# 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 firm performance and the role of bank incentives in shaping these effects. We do so by studying the program of loan guarantees implemented by the Peruvian government to help firms dealing with Covid-19 restrictions. We find that firms participating in the program experienced an expansion of 61% in their balance of credit and a reduction of 12 ppts in delinquency rates. The decline in delinquency rates of small firms is three times bigger than that of large firms. However, small firms are less likely to participate in the program, and even upon participation, they obtain less credit relative to large firms. Our results indicate that targeting small businesses is critical to improve the effectiveness of the program. We provide evidence that governments could do so by providing more guarantees to banks that are specialized in small firms.

# 1 Introduction

Loan guarantees are a key policy tool used by governments to promote economic development and deal with recessions. They are usually implemented through private banks to avoid political incentives of public banks that might conflict with social goals. However, private banks might also have incentives that are not necessarily aligned with maximizing social welfare. In this paper, we estimate the effects of loan guarantees in the context of the Covid-19 recession and explore the role of private bank incentives in shaping these effects.

To understand how loan guarantees affect firm performance, we study the effects of *Reactiva Perú*, the program of loan guarantees implemented by the Peruvian government in May 2020 to help firms dealing with Covid-19 restrictions. We use loan-level data covering the universe of lending relationships that firms hold 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, credit rating, and the year when firms obtained their first credit.

We estimate the effects of the program using a difference-in-differences strategy that exploits the heterogeneity 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. (2020). We identify the effect of the program 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 provide event study graphs showing that our measure of treatment has null effects on credit before the program, consistent with the parallel trends assumption. Second, even though our identification does not require 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.

In the first part of the paper we estimate 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 firm time-varying fixed effects. We find that banks with one standard deviation higher treatment expand credit supply by 21% after the program. We also estimate a decline of 30% in the supply of non-guaranteed loans of highly treated banks, consistent with these public guarantees crowding out the normal activity of banks. Then, we estimate the role of lending relationships in shaping firm access to guaranteed loans. We do so by aggregating our data at the firm level. We compute a measure of firm-level treatment equal to the weighted average treatment of banks, where weights are based on the balance of loans that firms had with each bank in December 2019. We find that firms that are one standard deviation better connected to treated banks experience a 9% increase in total loans after the program, suggesting an important role of lending relationships in the allocation of guaranteed loans. We also find that the balance of non-guaranteed loans of better connected firms declines by 4.6%, consistent with the crowding out hypothesis. Finally, we estimate the effect of the program on firm performance using a difference-in-differences instrumental variable approach. We instrument firm participation using our firm-level treatment. We estimate that firms participating in the program experience an expansion of 61% in their balance of loans and a contraction of 12 ppts in the probability of experiencing repayment delays.

The second part of the paper studies the heterogeneous effects of the program and the allocation of guaranteed loans. We split our sample of firms in three groups based on the balance of loans that firms had in December 2019. We find that small borrowers participating in the program exhibit a decline of 18 ppts in the probability of experiencing repayment delays, while large firms exhibit a reduction of only 8 ppts. This is consistent with small firms being more financially constrained during the pandemic so that a positive credit supply shock has larger effects on their performance. Then, we explore how these guarantees were allocated. In particular, we are interested in studying whether guaranteed loans were mainly allocated towards small firms or not. We find that actually small firms are less likely to obtain a guaranteed loan relative to large borrowers. This difference is smaller if we look across firms within the same bank, which suggests that one way of targeting small firms is by allocating more guarantees to banks that are specialized in small businesses. Then we explore the intensive margin of the allocation of loans. We find that, upon participation, small firms receive less credit relative to large borrowers.

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 stronger among small firms, they are less likely to participate in the program, and even upon participation, they obtain less credit relative to large firms. Our results indicate that targeting small businesses is critical to improve the effectiveness of the program. We provide evidence that one way to do so is by providing more guarantees to banks that are specialized in small businesses.

**Literature** Our paper is related to three main strands of the literature. First, we contribute to the literature studying the effects of loan guarantees (Lelarge et al. (2010), Ru (2018), González-Uribe and Wang (2019), Barrot et al. (2020), Mullins and Toro (2018), Haas Ornelas et al. (2020), Bachas et al. (2021)). We contribute to this literature in two ways. First, we study the effects of loan guarantees on financial stability over the business cycle. We find that firms participating in the program are less likely to experience 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 the agency issues associated with guaranteed loans that might increase risk. Our second contribution is to focus on the role of bank incentives in shaping the effectiveness of loan guarantees. We document that even though small borrowers are more sensitive in terms of delinquency rates, they are less likely to participate in the program, and even upon participation, they receive less credit relative to large borrowers. We discuss the role of targeting small firms to improve the effectiveness of the program.

