financial institutions and is highly concentrated. The four largest banks account for 72.7% of corporate loans in 2019. Banks provide five types of credit, as we described above, and the structure of the market varies across these types of loans. Table 1 provides some statistics of the banking sector in each of these segments. We can notice that XX banks operate in the segment of micro-credit, with an average size of USD XX millions. The distribution is highly skewed, the median is USD XX millions. On the other hand, in the segment of loans to corporations, we have XX banks with an average size of USD XX million and a median size of USD XX million. The market of loans to corporations is more concentrated, the top 3 banks account for XX% of the market, while the same share in the segment of micro-credit is XX%.

Table 2 reports summary statistics for firms with a positive balance of loans in December 2019. Panel A shows that the average firm had a balance of USD XX thousand and XX% of firms exhibit repayment delays. The age of the average firm, defined as the number of years since its first loan, is XX years. We observe XX firms borrowing in the bank credit market. Panels B to F provide the same statistics for firms with different types of credit. We can observe that *smaller firms* are riskier and younger on average.

Table 1: Peruvian Banking Sector

	Total Loans		Num. of	Share	Share
	Mean	Median	Banks	Top 3	Top 5
	(1)	(2)	(3)	(4)	(5)
Total					
Loans to:					
Micro-credit					
Small firms					
Medium-size firms					
Large firms					
Corporations					

Notes: Corporate loans in December 2019. XXXX

Table 2: Characteristics of Borrowers

	Total Loans		Delay Ind.		Age		Num. of firms
	Mean	Median	Mean	Median	Mean	Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total							
Loans to:							
Micro-credit							
Small firms							
Medium-size firms							
Large firms							
Corporations							

Notes: Corporate loans in December 2019. XXXX

We provide summary statistics of the allocation of loans in Table 3. The program provided guarantees on loans valued at USD XX million, which represents XX% of the balance of loans in December 2019. The program benefited XX clients, XX% of the number of firms borrowing by December 2019. The relevance of the program varies across the different types of borrowers. The value of guarantees on micro-credit is USD XX million, which represents XX% of the balance of loans in this segment in 2019, while this value is USD XX million for large firms, XX% of the balance of loans.

Table 3: Guaranteed Loans by Type of Credit

	Guaranteed Loans		Benefited Clients	
	Value	Share of 2019	Value	Share of 2019
	(1)	(2)	(3)	(4)
Total				
Loans to:				
Micro-credit				
Small firms				
Medium-size firms				
Large firms				
Corporations				

Notes: Corporate loans in December 2019. XXXX

3 Empirical Framework

We exploit differences in banks takeover of loans guarantees to estimate the effect of the program on the supply of credit. We construct a continuum measure of treatment in the spirit of the "reimbursement shock" proposed by Granja et al. (2020). We compute this treatment for each bank b in each segment k of the market of corporate loans, i.e., for loans to micro-enterprises, small firms, medium-size firms, large firms, and corporations.

$$\text{Treatment}_{bk} = \frac{\text{Share of Covid-19 Loans}_{bk} - \text{Share of Total Loans}_{bk}}{\text{Share of Covid-19 Loans}_{bk} + \text{Share of Total Loans}_{bk}} \times 0.5 \tag{1}$$

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 in December 2020.

We identify the effect of the program by comparing the evolution of the balance of loans that firms hold with more treated banks relative to less treated ones, before and after the program, using a difference-in-difference approach. Our identifying assumption is that absent the program, the credit provided by more and less treated banks would have followed parallel trends.

