Graduate Institute of International and Development Studies
International Economics Department
Working Paper Series

Working Paper No. HEIDWP18-2023

Impact of the Loan Guarantees Program Reactiva on the Performance of Peruvian Companies

Marcos Ceron
Central Reserve Bank of Peru

Gerald Cisneros
Central Reserve Bank of Peru

Rafael Nivin
Central Reserve Bank of Peru

Chemin Eugène-Rigot 2
P.O. Box 136
CH - 1211 Geneva 21

Impact of the Loan guarantees Program Reactiva on the Performance of Peruvian companies

Marcos Ceron, Gerald Cisneros and Rafael Nivin * [1]

September 2023

Abstract

Amid the global COVID-19 crisis, governments worldwide introduced measures to support private enterprises. This study utilizes a newly curated panel database, encompassing the financial records of firms in Peru, to investigate the impact of a substantial government-backed loan guarantee program, known as "Reactiva Peru", on the performance of medium-sized Peruvian firms. To address the non-random allocation of loans, our empirical approach combines matching techniques and difference-in-differences methods, drawing upon previous research (Girma et al., 2007; Heyman, 2007). Our findings reveal that the Reactiva program led to heightened liquidity levels among beneficiary firms, albeit with an associated increase in indebtedness. Regarding profitability, the observed impacts on treated companies were not notably positive, except for a modest uptick in the net profit margin. This study contributes valuable insights into the efficacy of public credit support programs during crises, highlighting both their advantages and potential trade-offs for medium-sized enterprises.

Keywords: Loan Guarantees, COVID-19 pandemic, credit risk, bank lending.

JEL: G18, G21, G28, H81.

*Central Reserve Bank of Peru

[1]The authors thank Prof. Rafael Lalive from University of Lausanne for the academic supervision of this paper. This research took place through the coaching program under the Bilateral Assistance and Capacity Building for Central Banks (BCC), financed by SECO, and the Graduate Institute in Geneva. The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Central Reserve Bank of Peru.

1 Introduction

The 2019 pandemic represented a sudden and substantial shock to both the global and local economies. In an effort to contain the spread of COVID-19, the Peruvian government declared a state of emergency and mandatory social distancing measures in March 2020. This decision led to the suspension of most productive activities, resulting in a reduced capacity for companies to generate income and an increased risk of default with their suppliers, employees, and financial institutions. To address the risk of a breakdown in the payment chain and the rise in credit risk within the financial system, the Peruvian government implemented the ”Reactiva Peru” program, a program of loan guarantees. The primary objective of this program was to provide liquidity to companies so they could meet their obligations and remain operational, thereby preventing a disruption in the payment chain and maintaining the stability of the financial system.

There is evidence that the Reactiva program helped to preserve the financial stability (by reducing the probability of default of firms) and facilitated access to credit (BCRP 2021, Burga et al. 2021). However, direct evidence of its impact on the performance of Peruvian firms is lacking. Therefore, this study aims to assess the impact of the Reactiva Program on the liquidity and other performance indicators of Peruvian firms. To achieve this objective, we use data from the Credit Report of Debtors (RCD) in conjunction with information from the Report 28. The Report 28 contains a summary of the balance sheet and income statement of debtor companies in the financial system, which are required to submit these reports semi-annually to the financial institutions they owe. These reports are also submitted to the Superintendency of Banking, Insurance, and Pension Fund Administrators (SBS) semi-annually.

Since the allocation of loans through Reactiva was not random, our empirical strategy for evaluating its impact on firms performance involves a combination of matching techniques and difference-in-differences techniques, as outlined in Girma et al 2007 and Heyman 2007. This strategy is grounded on the fact that the Peruvian government established some specific rules for granting the Reactiva Loan, such as maintaining a good credit rating clasification (”Normal” or at least ”With potential problems”) for at least 90% of their loans. Furthermore, it is common practice for banks to review the financial statements of companies that apply for credit when considering the approval of loans and that information is partially available to us through the Report 28. Therefore, in this context, the ”selection on observables” assumption becomes more plausible, justifying the use of our empirical strategy.

Our empirical strategy to evaluate the impact of the Reactiva program on firm performance unfolds in two stages. In the initial stage, we estimate the likelihood of a company receiving Reactiva, employing logit models. Subsequently, we conduct matching between treated and untreated companies based on their propensity scores. In the second stage, we leverage the weights derived from the matching step to estimate the impact of the Reactiva program through a difference-in-differences framework. Our dataset comprises approximately 3000 medium and large companies for which we have available information for December 2018 and December 2019.

Before assessing the impact of Reactiva on performance ratios from the Report 28, we evaluate its impact on indicators available in the Credit Report of Debtors (RCD). Consistent with the results of Burga et al. (2021), we found that companies receiving Reactiva reported a lower probability of being bad payers both at the end of 2020 and the end of 2021 (an impact of around 8 percentage points). Similarly, the probability of having a "normal" credit rating (compared to the categories "with potential problems", "deficient", or "lost") was about 10 percentage points higher for companies that received Reactiva. Additionally, we found that treated companies increased their access to credit by about 40% more than companies that did not participate in the program by the end of 2020 (and 50% by the end of 2021).

Focusing on the performance indicators of firms, firstly, we assessed the impact on liquidity indicators, specifically the liquidity ratio and the quick ratio. It was observed that companies that received the Reactiva program reported improved liquidity levels by the end of 2020, with positive effects continuing, albeit to a lesser extent, in December 2021. In particular, liquidity ratios were approximately 15% to 20% higher in companies that received Reactiva compared to those that did not. Similarly, the Acid test ratio, which is a stricter liquidity gauge, was 20% higher in treated companies in December 2020, signifying that treated companies were better equipped to meet their short-term financial obligations. All of this suggests that the Reactiva program effectively assisted companies in meeting their financial commitments, preventing disruptions in the payment chain.

Moving on, it was observed that solvency levels decreased in companies that received a Reactiva loan. Specifically, in December 2020, the debt ratio (Total assets/Total liabilities) was, on average, 6% higher for treated firms (with a similar impact in December 2021). Likewise, in December 2020, the debt-to-equity ratio (Debt/Net Equity) was approximately 15% higher for treated companies (with a similar trend in December 2021). These lower solvency levels could be seen as a concern because they imply that companies benefiting from Reactiva had reduced capacity to meet long-term debts compared to companies that did not receive the program. Finally, we assessed the impact of the Reactiva program on certain profitability indicators. Our findings showed that profitability metrics did not exhibit significant improvements in treated companies, except for the net profit margin, which increased by around 1.5 percentage points for treated firms in December 2020. However, other indicators did not reveal statistically significant improvements.

In summary, we can conclude that the Reactiva program was associated with higher liquidity levels, but this came at the cost of increased indebtedness for treated companies. In terms of profitability, no clear positive impacts were observed in treated companies, except for a modest increase in the net profit margin. These results indicate that the Reactiva program effectively achieved its primary goal of providing short-term liquidity to companies while ensuring the stability of the financial system. However, the downside was a higher level of indebtedness, which could pose future challenges for these companies. Furthermore, the expected positive impact on profitability did not materialize, suggesting that the program primarily helped companies meet their short-term obligations rather than enhancing their profit generation capabilities.

The subsequent sections of this work are structured as follows: Section 2 provides a concise overview of the Reactiva program, while Section 3 delves into the dataset used for this study, offering a more comprehensive explanation of the criteria used to classify a firm as a beneficiary of the program. Moving on to Section 4, the study details its empirical strategy for evaluating how Reactiva impacted firm performance. The findings of the analysis are presented in Section 5, and the study concludes with its final remarks in Section 6.