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. (2020), Li and Strahan (2020), Autor et al. (2022), Joaquim and Netto (2022)). Our contribution to this literature is threefold. First, we use administrative loan-level data to estimate the effect of Covid-19 loan guarantees on credit supply controlling for firm-level demand shocks. Our results provide evidence supporting the validity of the treatment measure proposed by Granja et al. (2020). Second, we estimate the heterogeneous effects of the program and study how banks allocate guaranteed loans. To the best of our knowledge, our paper is the first one documenting that the program has bigger effects on delinquency rates among small firms and however, they are less likely to obtain guaranteed loans relative to large borrowers. Our findings provide clear evidence that targeting small firms is crucial to improve the effectiveness of loan guarantees. 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. We add to this discussion by showing that this pattern is also present in the context of loan guarantees in Peru, and by providing empirical evidence that the program has bigger effects on firms that are less likely to participate: small firms. Third, we study 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.

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 to this literature in three ways. First, we study the effects of loan guarantees, the most common policy worldwide during the Covid-19 crisis. Second, we study the response of financial stability, which is a priori unclear because of agency problems that are inherent in bank credit markets. Third, we estimate the heterogeneous effects of the program and the allocation of guaranteed loans. Our results show that targeting small firms is key to increase the effectiveness of this policy.

The remaining of this paper is organized as follows. Section 2 describes our data and provides some details of the institutional background. We discuss our empirical framework in section 3 and present our main results in section 4. Section 5 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, the type of loan[1], and the city where the loan was 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 program of loan guarantees introduced by the Peruvian government to help firms dealing with Covid-19 restrictions. The program was implemented by the Central

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

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 97% and the loan-size weighted average was 90%.

Private banks were responsible of screening borrowers and allocating Covid-19 loans. These loans were issued 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 participated in the program issuing USD 16 billion, which represented 17% of the balance of loans that firms had by December 2019.

## 2.3 Descriptive statistics

The Peruvian banking sector is composed of 52 financial institutions and is highly concentrated. The four largest banks accounted for 73% 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 market of loans to corporations is more concentrated, the four largest banks account for 91% of the market, while this share is only 52% in the segment of micro-credit.

Table 2 reports summary statistics for firms with a positive balance of loans in December 2019. The average firm had a balance of loans equivalent to USD 6 thousand and 12% of firms exhibited repayment delays. The age of the average firm, 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. 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 or corporations.

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

**Table 1:** Peruvian Banking Sector

| | Total Loans Mean | Total Loans Median | Number of Banks | Share Top 5 Banks |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Total | 5 749 | 505 | 52 | 71 |
| *Loans to:* | | | | |
| Micro-credit | 77 | 28 | 42 | 52 |
| Small firms | 190 | 50 | 45 | 50 |
| Medium-size firms | 263 | 13 | 48 | 82 |
| Large firms | 491 | 8 | 27 | 82 |
| Corporations | 1 272 | 166 | 13 | 91 |

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 segment of the market of corporate loans. Total loans are expressed in USD million.

**Table 2:** Characteristics of Borrowers

| | Total Loans Mean | Total Loans Median | Repayment Delay Mean | Repayment Delay Median | Age Mean | Age Median | Num. of firms |
|---|---|---|---|---|---|---|---|
| | (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 reports the mean and median of the distribution of total loans and age across firms. Repayment delay is an indicator variable equal to one if the firm exhibits some delays in repayment. 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.

We provide summary statistics of the allocation of loans in Table 3. The program provided guarantees on loans valued at USD 16 billion, which represents 29% of the balance of loans in December 2019. The program benefited 473 thousand clients, 17% of the number of firms with a positive balance of loans by December 2019. The relevance of the program varies across the different segments of the market. The value of guaranteed loans in the segment of micro-credit is USD 430 million, which represents 37% of the balance of loans in this segment in 2019 and benefited 14% of clients. This value is USD 4 billion for large firms, 34% of the balance of loans and 82% of clients by the end of 2019.