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

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

where Y_{ibt} denotes the balance of total loans and non-Covid-19 loans that firm i has with bank b in quarter t, and $\text{Treatment}_{bk(i)}$ 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} denotes firm-by-quarter fixed effects to remove any demand 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 time-varying heterogeneity among banks of different size. For example, a potential concern is that bigger banks are more likely to serve larger firms that are better prepared to deal with Covid-19 restrictions using internal resources. On the other hand, bigger banks might also be able to bid a lower interest rate and take more guarantees. Then, if we do not control for bank-size specific time-varying fixed effects our results could be biased. 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 takeover of guaranteed loans and to estimate the effects of the program on firms delinquency rates. We do so by constructing a measure of firm exposure to the program as follows:

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

where L_{bi} denotes the balance of loans 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:

$$\ln Y_{ijct} = \beta \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{jt} + \delta_{ct} + \delta_{q(i),t} + u_{ijct} \tag{4}$$

where Y_{ijct} denotes the balance of total loans, non-Covid-19 loans, and delinquency rates of firm i that operates in indistry j and city c in quarter t. We include firm-specific fixed effects δ_i to control for any time-invariant heterogeneity across firms. δ_{jt} denotes sector-time fixed effects that account for any shock taking place at the industry level, and δ_{ct} controls for city-level shocks. We also include time-varying fixed effects $\delta_{q(i),t}$ for each quartile of the firm-size distribution measured by firms balance of total loans in December 2019. Finally, we cluster standard errors at the firm level.

Our parameter of interest β measures the average effect of having stronger lending relationships with highly treated banks. Notice that 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 Paycheck Protection Program in the US, banks might prefer to attend firms with higher balance of loans to avoid large losses if these firms default. Moreover, banks might also have low incentives to provide loans to firms that operate in industries that were mostly hit by Covid-19 restrictions as they have less chances to survive. Thus, a naive specification that does not account for firm size or industry would lead to a biased estimation if, for example, smaller firms were worse connected to highly exposed banks.

4 Results

4.1 Bank-firm level effects

We start by estimating the effect of the program on the supply of credit. We estimate equation (2) using the log of total loans as a dependent variable. Our results are reported in columns 1-3 in Table 4. We find that one standard deviation higher treatment leads to a 21% increase in credit supply in our benchmark specification reported in column 3. Our results are robust to different specifications as those reported in columns 1 and 2.

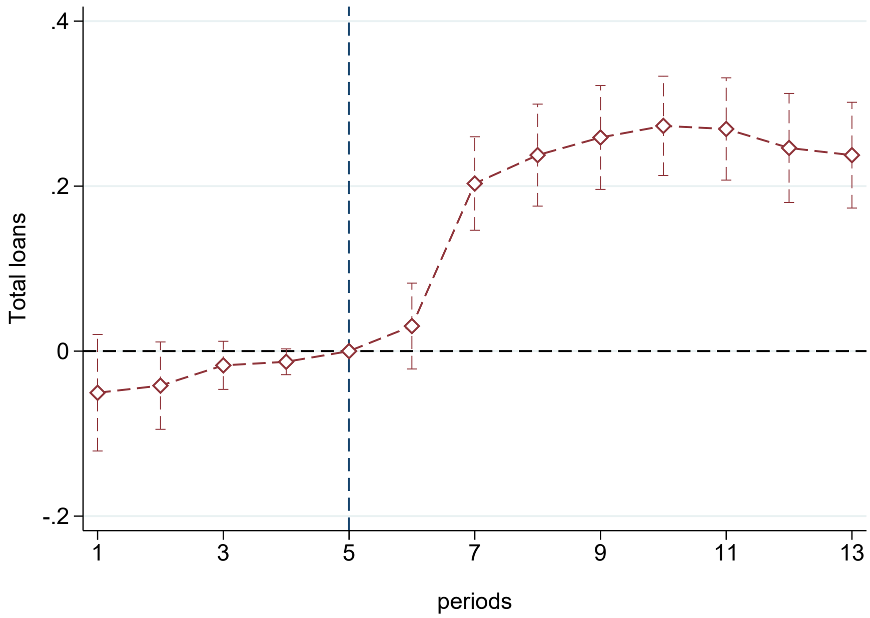
Figure 1 plots the event study graphs for the response of the balance of loans. We show the estimated quarterly treatment effect before and after the program, including the same fixed effects used in our benchmark specification. We normalize the quarter before the program to zero. The figure shows null effects of being treated before the policy, which is consistent with our identifying assumption. The balance of loans experience a significant and persistent increase since the second 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 the supply of credit of more treated banks.