2 Reactiva Program

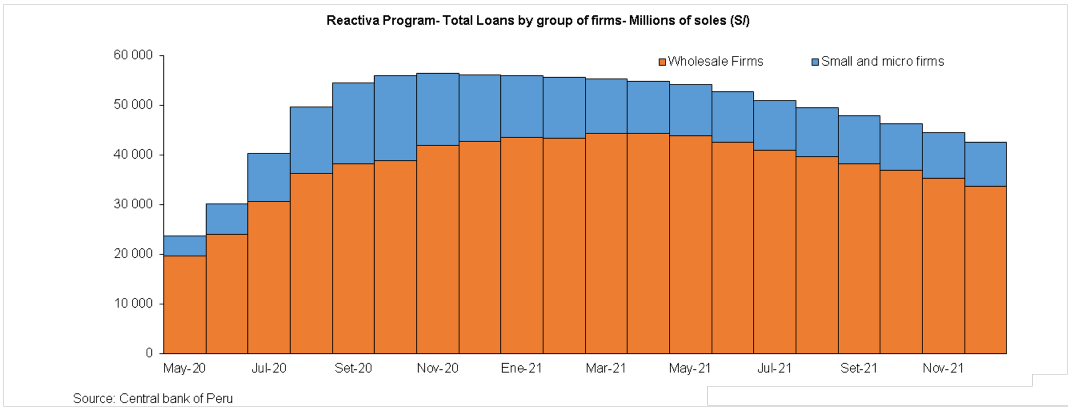
The Reactiva program, officially established on April 6, 2020, through Legislative Decree 1455, had the primary objective of offering secure liquidity funding to companies that were struggling with immediate financial commitments to their employees and suppliers of goods and services. This initiative involved the provision of loans denominated in the national currency, and these loans were extended by financial institutions with guarantees provided by the National Government. In order to be eligible for participation in this program, companies were required to meet the following criteria:

- They should not have outstanding tax debts with the country's tax institution (SUNAT) exceeding 1 UIT (S/ 4950 or approximately $1400) at the time of application.
- They should have a favorable credit rating.

- Only companies from the real sector of the economy were eligible; those belonging to the financial system were not included.

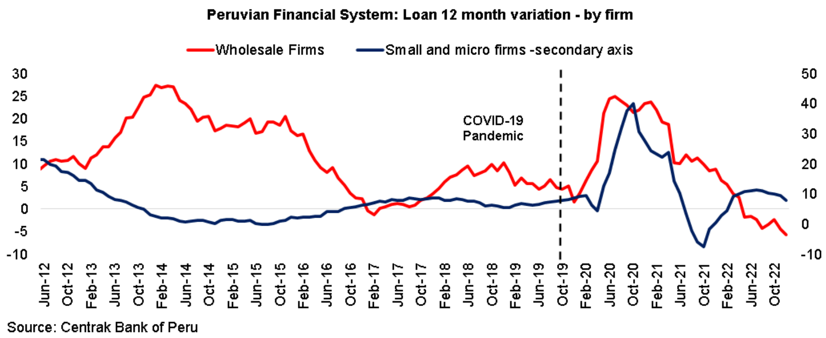
It's worth emphasizing that Reactiva loans came with certain limitations, including a maximum loan duration of 36 months and a cap on the loan amount at S/ 10 million, approximately equivalent to $2.7 million. Reactiva loans were accessible to a wide spectrum of businesses, encompassing both wholesale entities (comprising corporate, large, and medium-sized companies, categorized according to the Financial Supervisor Institution in Peru, or SBS) and retail businesses (encompassing small and micro-enterprises, classified based on their indebtedness in the financial system). For context, corporate firms are defined by their annual sales exceeding S/ 200 million over the last two years, large firms fall within the range of annual sales greater than S/ 20 million but not exceeding S/ 200 million over the same period, and medium-sized firms are included if they have a total indebtedness in the financial system surpassing S/ 300 thousand within the past six months. In contrast, small firms have total indebtedness within the financial system ranging from S/ 20 thousand to S/ 300 thousand within the last six months, while micro-businesses are characterized by indebtedness in the financial system (excluding home mortgage loans) not exceeding S/ 20 thousand within the same time frame. Figure 1 illustrates the trajectory of credit balances categorized by the type of company.

Figure 1: Reactiva Program loans by type of firm (S/ Millions).



By the end of the first half of 2020, the disbursement of loans had reached a total of S/ 30.2 million. Despite the majority of beneficiaries being small and micro firms, accounting for 92% of the total, a substantial portion, approximately S/ 24.0 million or 80% of the disbursement by the end of June 2020, was allocated to wholesale companies (comprising corporate, large, and medium-sized businesses). Throughout 2020, wholesale companies consistently represented over 70% of the placements facilitated through the Reactiva Peru program, hereinafter referred to as Reactiva.

Figure 2: Reactiva Program loans by type of firm (S/ Millions).



Moreover, during the initial two months of 2020, a slight dip in 12-month loan growth occurred, attributed to the early impact of the pandemic. This decline in growth was linked to government-imposed mobility and economic restrictions. However, subsequent months in 2020 witnessed an increase in loans, both to wholesale companies and those associated with small retail enterprises. This rebound, which later turned into higher-than-anticipated growth, persisted until the conclusion of the third quarter of 2020, after which a slowdown in credit was noted in both sectors. The expansion of loans can be attributed to the "Reactiva program," which injected more than 56.4 billion soles into the financial system, providing a substantial boost to the economy.

3 Data

In order to evaluate the impact of the loan program on the performance of Peruvian firms, we use two sources of data. The first source is the Consolidated Credit Report (RCC), linked to the Peruvian Financial System, which comprises comprehensive monthly data on loans at the debtor-bank level. This dataset offers vital financial insights into firms, including their debt levels with each financial institution, delinquency status, credit classifications, and the amount of debt received through the Reactiva program. The second data source is the Report-28, a semiannual report containing summarized balance sheet and income statement information for selected Peruvian firms. Financial institutions collect this data from their debtors and report it to the Financial Regulator (SBS). It is important to note that Report-28 data is exclusively available for wholesale firms, encompassing corporate, large-sized, and medium-sized entities.

For this study, we have focused our analysis on medium-sized firms for which we could obtain balance sheet information for the December 2018 and December 2019 periods. We opted for this selection due to the semiannual nature of Report-28 data, with the first-semester information often being incomplete and available for only a portion of the firms in our dataset. Consequently, we restricted our analysis to end-of-the-year balance-sheet information to maintain a more robust sample size, resulting in a dataset comprising nearly 3,000 medium-sized firms[1].

3.1 Treatment definition

To identify firms that received the Reactiva loan, we rely on data from the Credit Registry, which allows us to track when and how much each firm received through this program. However, it is important to note that some firms did receive Reactiva loans, but the amounts were relatively small compared to their usual financial system borrowings. For example, we have observed firms that, prior to the pandemic, had outstanding debts with the financial system ranging from S/ 500 thousand to S/ 1 million but received Reactiva loans of only S/ 5,000 (approximately $1,400) during 2020. Clearly, in such cases, receiving this small amount of credit through Reactiva is unlikely to have a significant impact on a firm's performance.