**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 | 16 | 29 | 473 | 17 |
| *Loans to:* | | | | |
| Micro-credit | 0.4 | 37 | 174 | 14 |
| Small firms | 4 | 42 | 2,566 | 22 |
| Medium-size firms | 6 | 46 | 28,771 | 81 |
| Large firms | 4 | 34 | 121,756 | 82 |
| Corporations | 1 | 3 | 319,864 | 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 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 $\delta_{ib}$ to control for match-specific time-invariant characteristics like bank specialization in a given industry. $\delta_{it}$ 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 $\text{Treatment}_{bk}$ 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 $\delta_i$ to control for any time-invariant heterogeneity across firms. $\delta_{jt}$ denotes sector-time fixed effects that account for any shock taking place at the industry level, and $\delta_{ct}$ 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 $\beta$ 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 Average Effects

## 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.

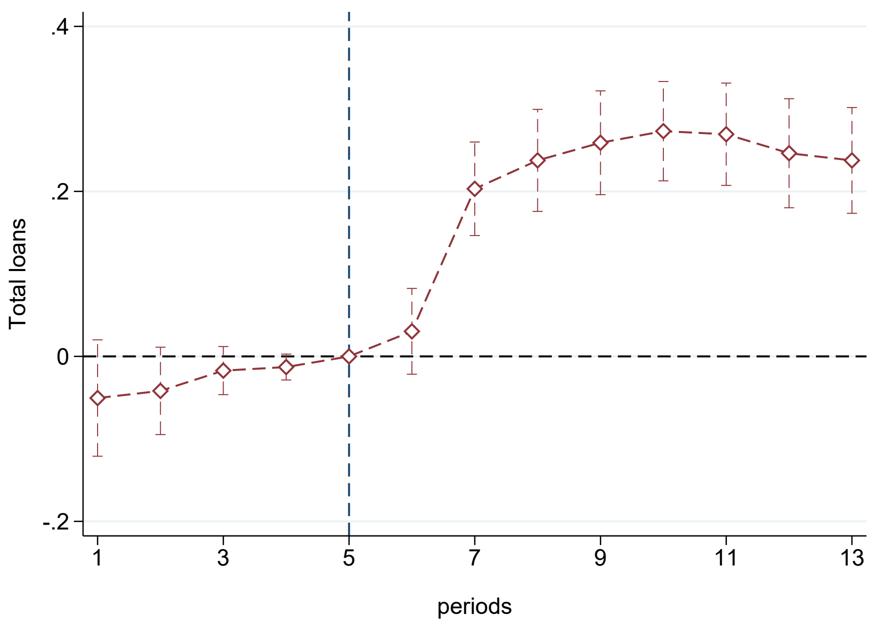
Figure 1 plots the event study graphs for the response of the balance of loans. We show the estimated quarterly treatment effect before and after the program, including the same fixed effects used in our benchmark specification. We normalize the quarter before the program to zero. The figure shows null 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) |
| Treatment$_{bk}$ × 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