Table 4: Effect of the Program on Credit Supply

	Total Loans			Non-Covid-19 Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_{bk} \times \text{Post}_t$	0.145***	0.226***	0.214***	-0.463***	-0.262**	-0.303***
	(0.042)	(0.034)	(0.036)	(0.133)	(0.117)	(0.114)
Fixed Effects						
Bank	✓	✗	✗	✓	✗	✗
Firm	✓	✗	✗	✓	✗	✗
Quarter	✓	✗	✗	✓	✗	✗
Firm-Quarter	✗	✓	✓	✗	✓	✓
Firm-Bank	✗	✓	✓	✗	✓	✓
Bank size-Quarter	✗	✗	✓	✗	✗	✓
Observations	2,406,561	1,205,241	1,205,193	2,354,898	1,154,385	1,154,329

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 1: Effect of the Program on Total Loans

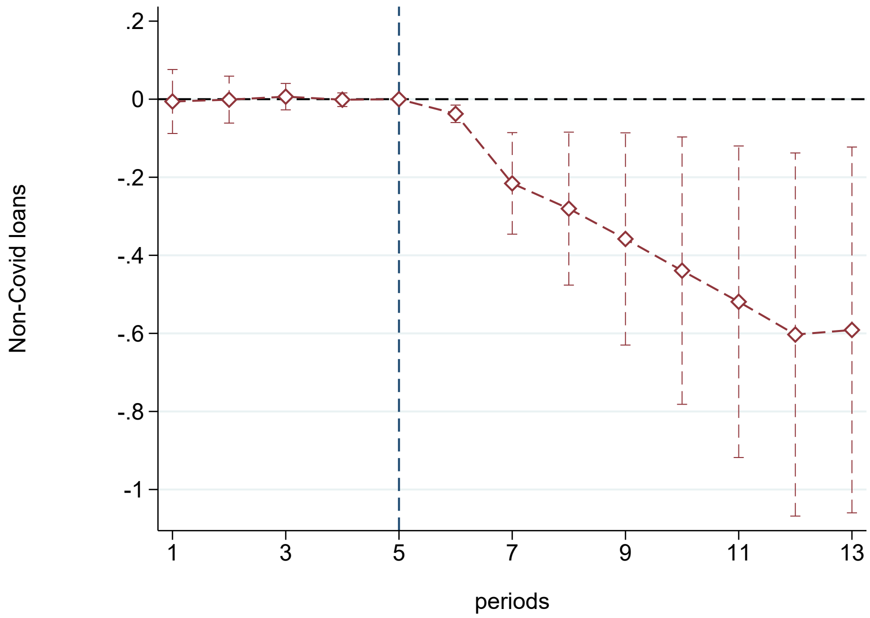


This figure plots the quarterly effects of the program on total credit at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. The confidence interval is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

A critical question is whether these public credit policy crowds 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 the supply of non-Covid-19 loans. We estimate equation (2) using the log of the balance of non-Covid-19 loans as a dependent variable. We report our results in columns 4-6 in Table 4. We estimate that one standard deviation higher treatment leads to a decline of 30% in the supply of non-Covid-19 loans.

We plot the event study graphs for the response of non-Covid loans in Figure 2. 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 2: 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. 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 the treatment measure defined in equation (3). This measure is a weighted average of banks exposure to the program, where the weights are based on the balance of loans that firms have with each bank. This variable indicates how well connected firms are with highly exposed banks. Notice that while the program led to an expansion of credit provided by highly treated banks, this does not mean that firms that are better connected will receive more credit. If lending relationships were fully flexible, firms that are not well connected will easily switch towards highly exposed banks to obtain more credit. On the other hand, if lending relationships were sticky, banks that are better connected will experience an expansion in credit relative to worse connected firms.