To address this issue, we define a firm as a "treated" firm if two conditions are met: i) it received at least S/ 30,000 through Reactiva, and ii) the amount of Reactiva credit represents at least 25% of its total debt with the financial system between June and December 2020. Using this treatment definition, we find that 37% of medium-sized firms in the economy received a Reactiva loan. When we narrow our analysis to medium firms with information from the R-28, approximately 75% of that subset received a Reactiva Loan.

Table 2 presents statistics for both treated and non-treated firms, highlighting significant differences between the two groups. In the overall sample of medium-sized firms, treated firms display notably stronger indicators of repayment capacity. For instance, in January 2020, the non-performing loan fraction was 31% for firms that did not receive Reactiva, whereas it was a mere 0.6% for firms that did receive Reactiva. Similarly, the proportion of firms with a good credit rating (classified as "Normal" or "good debtors" in the RCC) stood at 97% in the treated subgroup, but it was only 63% in the non-treated subgroup. Furthermore, substantial disparities exist in the amount of debt with the financial system. Treated firms carried an average outstanding debt of S/ 1.1 million, compared to S/ 1.5 million for non-treated firms. The 25th, 50th, 75th, and 90th percentiles of debt amounts were also higher for non-treated firms. These findings collectively underscore significant distinctions between treated and non-treated firms, particularly in terms of their payment behavior and indebtedness to the financial system.

However, when we narrow our analysis to the subset of medium-sized firms with information available in the Report-28, we find that they are quite similar in terms of payment capacity.

[1] In the whole Peruvian economy, there are around 35 thousand of these medium-sized firms.

Table 1: Statistics for medium-sized firms by treatment status

	All Medium firms		Medium firms in R-28	
	Reactiva	No Reactiva	Reactiva	No Reactiva
% NPL	0.6	30.9	0.6	7.6
Good rating	96.6%	62.6%	96.2%	79.5%
Avg Debt (Thousand S/)	1 154.4	1 533.6	2 196.4	8 940.2
p10 (Thousand S/)	265.8	246.3	629.1	796.7
p25 (Thousand S/)	349.6	368.9	1 126.3	1 562.9
p50 (Thousand S/)	537.4	618.0	1 973.4	3 225.7
p75 (Thousand S/)	988.9	1 175.8	3 506.3	8 220.6
p90 (Thousand S/)	2 192.4	2 453.0	6 082.9	21 610.0
N. Firms	13 106	21 899	2 193	738

Source: RCC, R-28.

Specifically, the percentage of firms with a good credit rating and the fraction of non-performing loans closely mirror those in the overall sample. Nevertheless, striking disparities emerge when we focus on the level of indebtedness with the financial system. Treated firms exhibit an average debt with the financial system that is nearly twice the average for the entire sample, whereas non-treated firms have an average debt amounting to almost six times the overall sample average. These statistics lead to two key conclusions: firstly, treated and non-treated firms exhibit significant dissimilarities in both the complete medium-sized firm sample and the subset with balance information. Secondly, our sample of firms with balance information represents a subset of the largest medium-sized firms in the Peruvian economy.

4 Empirical strategy

In order to evaluate the impact of Reactiva in the firms's performance, we estimate the following difference-in-difference equation:

$$Y_{f,t} = \alpha_f + \alpha_{i,t} + \sum_{k=2018, k\neq 2019}^{2021} \beta_k * T_f * 1[t=k] + \epsilon_{f,t} \tag{1}$$

Where the dependent variable $Y_{f,t}$ represents some firm's performance indicator such as the (log) the level of debt with the financial system or some financial ratios associated with firm's liquidity or solvency. α_f represents a firm fixed-effect, $\alpha_{i,t}$ represents an industry-year fixed effect that is included in order to capture differences in the exposition to the pandemic between different industries in the economy. The term T_f is a dummy variable that takes the value of 1 for firms that were treated by the Program Reactiva (based on defenition described previously). The estimates of β_{2020} and β_{2021} from Equation 1 will give us the impact of the program Reactiva on the firm's performance if the treatment was randomly assigned between firms.

However, estimating the impact of Reactiva on the firm' performance presents a challenge due to the potential non-random selection of firms into the treatment. As we already shown in the previous section, firms that received Reactiva possess distinct characteristics that consistently set them apart from non-treated firms. Similarly, the program was designed in such a way that firms had to fullfil some requirements in order to apply for a Reactiva loan. This means that our estimates will become biased if the non-randomness of the treatment is not taken into account (Heyman, 2007). We therefore use an alternative method, following the methodology considered in Girma et al (2007) and Heyman (2007)[2] which is propensity score matching (PSM) combined with the more general difference-in-differences technique. As mentioned by Blundell and Costa Dias (2009) "Matching attempts to reproduce the treatment group among the non-treated, this way reestablishing the experimental conditions in a nonexperimental setting".

Therefore, our empirical strategy is divided in two parts. In the first part we estimate logit models in order to predict the propensity (probability) that a firm will receive a Reactiva Loan. Once we have those estimated probabilities, we match to each treated firm a subgroup of non-treated firms according to a matching technique. In our baseline specification, we utilize Kernel (Epanechnikov) Matching, while we explore other matching techniques such as Nearest-Neighbor (N-N) matching, Kernel matching with different functions (Gauss and Uniform), and Radius Matching as part of a robustness exercise.

Kernel Matching establishes a neighborhood for each treated firm using a specified bandwidth, denoted as h. Within this neighborhood, it constructs the counterfactual by considering all non-treated firms, rather than just the nearest observation as in the case of N-N matching. Once a neighborhood is defined for each treated observation, the next step involves determining appropriate weights to link the selected set of untreated observations to each treated observation. In the Kernel Matching estimator, the weights assigned to each firm j in the control group (C) to match with treated firm i are determined using the following Equation:

$$g(p_i, p_j) = \frac{K[\frac{p_i - p_j}{h}]}{\sum\limits_{k \in C} K[\frac{p_i - p_k}{h}]} \tag{2}$$

Where p_i and p_j are the estimated probabilities of being treated (Receiving Reactiva) for firms i and j and h represents the bandwidth. The Epanechnikov kernel function K is given by the following Equation:

[2]Both papers study the impact of foreign ownership/acquisition on the performance of firms in Sweeden and U.K., respectively.

$$K(z) = \frac{0.75(1-0.2z^2)}{\sqrt{5}} \tag{3}$$

If $|Z| < \sqrt{5}$, and 0 otherwise. Finally, once we have constructed these weights, we use them as weights to estimate Equation 1 in order to obtain the Impact of Reactiva on firm's performance[3]. More details on this estimation strategy can be found in Heyman (2007), Girma et al (2007), Blundell and Costa Diaz (2009) and the references cited there, while a more detailed discussion of non-parametric matching estimators including Kernel and local linear regression methods see, Heckman, Ichimura, and Todd (1997).

4.1 Matching

Here we present the logit regression to estimate the probability of firms receiving Reactiva. We have included several explanatory variables that we expect to influence the selection into the treatment, in accordance with the program's established rules. All explanatory variables related to participation in the treatment are collected for the December 2019 period, which is the last period before the loan program's implementation. We include a dummy variable that takes the value of one for firms with no non-performing-loans and a dummy variable for firms with good credit rating ("Normal"). We also include the number of bank relationships associated with each firm, which serves as a proxy for the firm's level of connectivity with the financial system. In particular, we would expect that firms more connected with the financial system are more likely to access to the Reactiva Program. We also include the Debt-ratio, as heavily indebted firms are expected to be less likely to receive the program. Finally, we include the total assets (and its square) and the level of debt with the financial system (and its square). These variables are expected to capture differences in the participation in the treatment based on the size of the firms and on the level of debt that they already have with the financial system.