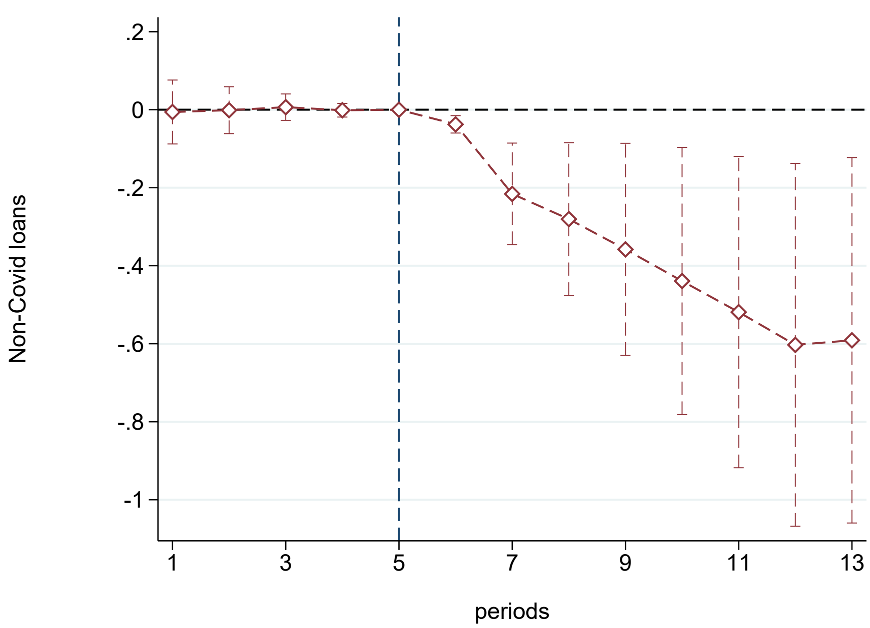



This figure plots the quarterly effects of the program on total credit at the bank-firm level. The dependent variable is in logs. The program is implemented in the second quarter of 2020. Each dot is the coefficient on the interaction of treatment and quarter fixed effects. The confidence interval is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

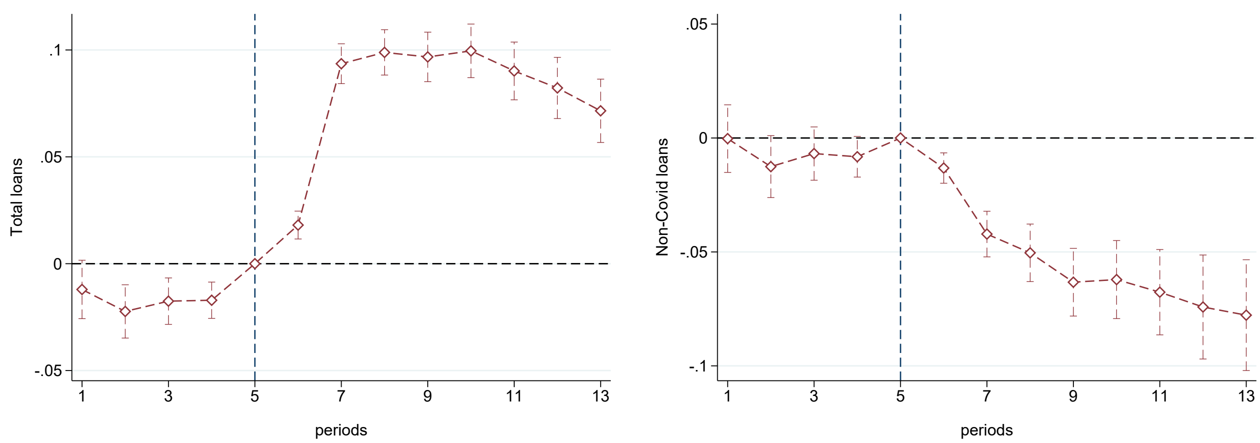
While this result shows that better connected firms obtain more credit, it does not tell us whether non-Covid-19 loans can partially help worse connected firms. We address this question by estimating equation (4) using the balance of non-Covid-19 loans as our dependent variable. We report our results 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 | Non-Covid-19 | Delinquency |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treatment$_i$ $\times$ 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



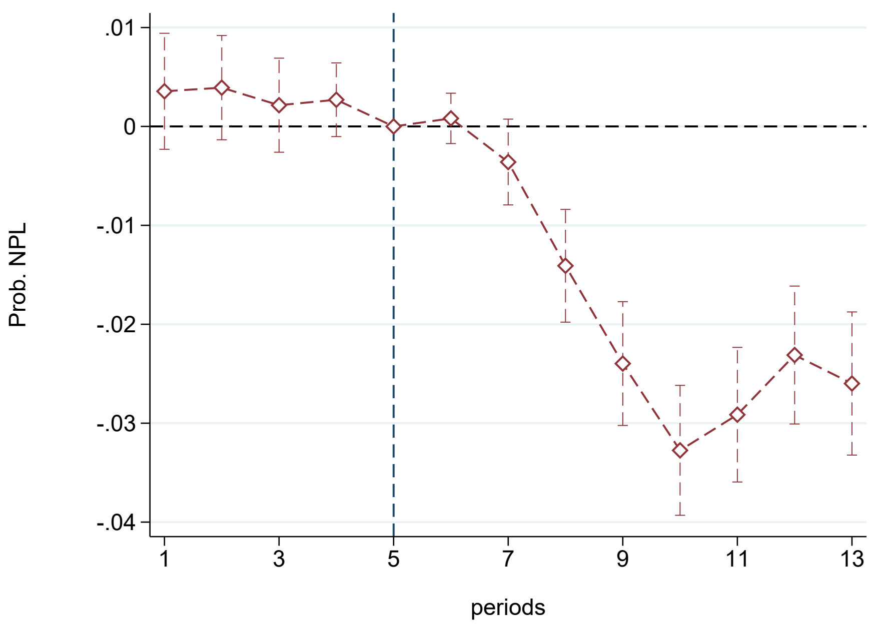

(a) Total Loans (b) Non-Covid-19 Loans

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 $\delta$ 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<br>(1) | Non-Covid-19<br>(2) | Delinquency<br>(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.