To 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 firms that are one standard deviation better connected experience a 9% increase in total loans after the program. We report the quarterly effect of the program on firms total loans in panel (a) of Figure 3. We observe null effects of being better connected in the pre-Covid-19 period. Following the program, we find that better connected firms have more credit even two years after the program was implemented. This result implies an important role of lending relationships in shaping the ability of firms to obtain Covid-19 loans.

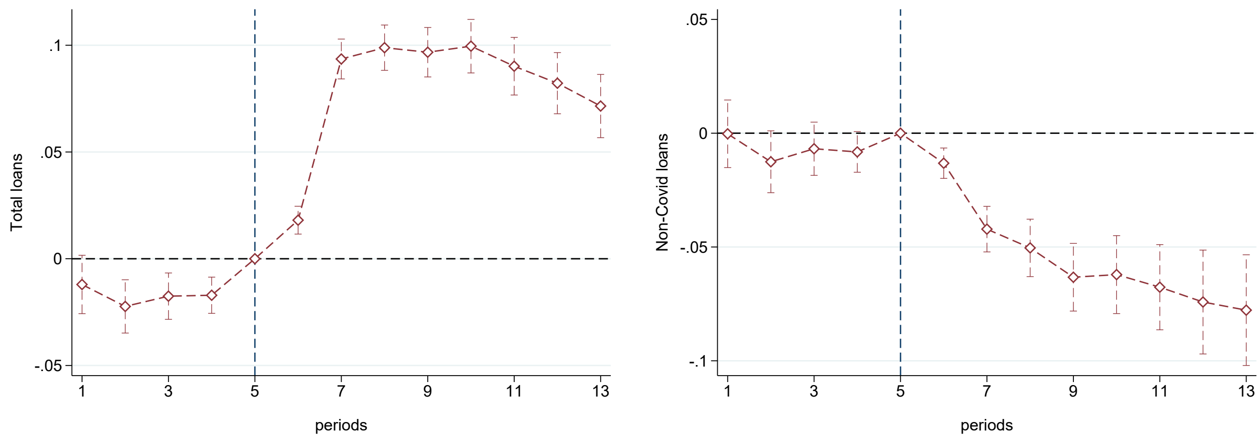
While this result shows that better connected firms obtain more credit, it does not tell us whether non-Covid-19 loans can partially help worse connected firms. We address this question by estimating equation (4) using the balance of non-Covid-19 loans as our dependent variable. We report our results in column 2 of Table 5. One standard deviation better connected firms have a 4.6% lower balance of non-Covid-19 loans relative to worse connected ones. As we discussed in the previous subsection, this result is consistent with public guarantees crowding out private banks normal activities. Our results also indicate that worse connected firms receive more non-Covid-19 loans, although this is not enough to offset the response of total credit. Panel (b) of Figure 3 reports the quarterly effect of the program. We observe no evidence of pre-trends.

Table 5: Lending Relationships, Credit, and Delinquency Rates

	Total (1)	Non-Covid-19 (2)	Delinquency (3)
$\text{Treatment}_i \times \text{Post}_t$	0.090***	-0.046***	-0.018***
	(0.005)	(0.006)	(0.002)
Fixed Effects			
Firm	✓	✓	✓
Firm size-Year	✓	✓	✓
Credit type-Year	✓	✓	✓
Age-Year	✓	✓	✓
Industry-Year	✓	✓	✓
City-Year	✓	✓	✓
Observations	498,157	497,694	498,157

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 3: Lending Relationships and Credit