The coefficients from the logit estimation, along with their p-values, are presented in Table 2. It's notable that all coefficients are statistically significant at the 1 percent level and have the expected signs. Specifically, firms with a good credit rating and firms with more bank relationships by the end of 2019 are more likely to be part of the program. Conversely, more heavily indebted firms (measured both relatively through the debt ratio and absolutely by their debt size with the financial system) and firms with non-performing loans in December 2019 are less likely to receive a Reactiva loan. Additionally, larger firms, measured by their asset size, are more likely to participate in the program up to a certain point, as indicated by the negative and statistically significant coefficient on the square of assets. Table 2 also presents a balance test between treated

[3] In order to avoid bad matches, we impose the common support condition (Caliendo, 2005)

and non-treated firms, both before and after matching. Table 2 also presents the balance test between treated and non-treated firms, before and after matching. We can observe that all the explanatory variables are not balanced before the matching (as observed in the column 6), but once we compare matched firms, we can observe that there are no significant differences between those groups.

Table 2: Logit regresion and Balance test.

Variable	Logit Estimation		Unmatched firms		t-test	Matched firms		t-test
	Coef.	(p-value)	Treated	Non-treated	$p > \|t\|$	Treated	Non-treated	$p > \|t\|$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy(NPL)	-0.787***	0.000	0.051	0.189	0.000	0.052	0.055	0.659
Dummy (Good Rating)	1.897***	0.000	0.964	0.786	0.000	0.963	0.963	0.959
N. Bank Relat.	0.507***	0.000	2.993	5.471	0.000	3.006	3.087	0.762
Debt Ratio	-0.008***	0.010	0.056	0.061	0.000	0.056	0.056	0.493
Assets (S/ Million)	0.061***	0.000	11.2	17.3	0.000	11.1	11.5	0.272
Sqr. Assets	-0.001***	0.000	226.1	654.6	0.000	222.8	269.2	0.016
Credit (S/ Million)	-0.338***	0.000	2.99	5.47	0.000	3.01	3.08	0.385
Sqr. Credit	-0.007***	0.000	18.2	67.9	0.000	18.3	18.7	0.821

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Results

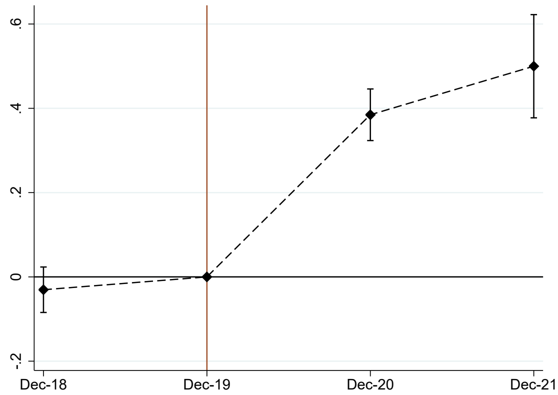
In this section we present the results of estimating Equation 1, considering the weights from the PSM obtained from the previous subsection. We start by presenting the results of the impact of Reactiva on the level of credit obtained from the financial system and the size of assets and liabilities. Then we evaluate the impact of the Reactiva program on some indicators associated with the repayment capacity of the firm. Finally we evaluate the impact of the program on some financial ratios associated with the firm's liquidity and the firm's solvency.

Figure 3 presents the estimated impact of the Loan program on the (log) stock of credit received from the financial system. We can observe that Treated firms, on average, experienced a 40% increase in loans by december 2020 compared to firms that did not receive Reactiva. The impact of the program is even higher by December 2021, when treated firms experienced an increase of around 50% in loans compared to non-treated firms. Notice that, as we would expect, the estimated coefficient of the impact of Reactiva on the stock of debt in December 2018 is very close to zero and not statistical significant, which can be taken as a placebo test.

Next, we evaluate the impact of the program on the repayment capacity of the firms. Figure 4a presents the impact on the probability of a firm of having non-performing loans[4], Figure 4b

[4]The dependent variable is a dummy that takes the value of 1 if the firm has a NPL.

Figure 3: Impact on Firm's Total Credit.



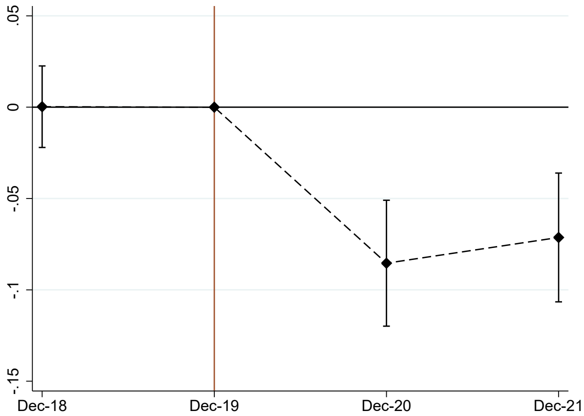
Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variable is the logarithm of the firm's stock of debt in the financial system. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

presents the impact on the probability of having a good Rating (Being a "Normal" debtor) and Figure 4c presents the impact on being a high risk debtor[5]. We can observe that in all the cases treated firms reported increases of around 5 to 10 pp in the probability of being good payers. Now we turn the attention to some indicators of firms' performance. The Reactiva program was implemented with the objective of providing liquidity and working capital to firms and preventing the economy's payment chain from breaking. In order to evaluate the level of firm's liquidity we have considered two indicators: the Liquidity ratio, defined as the current assets divided by the current liabilities and the Acid test, which is the most stringent calculation of short-term liquidity and is defined as quick assets (current assets minus inventory) divided by current liabilities. Figure 5 presents the estimated impact of the Reactiva program on firm liquidity. Treated firms demonstrated a higher liquidity ratio compared to non-treated firms. The impact was notable, with treated firms experiencing an increase of around 15% in their liquidity ratio by December 2020 and a 7% increase by December 2021. Additionally, the Acid-test, which is a more stringent measure of short-term liquidity, showed even more substantial impacts. Treated firms reported increases of approximately 20% and 17% in their Acid-test ratios compared to non-treated firms in December 2020 and December 2021, respectively. These results indicate that the Reactiva program effectively fulfilled its objective of providing liquidity to firms, enabling them to meet their short-term obligations and maintain financial stability.

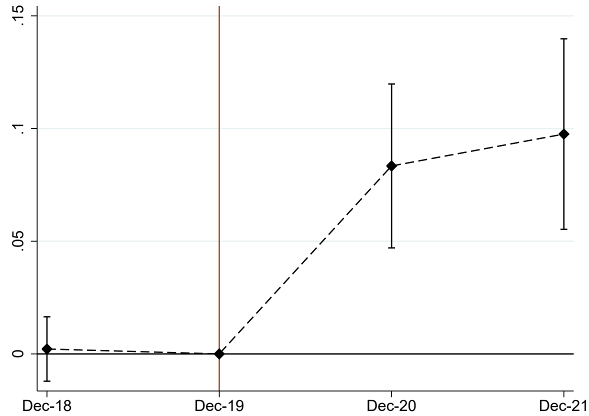
Next, we evaluate the impact on solvency indicators. These metrics are essential for assessing a firm's ability to meet its long-term obligations and the likelihood of potential default on its debt

[5]In this case, a debtor is considered a high risk debtor if he has some loans reported as overdue credits or credits in judicial collection.