# 5 Heterogeneity and allocation of Covid-19 loans

In this subsection we study the heterogeneous effects of the program and ask 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.

## 5.1 Heterogeneous Effects

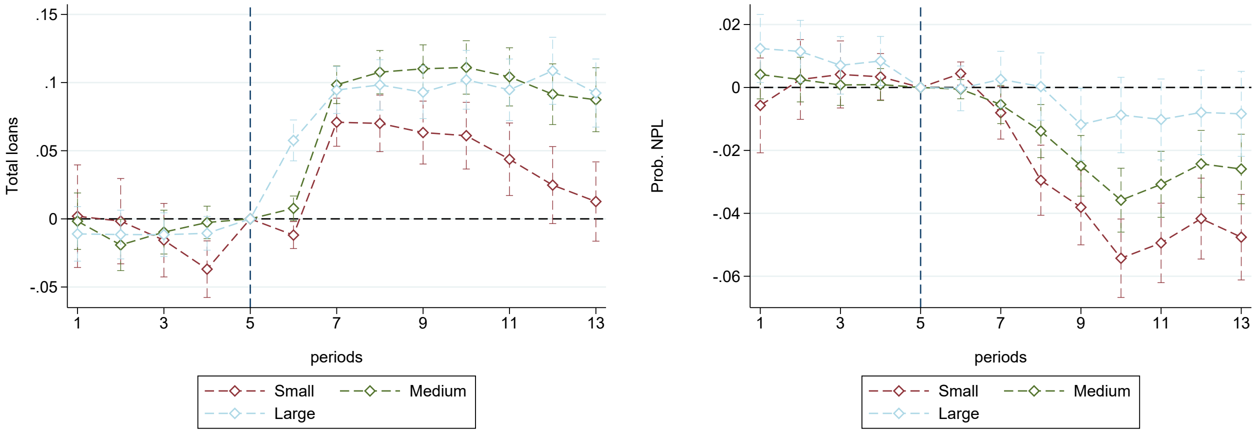
We start by estimating the response of credit. Columns 1 to 3 in Table 7 report our results. We find that lending relationships play a more important role in shaping large firms' access to credit. One standard deviation better connections lead to a 10% expansion in credit among large firms and only 5% 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.

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

| | Small<br>(1) | Medium<br>(2) | Large<br>(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.

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.

## 5.2 Allocation of Covid-19 loans

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 $\text{Access}_{ijckb}$ 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 $\alpha_1$ and $\alpha_2$ that measure the difference in the probability of obtaining a Covid-19 loan for medium and large firms relative to 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.

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

| | Small<br>(1) | Medium<br>(2) | Large<br>(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.

Our results suggest that large firms are more likely to obtain a Covid-19 loan. However, this does not tell us about the intensive margin. Even though small firms are less likely to participate in the program, it might still be the case that upon participation small firms exhibit a bigger increase in their balance of loans. To study the intensive margin we estimate the effect of the program on the balance of loans for each group of firms using our difference-in-differences instrumental variable specification (5). Our results are reported in Table 10. We find that small firms participating in the program receive 36% more credit in the post-program period while large firms receive 64% more loans. Our results indicate that small firms are not only less likely to participate in the program but they also receive less credit when participating relative to large firms. Since small firms experience a bigger decline in delinquency rates, our results indicate that governments can improve the effectiveness of loan guarantee programs by targeting small firms as private banks disproportionally grant guaranteed loans to large firms.

# 6 Conclusions

Loan guarantees are a key financial policy tool used by governments to promote economic development and deal with recessions. They are usually implemented through private banks to avoid political incentives that might not be aligned with social incentives. In this paper we estimate the effects of loan guarantees during the Covid-19 recession in Peru and analyze how private bank incentives shape the effectiveness of this policy.