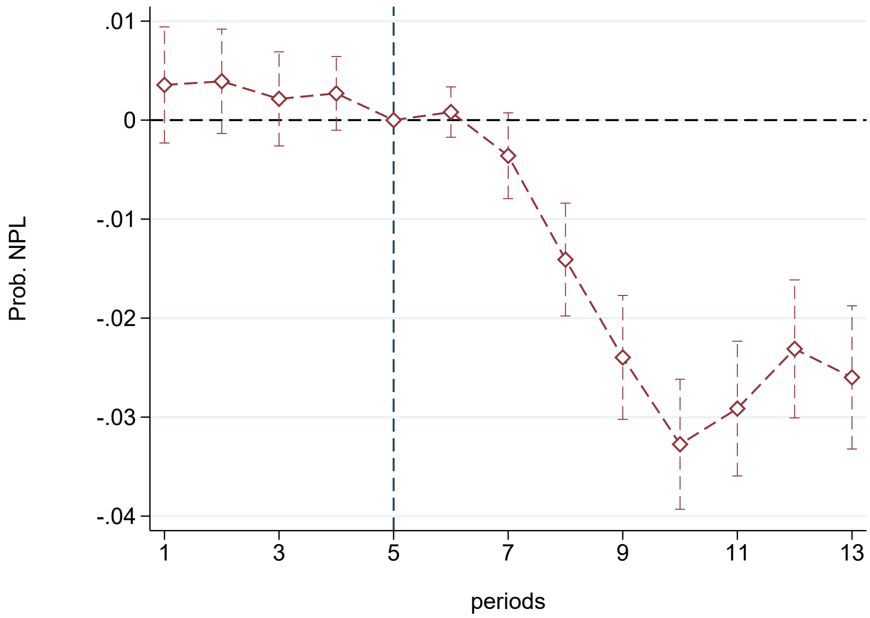
(a) Total Loans (b) Non-Covid-19 Loans

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. The confidence interval is at the 95% level.

We now explore the response of firm performance. We construct a measure 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 our measure of delinquency rates 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 1.8 ppts the probability of experiencing repayment delays. Figure 4 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 a key role of lending relationship in shaping firms 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 does not offset the expansion of guaranteed loans experienced by firms that are attached to highly treated banks.

Figure 4: 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. 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 the 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:

$$\begin{aligned} \ln Y_{ijct} &= \delta \times \text{Access}_{ijct} + \delta_i + \delta_{jt} + \delta_{ct} + \delta_{q(i),t} + u_{ijct} \\ \text{Access}_{ijct} &= \beta \times \text{Treatment}_i \times \text{Post}_t + \delta_i + \delta_{jt} + \delta_{ct} + \delta_{q(i),t} + u_{ijct} \end{aligned} \tag{5}$$

We define firms access to the program as an indicator variable equal to one after the program implementation only for firms receiving a Covid-19 loan. The parameter of interest δ measures the 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 hold a 61% higher balance of total loans after the program and firms that do not participate obtain 30% more Covid-19 loans.

The program reduced the probability of experiencing repayment delays in 12 ppts.

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

	Total (1)	Non-Covid-19 (2)	Delinquency (3)
$\text{Access}_i \times \text{Post}_t$	0.614***	-0.312***	-0.124***
	(0.030)	(0.040)	(0.014)
Fixed Effects			
Firm	✓	✓	✓
Firm size-Year	✓	✓	✓
Credit type-Year	✓	✓	✓
Age-Year	✓	✓	✓
Industry-Year	✓	✓	✓
City-Year	✓	✓	✓
Observations	498,157	497,694	498,157

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.

4.3 Heterogeneity and allocation of Covid-19 loans

In this subsection we explore the heterogeneous effects of this program and whether banks allocated Covid-19 loans towards more sensitive firms or not. We rank firms according to their balance of credit in December 2019 and split them in three groups: small, medium, and large firms.