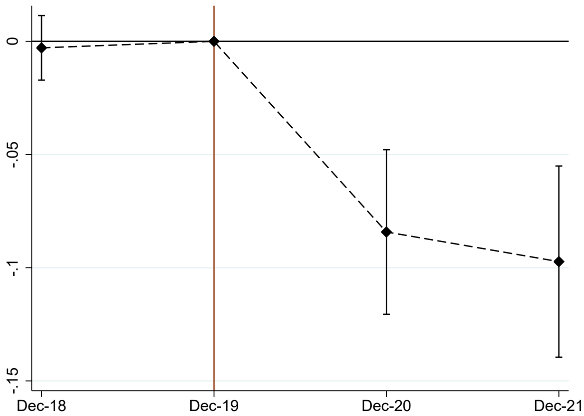
Figure 4: Impact on Delinquency rates.



(a) Probability of NPL



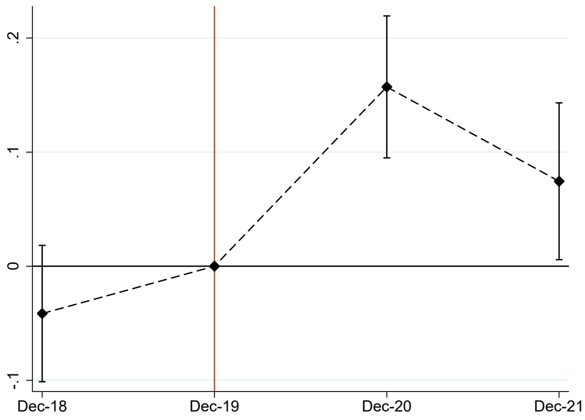
(b) Probability of being "Normal"



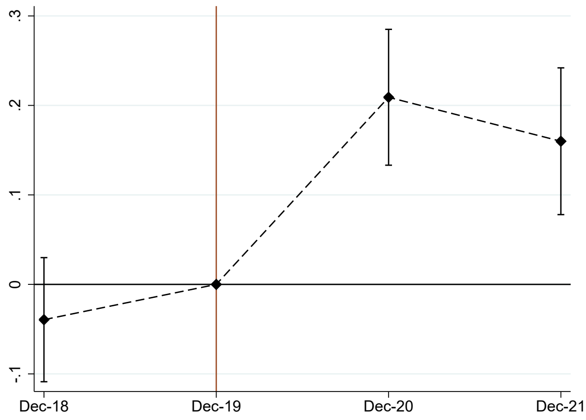
(c) "High-risk" debtor

Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variable is a dummy variable that takes the value of 1 is the firm has a delinquent credit, is considered "Normal" or has a fraction of its debt catalogued as "High risk", respectively. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

Figure 5: Impact on Firm's Liquidity.



(a) Liquidity Ratio



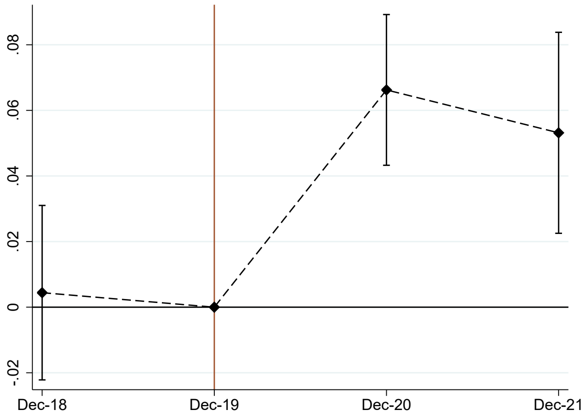
(b) Acid-Test

Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variable is in logarithms. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

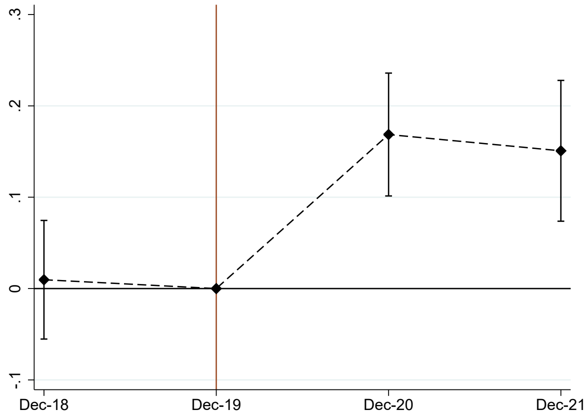
in the future. We consider two standard solvency ratios (the debt ratio, defined as as the total liabilities divided by total assets) and the Debt-to-Equity ratio. Additionally, we consider two ratios similar in spirit to the previous ones but that instead of considering total liabilities in the numerator, they include the total stock of debt with the financial system (credit-to-assets and credit-to-equity ratios).

Figure 6 present the results of these exercises. We can see that, on average, treated firms present higher levels of leverage than their non-treated counterparts. In particular, the debt ratio is around 6% and 5% higher for treated firms in December 2020 and December 2021, respectively. In other words, a higher fraction of the assets of treated firms is funded by debt, instead of by their own equity. Regarding the Debt-to-equity ratio, we can observe that treated firms reported increases of around 15% on december 2020 and 2021, compared to non-treated firms. Similar qualitatively conclusions are obtained when we consider the alternative solvency ratios in Figures 6c and 6d. However, in this case the magnitudes are bigger. In particular, the level of indebtedness with the financial system, relatively to the total assets, is around 40% higher for treated firms(and around 25% higher, when measured with respect to the firm's equity). These findings highlight that treated firms, while benefiting from increased liquidity through the Reactiva program, experienced lower solvency levels, potentially reducing their capacity to meet long-term debt obligations compared to firms that did not receive the program.
Next, we evaluate the impact on some firm's profitability indicators to evaluate whether treated firms were more efficient than non-treated firms in generating income. The results of this exer-

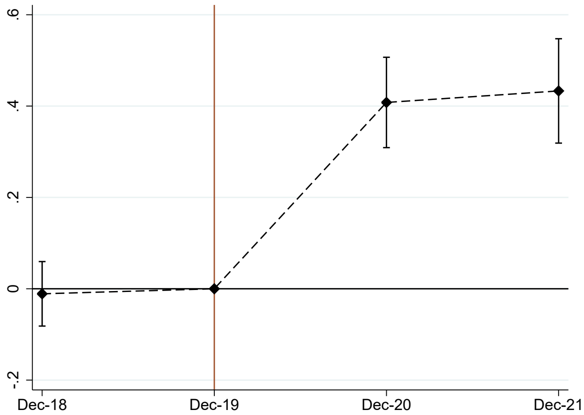
Figure 6: Impact on Firm's Solvency.