We find that loan guarantees are effective in expanding credit supply and reducing delinquency rates for the average firm in the economy. Even though the decline in delinquency rates is bigger among small firms, they are less likely to participate in the program, and even upon participation, they obtain less credit relative to large firms. Our results indicate that targeting small businesses is critical to improve the effectiveness of the program. We provide evidence that one way to do so is by providing more guarantees to banks that are specialized in small businesses.

Our current work is focused on two main blocks. First, we are working on estimating the response of real outcomes such as employment, capital, and sales. Second, we intend to quantify the potential gains from targeting small firms through the lens of a model where banks prefer to provide guaranteed loans to large borrowers to avoid bigger losses of default.

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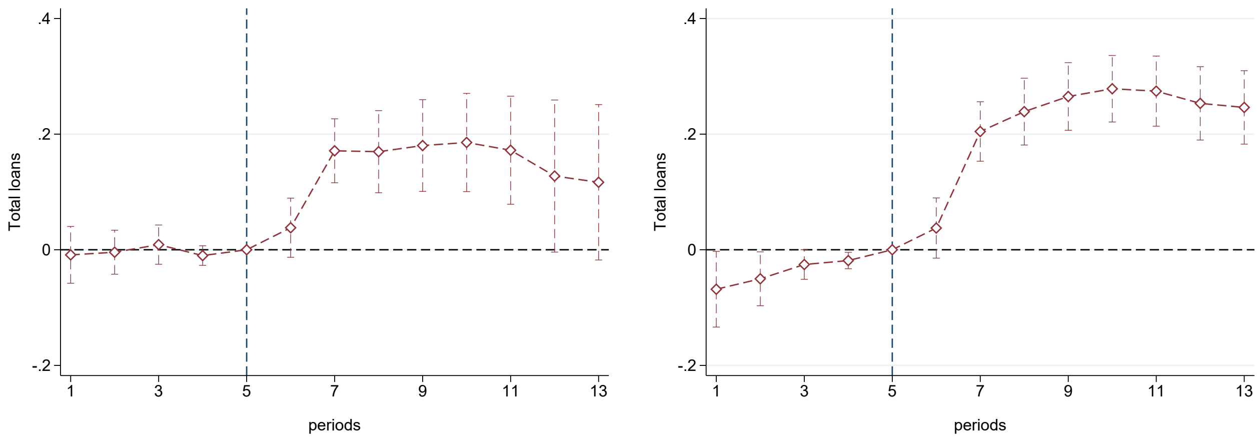
# Appendix

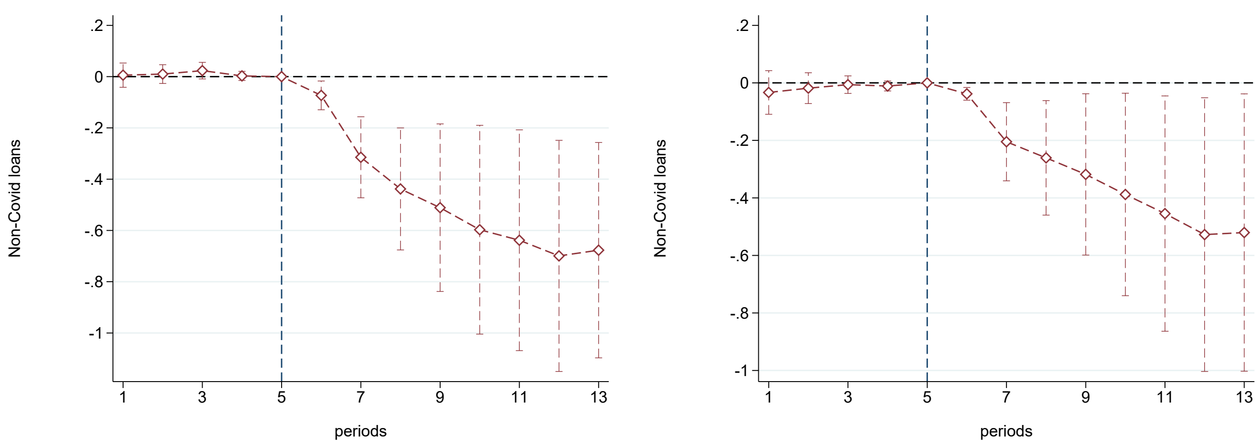
**Figure A1:** Effect of the Program on Total Loans




(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.