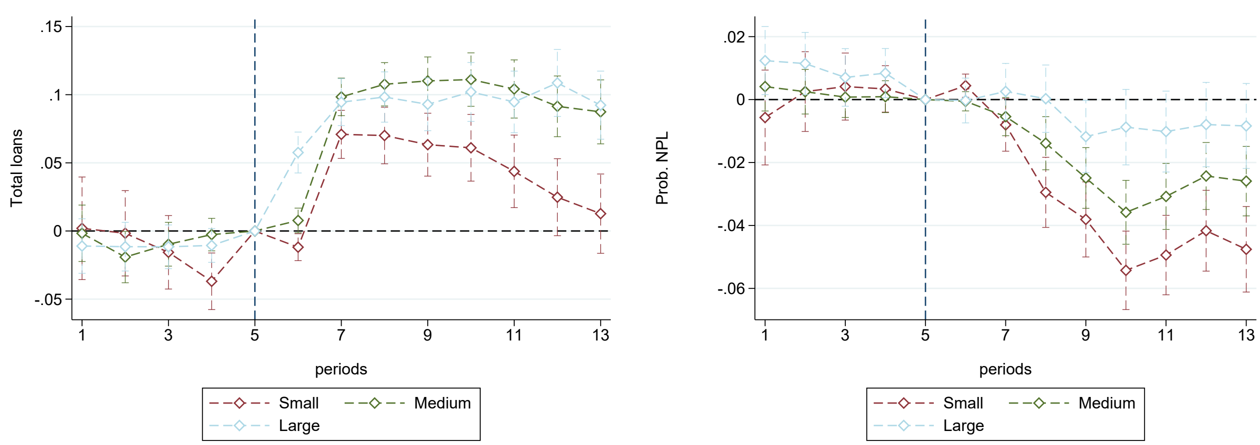
We start by estimating the response of credit. Columns 1 to 3 in Table 7 report our results. We find that lending relationships play a more important role in shaping large firms' access to credit. One standard deviation better connections lead to a 10% expansion in credit among large firms and only 5% among small 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. Small firms that are better connected experience a contraction of 2.6 ppts in the probability of experiencing repayment delays, while this effect is only 1.3 ppt among large firms. We plot the event-study graphs for both variables in Figure 5. We find no evidence of pre-trends. The dynamic effects show that large firms with better lending relationships obtain credit more rapidly than small firms and this expansion of credit is also more persistent. Delinquency rates exhibit a significant and persistent decline among small firms and a very small contraction among large firms.

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

	Total Loans			Delinquency		
	Small	Medium	Large	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment$_i$ × Post$_t$	0.051***	0.089***	0.100***	-0.026***	-0.018***	-0.013***
	(0.008)	(0.007)	(0.009)	(0.004)	(0.003)	(0.004)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Firm size-Year	✓	✓	✓	✓	✓	✓
Credit type-Year	✓	✓	✓	✓	✓	✓
Age-Year	✓	✓	✓	✓	✓	✓
Industry-Year	✓	✓	✓	✓	✓	✓
City-Year	✓	✓	✓	✓	✓	✓
Observations	90,917	178,198	221,500	90,917	178,198	221,500

This table shows the effects of being better connected to treated banks on the balance of total loans and delinquency rates among firms with different levels of debt in December 2019. 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, Credit, and Delinquency Rates across Firms



This figure plots the quarterly effects of being better connected to treated banks on total credit and delinquency rates among firms with different levels of debt in December 2019. 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.

We then study the effects of the program on delinquency rates among these three groups of firms. We do so by estimating our difference-in-differences instrumental variable specification described in equation (5). Our findings are reported in Table 8. Small firms participating in the program experience a 18 ppts decline in the probability of experiencing repayment delays, while large firms exhibit a reduction of 8 ppts upon participating in the program.