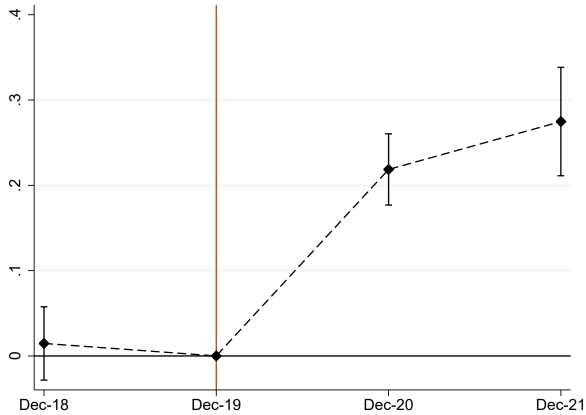
(a) Debt Ratio



(b) Debt-to-equity



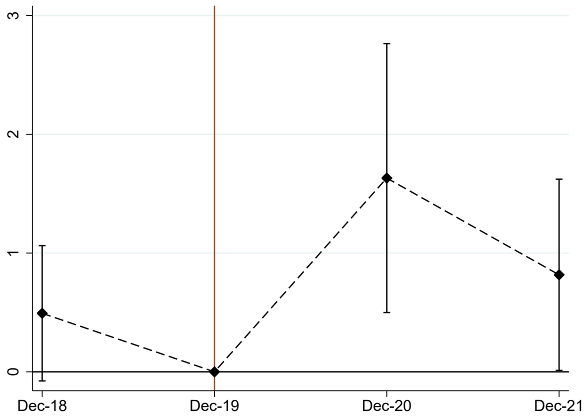
(c) Credit-to-Assets



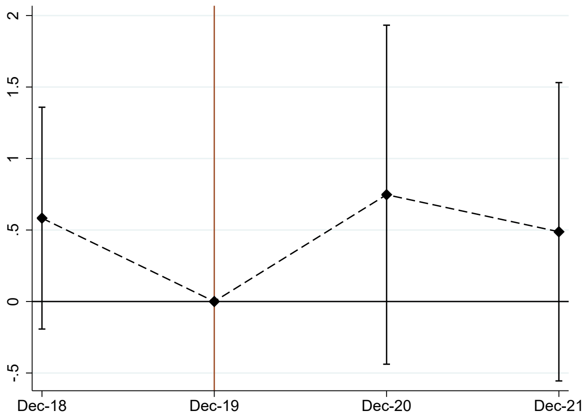
(d) Credit-to-equity

Note: The figure displays the effects of the program on different periods estimated from Equation 1. In Figure (a) the dependent variable is the (log) Credit-to-Equity ratio, calculated as the total debt with the financial System divided by firm's Net Worth. In Figure (b) the dependent variable is the (log) Credit-to-Debt ratio, calculated as the total debt with the financial System divided by firm's total liabilities. Figure (c) and (d) consider the (log)credit-to assets and (log)credit-to-equity as the dependent variables, respectively. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

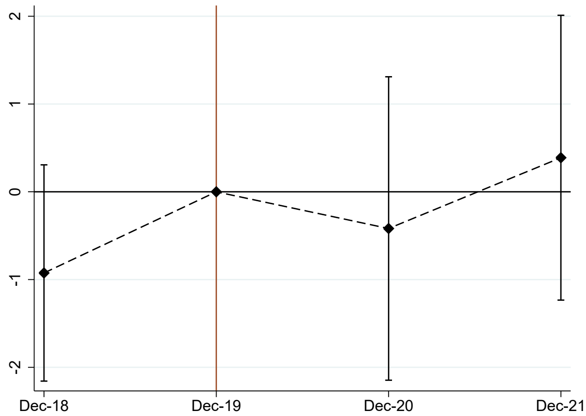
Figure 7: Impact on Profitability.



(a) Net profit margin



(b) Operating Margin



(c) ROE

Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variables are in levels. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

cise are presented in Figure 7. Figure 7a shows the impact on the net profit margin, Figure 7b illustrates the impact on the operating margin, and Figure 7c assesses the impact on the Return on Equity (ROE). The findings are not consistent across all profitability measures. Specifically, we observe statistically significant impacts in only one case: the net profit margin. Treated firms experienced an increase of 1.5 percentage points (pp) and 0.7 pp in December 2020 and December 2021, respectively, in their net profit margins. However, the other two profitability indicators (operating margin and ROE) do not show statistically significant impacts on the performance of treated firms. This suggests that the Reactiva program had a limited and mixed impact on the profitability of the treated firms.

Finally, we explored alternative dependent variables to gain a more comprehensive understanding of how treated firms were affected by the program. The results of these additional analyses are presented in the Appendix. Figure A-1 reveals that treated firms, on average, saw an increase in their total assets of approximately 10%, while their total liabilities increased even more (around 14%). This aligns with the previously reported increase in the debt ratio for treated firms. In Figure A-3, we observe that treated firms increased their levels of current assets by around 13% in December 2020 and December 2021. This indicates that, in the short term, these firms were able to generate more income than their non-treated counterparts, while simultaneously not accumulating higher levels of short-term liabilities. Furthermore, in Figure A-3(c), we can see that the working capital of these treated firms increased by approximately 18% by the end of 2021. These findings provide additional insights into how the Reactiva program impacted the financial dynamics and liquidity management of treated firms.

5.1 Robustness

In this section we check the robustness of our previous results in two ways. First, we consider different matching techniques and compare those results with the previous results. We consider the Nearest-Neighbor matching with replacement (1 to 1, 2 to 1 and 4 to 1), the Radius Matching (with a caliper of 0.01) and Kernel matching, considering a Gauss and a Uniform kernel. As a reference, we also present the results of estimating equation 1 without any propensity score matching.

Table 3 presents the results for the impact on the probability of having a non-performing loan on December 2020 and December 2021. We can observe that all the matching techniques provide quantitatively very similar results. In particular, treated firms were around 8 percentage points less likely to have a non-performing loan on December 2020 (and 7 percentage points less likely

Table 3: Impact on Probability of having non-performing loans

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**	**Kernel**		
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	0.075***	-0.029	-0.017	-0.011	-0.002	0.004	0.002	0.000
	(0.000)	(0.246)	(0.399)	(0.572)	(0.905)	(0.775)	(0.904)	(0.985)
Dec-2020	-0.024	-0.082***	-0.078***	-0.088***	-0.082***	-0.080***	-0.086***	-0.085***
	(0.140)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dec-2021	-0.017	-0.080***	-0.074***	-0.074***	-0.076***	-0.068***	-0.070***	-0.071***
	(0.327)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N Obs.	10835	9237	9553	9780	9889	9934	9934	9934
Adj-R2	0.525	0.464	0.457	0.461	0.466	0.466	0.468	0.468
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.

on December 2021)[6]. Tables A-1, A-2 and A-3 in the appendix present the impact of Reactiva on the level of credit, the liquidity ratio and the debt ratio. As before, all the matching techniques provide very similar estimates [7].

It's crucial to emphasize the importance of employing Propensity Score Matching (PSM) in conjunction with a difference-in-differences (DID) specification. Without this combined approach, we might erroneously conclude that there was no impact on the likelihood of firms having non-performing loans, as demonstrated in Column 1 of Table 3. Alternatively, we could incorrectly deduce that the magnitude of the Reactiva program's impact on the level of credit was an increase of approximately 70% relative to non-treated firms, when the actual estimated impact on credit, provided by the matching estimates, is closer to 40% for December 2020. This exercise underscores the critical importance of using both techniques together to ensure accurate estimations of program effects.

In our second robustness analysis, we adopt a slightly less stringent definition of treatment. Here, a firm is categorized as treated if it received a minimum of S/ 30 000 and if the Reactiva credit constitutes at least 10% of its total debt with the financial system between June and December 2020. The results of this alternative definition are presented in Tables A-4 and A-5 in the appendix, specifically for the impact on liquidity ratio and debt ratio. It's evident that the outcomes are qualitatively and quantitatively similar to the baseline results. Treated firms still exhibit higher liquidity levels but also increased exposure to debt, particularly long-term debt.