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

	Small	Medium	Large
	(1)	(2)	(3)
$\text{Access}_i \times \text{Post}_t$	-0.179***	-0.130***	-0.080***
	(0.026)	(0.022)	(0.026)
Fixed Effects			
Firm	✓	✓	✓
Firm size-Year	✓	✓	✓
Credit type-Year	✓	✓	✓
Age-Year	✓	✓	✓
Industry-Year	✓	✓	✓
City-Year	✓	✓	✓
Observations	94,269	181,628	222,251

This table shows the effect of the program on delinquency rates 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 results indicate that the program was particularly effective in reducing delinquency rates among small firms. A crucial question is whether banks allocated Covid-19 loans towards this group of firms or not. We explore this in two ways. First, we study the allocation in the extensive margin. We estimate the following bank-firm level equation:

$$\text{Access}_{ijckb} = \alpha_0 + \alpha_1 \times \text{Medium}_i + \alpha_2 \times \text{Large}_i + \Gamma X_i + \delta_j + \delta_c + \delta_k + \delta_b + u_{ijckb} \tag{6}$$

where Access_{ijckb} is an indicator of whether firm i that operates in industry j, city c and segment k obtains a Covid-19 loan with bank b or not. Our coefficients of interest are α_1 and α_2 that measure the difference in the probability of obtaining a Covid-19 loan for medium and large firms relative to small businesses.

Our results are reported in Table 9. We find that medium-size and large firms, despite of being less sensitive in terms of delinquency rates, are more likely to obtain a Covid-19 loan than small firms in all our specifications. We can notice in column 5 that a significant part of the difference in the probability of large firms participating in the program relative to small firms is driven by the type of banks from which firms borrow. Overall, our results suggest that the government can improve the effect of the program on delinquency rates by targeting small firms. To do so, the government might provide more guarantees to institutions that are specialized in the segment of small businesses.

Table 9: Probability of Participating in the Program

	Indicator of firm access to the program				
	(1)	(2)	(3)	(4)	(5)
Medium	0.025***	0.029***	0.029***	0.049***	0.041***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Large	0.169***	0.175***	0.179***	0.113***	0.058***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Controls					
Riskiness	✗	✓	✓	✓	✓
Age	✗	✗	✓	✓	✓
Age^2	✗	✗	✓	✓	✓
Fixed Effects					
Industry	✓	✓	✓	✓	✓
City	✓	✓	✓	✓	✓
Type of credit	✗	✗	✗	✓	✗
Bank	✗	✗	✗	✗	✓
Observations	293,126	293,126	293,126	293,126	293,118

This table shows the results of estimating equation (6). Firm size is defined by the balance of loans in December 2019. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parenthesis.

Key message: banks are more likely to provide Covid-19 loans to large firms that are less sensitive in terms of delinquency rates. This result does not tell us about the intensive margin. Even though small firms are less likely to participate in the program, they might still receive a larger amount of Covid-19 loans upon participation. We test whether this is the case or not by estimating the effect of the program on the value of total loans using our difference-in-differences instrumental variable specification. Our results are reported in Table XXXX. We find that YYYY.

Table 10: IV Estimates of the Effect of the Program on Credit across Firms

	Small (1)	Medium (2)	Large (3)
$\text{Access}_i \times \text{Post}_t$	0.357***	0.637***	0.638***
	(0.055)	(0.045)	(0.053)
Fixed Effects			
Firm	✓	✓	✓
Firm size-Year	✓	✓	✓
Credit type-Year	✓	✓	✓
Age-Year	✓	✓	✓
Industry-Year	✓	✓	✓
City-Year	✓	✓	✓
Observations	94,269	181,628	222,251

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.

Key message: targeting towards more constrained firms would increase effectiveness by XX%

5 Conclusions

Government guarantees a crucial policy tool. Implemented through private sector to avoid political incentives. In this paper we estimate the effects of guarantees and analyze how private bank incentives shape the effectiveness of such policies.

We study the effects of Reactiva Perú, a program... We estimate that government guarantees were effective in reducing NPL, mainly across more credit constrained firms (size, age, debt, industry). We find that banks tend to allocate loans towards less sensitive firms, which dampens the effectiveness of these policies. [Counterfactual gains of targeting].

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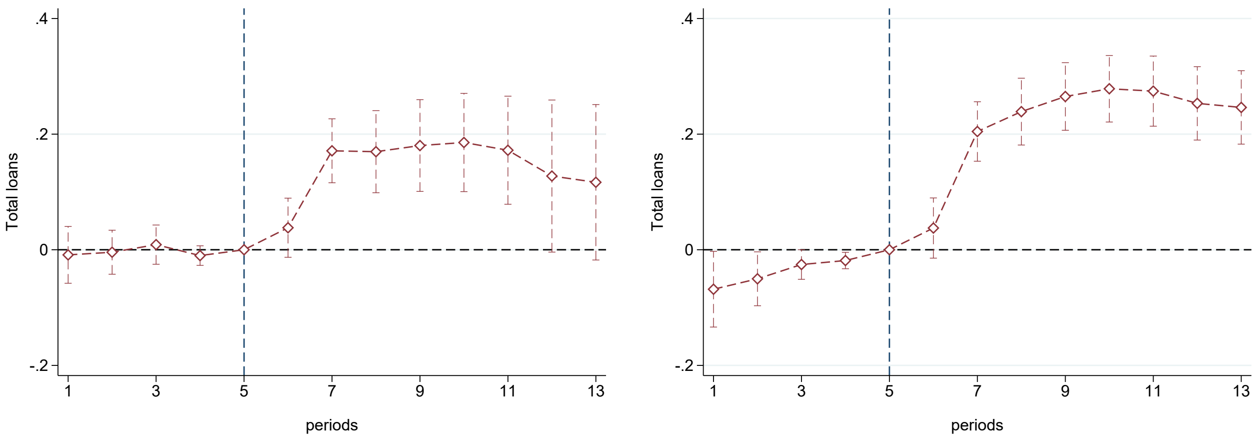
Appendix

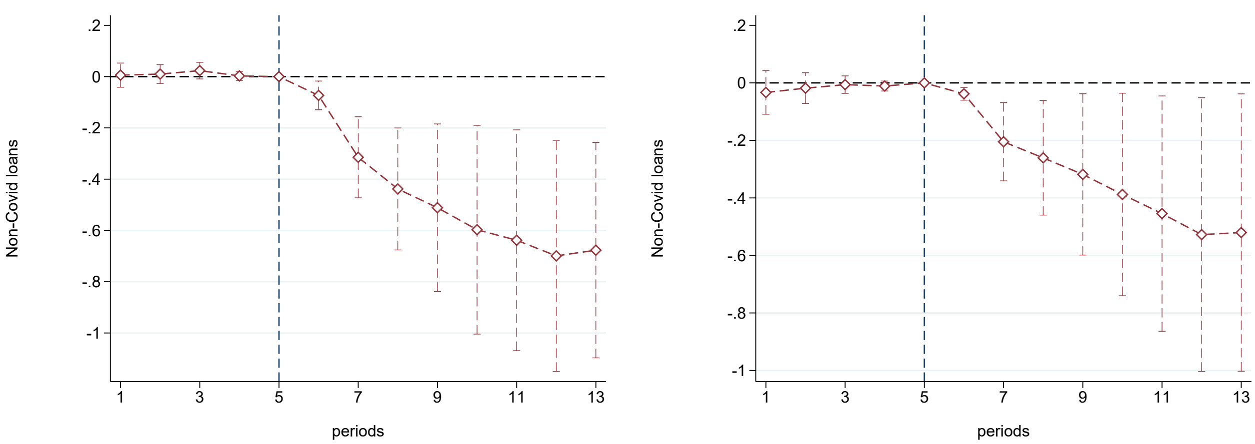
Figure A1: Effect of the Program on Total Loans



(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.

To Do List

Format figures, y-title, x-title, x-labels
Analysis for all the different type of loans
Model or back of the envelope calculation