[6]The coefficients plotted in Figure 4a are presented in the column 8 of Table 3.

[7]To save space, we do not present these robustness exercises for all the variables previously analyzed. All of them present qualitatively very similar estimated coefficients, compared to our baseline results.

We also conducted additional robustness checks by exploring different specifications for the logit model, and although these results are not included in the paper (but available upon request), they align qualitatively and quantitatively with those presented earlier in the study.

6 Conclusions

During the global COVID-19 crisis, governments worldwide implemented measures to support private enterprises, and Peru was no exception, introducing the "Reactiva Peru" program. This program, primarily designed to furnish liquidity to companies, aimed to enable them to meet their obligations, thus averting payment chain disruptions and preserving financial system stability. In this study, we leveraged a newly assembled panel database comprising financial records of Peruvian firms to investigate the impact of "Reactiva Peru", a substantial government-backed loan guarantee initiative, on medium-sized Peruvian companies.

Given that Reactiva loan allocation was not random, our empirical approach involved a combination of matching techniques and difference-in-differences techniques (Girma et al., 2007, and Heyman, 2007) to assess its influence on firms' performance. This approach was founded on the fact that the Peruvian government established specific rules for Reactiva Loan disbursement, making "selection on observables" a plausible assumption in this context, justifying our chosen empirical strategy.

Our findings indicate that the Reactiva program effectively bolstered liquidity levels for participating firms, albeit at the expense of increased indebtedness. Concerning profitability, we observed no clear positive impacts, except for a modest rise in the net profit margin. These results suggest that Reactiva successfully fulfilled its primary objective of providing short-term liquidity and ensuring financial system stability. However, the downside was heightened indebtedness, which may pose future challenges for these companies. Additionally, the anticipated positive impact on profitability did not materialize, implying that the program primarily aided companies in meeting short-term obligations rather than enhancing their profit-generating capabilities. This study provides valuable insights into the effectiveness of public credit support programs during crises, shedding light on their advantages and potential trade-offs for medium-sized enterprises. Nonetheless, it's essential to note that the conclusions drawn from this research cannot be directly extrapolated to all Peruvian firms, as our analysis focused solely on medium-sized firms due to data availability.

7 References

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

Burga, C. Cuba, W. Diaz, E. and Sanchez, E. (2022). "Loan Guarantees and Bank Incentives: Evidence from Covid-19 Relief Funds in Peru"

Blundell, R., Costa Dias, M., 2000. "Evaluation methods for non-experimental data". Fiscal Studies 21, 427–468.

Blundell, R., Costa Dias, M., 2009. "Alternative Approaches to Evaluation in Empirical Microeconomics," Journal of Human Resources, University of Wisconsin Press, vol. 44(3).
Dehejia, R., Wahba, S., 2002. "Propensity score matching methods for non-experimental causal studies". Review of Economics and Statistics 84, 151–161.

González-Uribe, J. and Wang, S. (2021). "The Real Effects of Small-Firm Credit Guarantees during Recessions". Working paper.

Girma, S., D. Greenaway, and R. Kneller, "Export Market Exit and Performance Dynamics," Economics Letters 80 (2003):181–8.

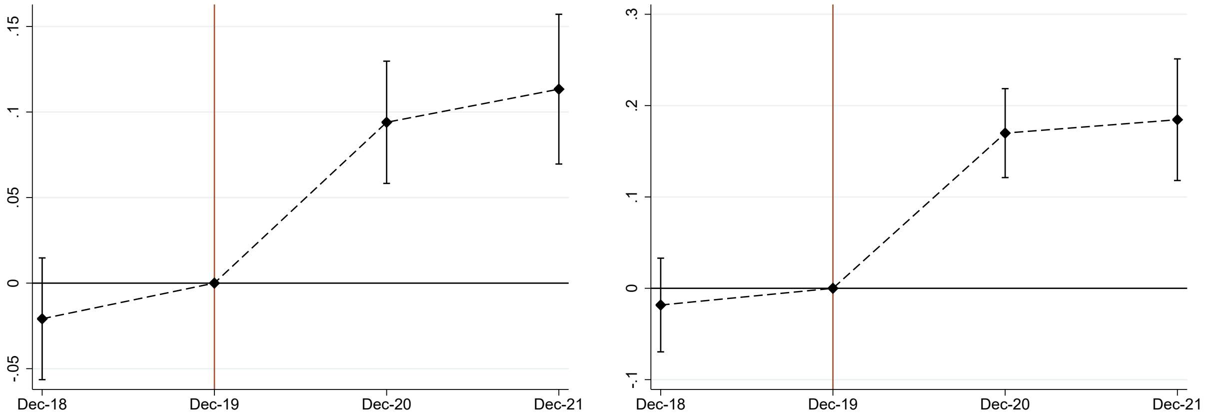
Girma, S. , Holger, G. 2007. "Evaluating the foreign ownership wage premium using a difference-in-differences matching approach," Journal of International Economics, Elsevier, vol. 72(1), pages 97-112.

Heckman, J., H. Ichimura, J. Smith, and P. Todd, "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," Review of Economic Studies 64 (1997):605–54.

Heyman, F. , Sjoholm, F., Tingvall, P., 2007. "Is there really a foreign ownership wage premium? Evidence from matched employer-employee data," Journal of International Economics, Elsevier, vol. 73(2), pages 355-376, November.

A Appendix.

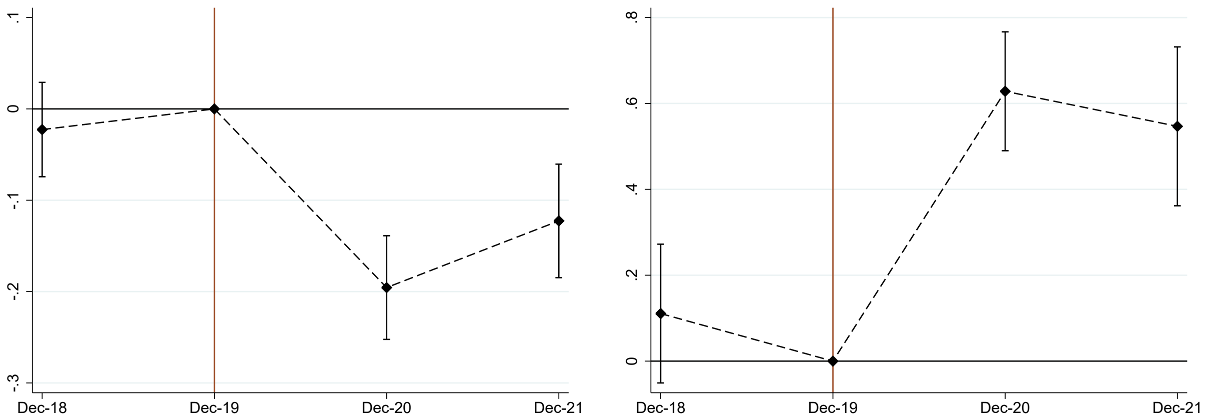
Figure A-1: Impact on Firm's Assets and Liabilities.



(a) Total Assets (b) Total Liabilities

Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variables are in logarithms. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

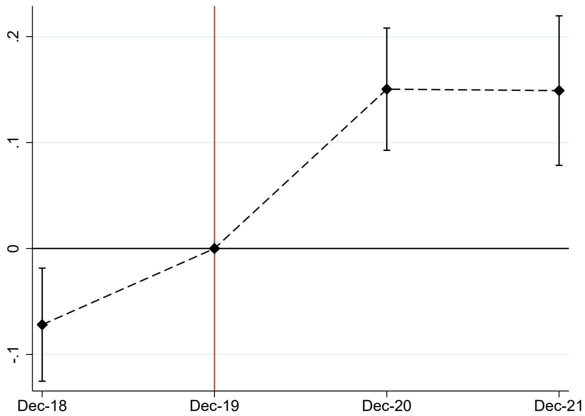
Figure A-2: Impact on Firm's Solvency.



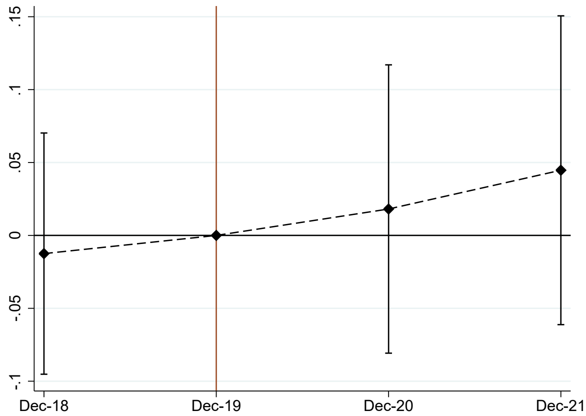
(a) Short-term Debt Ratio (b) Long-term Debt to Equity Ratio

Note: The figure displays the effects of the program on different periods estimated from Equation 1. In Figure (a) the dependent variable is the (log) Credit-to-Equity ratio, calculated as the total debt with the financial System divided by firm's Net Worth. In Figure (b) the dependent variable is the (log) Credit-to-Debt ratio, calculated as the total debt with the financial System divided by firm's total liabilities. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

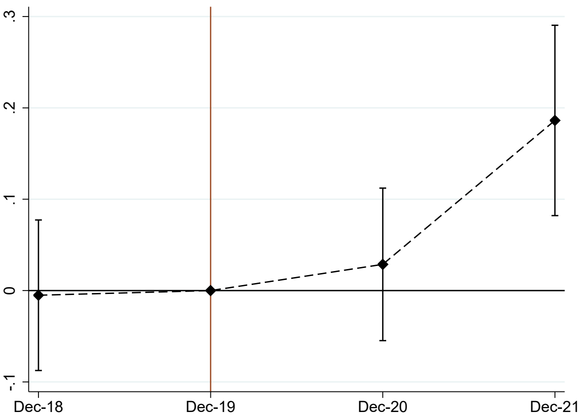
Figure A-3: Impact on other variables.



(a) Current Assets



(b) Current Liabilities



(c) Working Capital

Note: The figure displays the effects of the program on different periods estimated from Equation 1. The dependent variable are in logarithms. The Period of reference corresponds to December 2019, as the program was implemented between April and December of 2020. The confidence interval is calculated at the 90% level.

Table A-1: Impact on the level of credit

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**		**Kernel**	
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	-0.020	-0.038	-0.035	-0.038	-0.036	-0.025	-0.029	-0.030
	(0.643)	(0.224)	(0.273)	(0.263)	(0.254)	(0.450)	(0.373)	(0.353)
Dec-2020	0.709***	0.428***	0.426***	0.400***	0.387***	0.390***	0.387***	0.385***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dec-2021	0.733***	0.526***	0.513***	0.475***	0.489***	0.500***	0.496***	0.500***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	10835	9237	9553	9780	9889	9934	9934	9934
r2	0.783	0.741	0.729	0.739	0.747	0.752	0.750	0.748
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.

Table A-2: Impact on the liquidity ratio

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**	**Kernel**		
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	-0.036	-0.044	-0.055	-0.044	-0.048	-0.041	-0.043	-0.041
	(0.179)	(0.276)	(0.170)	(0.246)	(0.176)	(0.255)	(0.240)	(0.253)
Dec-2020	0.091***	0.142***	0.145***	0.152***	0.167***	0.162***	0.158***	0.157***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dec-2021	0.034	0.076	0.080	0.096**	0.080*	0.079*	0.078*	0.074*
	(0.252)	(0.129)	(0.116)	(0.030)	(0.055)	(0.052)	(0.059)	(0.075)
N Firms	11009	9256	9573	9801	9910	9955	9955	9955
Adj R2	0.635	0.614	0.601	0.604	0.605	0.600	0.599	0.600
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.

Table A-3: Impact on the debt ratio

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**	**Kernel**		
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	0.017	0.003	-0.002	-0.002	0.007	0.006	0.005	0.004
	(0.127)	(0.873)	(0.913)	(0.923)	(0.690)	(0.710)	(0.745)	(0.785)
Dec-2020	0.092***	0.069***	0.071***	0.072***	0.073***	0.066***	0.066***	0.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dec-2021	0.087***	0.044*	0.037	0.046**	0.053***	0.052***	0.052***	0.053***
	(0.000)	(0.071)	(0.183)	(0.057)	(0.010)	(0.003)	(0.004)	(0.004)
N	11011	9257	9575	9803	9912	9957	9957	9957
r2	0.814	0.794	0.789	0.797	0.802	0.801	0.801	0.801
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.

Table A-4: Impact on the liquidity ratio-Alternative definition of Treatment

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**	**Kernel**		
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	-0.034	-0.016	-0.047	-0.070	-0.074	-0.060	-0.054	-0.055
	(0.309)	(0.759)	(0.387)	(0.204)	(0.171)	(0.221)	(0.307)	(0.316)
Dec-2020	0.066*	0.222***	0.181***	0.159***	0.146***	0.166***	0.152***	0.157***
	(0.080)	(0.000)	(0.000)	(0.003)	(0.008)	(0.002)	(0.006)	(0.004)
Dec-2021	0.042	0.141***	0.106*	0.117**	0.073	0.101*	0.085	0.093
	(0.283)	(0.006)	(0.053)	(0.043)	(0.251)	(0.070)	(0.147)	(0.113)
N	11009	9575	9746	9847	9864	9906	9903	9903
r2	0.634	0.656	0.640	0.619	0.614	0.615	0.613	0.610
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.

Table A-4: Impact on the debt ratio-Alternative definition of Treatment

	Matching Method							
	No	**Nearest-Neighbor**			**Radius**		**Kernel**	
	Matching	NN-1	NN-2	NN-4	0.01	Gauss	Uniform	Epanechnikov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dec-2018	0.015	-0.022	-0.001	0.004	0.018	0.009	0.005	0.005
	(0.281)	(0.389)	(0.957)	(0.886)	(0.491)	(0.707)	(0.858)	(0.853)
Dec-2020	0.093***	0.062**	0.061**	0.065***	0.077***	0.069***	0.069***	0.069***
	(0.000)	(0.013)	(0.011)	(0.004)	(0.000)	(0.000)	(0.001)	(0.001)
Dec-2021	0.081***	0.036	0.052	0.044	0.060*	0.034	0.034	0.038
	(0.000)	(0.271)	(0.138)	(0.259)	(0.083)	(0.232)	(0.277)	(0.242)
N	11011	9577	9748	9849	9866	9908	9905	9905
r2	0.813	0.823	0.801	0.787	0.793	0.811	0.806	0.802
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values in parenthesis. This table shows the estimated coefficient β_h from Equation 1. The standard errors where clustered at the Firm level.