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The Effects of Business Credit Support Programs: Evidence from a Regression Discontinuity Design

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Abstract

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Keywords: government-backed loans, regression discontinuity, small and medium-sized enterprises, developing country, business loans, crisis.

JEL: H81, E26, H32, G20

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The Effects of Business Credit Support Programs: Evidence from a Regression Discontinuity Design

BALILA ACURIO AND ALESSANDRO TOMARCHIO [1]

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1 Introduction

This study examines the real effects of an unprecedentedly large government-backed loan program for firms in Peru during 2020-2021. Peru was among the countries that were most severely affected by the recent global COVID-19 pandemic, with a GDP contraction of 11% in 2020.

In response to the COVID-19 shock, many emerging countries applied a standard recipe that includes: (i) reducing interest rates as part of an expansionary monetary policy, (ii) increasing government expenditures, and (iii) extending business and household support programs. Peru, whose economy is almost completely populated by medium, small, and micro-firms, deployed a set of credit support programs, that are by far the most significant support for local entrepreneurial activity in the last 50 years. The first program, *Reactiva Perú* (RP), was launched in May 2020. In addition, the *Fondos de Apoyo Empresarial* (FAE) programs were launched between 2020 and the beginning of 2021 to provide credit to the most affected sectors, and small businesses in particular.

There are no precedents in Peru for the implementation of such policies. Therefore, the country lacked the expertise and know-how for launching such government-backed loan programs; this contrasts with the experience of countries like Brazil, Chile, and Colombia, who have been running such programs since the last century. In addition, it is important to mention that Peru has the a high level of economic informality, i.e. a large number of firms does not have a Tax ID. This is especially true for micro and small businesses (hereafter, referred to as small businesses). On the other hand, informal firms have access to the credit market, and roughly 90% of small business loans are issued to informal firms (see Table 1).

Table 1: Firms with credit records by size and situation

Size	Year													
	2017		2018		2019		2020		2021		2022		2023	
	No.	Perc %	No.	Perc %	No.	Perc %	No.	Perc %	No.	Perc %	No.	Perc %	No.	Perc %
Big	1 165	100.00%	1 131	100.00%	1 092	100.00%	1 118	100.00%	1 105	100.00%	1 085	100.00%	1 066	100.00%
Formal	1 165	100.00%	1 131	100.00%	1 092	100.00%	1 118	100.00%	1 105	100.00%	1 085	100.00%	1 066	100.00%
Medium	15 389	100.00%	15 285	100.00%	15 128	100.00%	15 685	100.00%	15 398	100.00%	15 149	100.00%	15 391	100.00%
Formal	13 020	84.61%	12 591	84.73%	12 847	84.92%	13 409	85.49%	13 200	85.73%	13 119	86.60%	13 311	86.49%
Informal*	2 369	15.39%	2 334	15.27%	2 281	15.08%	2 276	14.51%	2 198	14.27%	2 030	13.40%	2 080	13.51%
Small	3 274 007	100.00%	3 528 504	100.00%	3 825 333	100.00%	3 595 899	100.00%	3 883 320	100.00%	4 109 636	100.00%	4 517 112	100.00%
Formal	203 893	6.23%	210 935	5.98%	219 598	5.74%	232 261	6.46%	246 561	6.35%	271 337	6.60%	299 525	6.63%
Informal	3 070 114	93.77%	3 317 569	94.02%	3 605 735	94.26%	3 363 638	93.54%	3 636 759	93.65%	3 838 299	93.40%	4 217 587	93.37%

* We define an informal firm as one that is not registered with a Tax ID (RUC) in the financial system.

The rest of this paper is divided as follows. Section 2 presents the basic context of government-backed loan programs through a review of previous literature. Section 3 describes the empirical strategy and presents our estimations of the effect of the programs. Section 4 presents the results of the analysis and robustness checks. Finally, Section 5 concludes the study.

2 Literature Review

Government-backed loan programs were considered a crucial policy measure during the COVID-19 pandemic, especially for small and medium-sized enterprises (SMEs). These programs aim to alleviate the constraints imposed by the confinement or quarantine measures. For instance, Beck and Demirguc-Kunt (2006) show that these types of programs are particularly relevant for SMEs, which often face significant barriers to accessing traditional credit markets because of perceptions of higher risks and a lack of collateral. Given the context in which the pandemic significantly increased risks for small businesses, a large-scale business support program could is considered necessary to prevent massive closures or extensive staff/employee lay-offs.

This study exploits a regression discontinuity design (RDD) as a quasi-experimental approach that uses discontinuities in the eligibility criteria of programs to identify causal effects. This method is particularly effective in assessing business credit programs, where eligibility often depends on specific thresholds such as firm size, revenue, or credit score (Imbens and Lemieux (2008)). Research using RDD has consistently found that credit support programs have positive effects on firm performance (Brown and Earle (2017)). Additionally, business credit programs help relax credit constraints, enabling firms to invest more in capital and innovation. Banerjee and Duflo (2014) used regression discontinuity (RD) to show that firms receiving credit support increased their investments in machinery and technology, leading to enhanced productivity and competitiveness. Finally, it is believed that the effect of credit support programs can vary across firms and industries. The evidence suggests that smaller and younger firms benefit more from such programs because of their higher initial credit constraints (see e.g. Czarnitzki and Hottenrott (2011), Howell (2017)).

Additionally, during the last few years, several studies have analyzed the impact of RP on the Peruvian market. Burga et al. (2023) found that the program expanded credit supply and reduced delinquency rates. They also suggested that it is important to focus on the more sensitive firms. In analyzing medium-sized formal businesses, Ceron et al. (2023) showed that Reactiva led to heightened liquidity levels but did not have a notably positive impact on profitability. Acurio et al. (2023) showed that the program had a positive impact on employment and increased banks' willingness to take risks, as captured by an increase in the risk of their non-RP program credit portfolios. Finally, Casavilca and Sarmiento (2024) reported that the borrower's average monthly total debt increased due to *Reactiva* and had a positive impact on the employment variables of the treated firms.

Thus, our research makes some unique contributions to this subject. First, all the studies mentioned above use some version of a difference-in0differences strategy to determine the impact of the program. Instead, we use a RDD that exploit a threshold in the eligibility rule. Second, we use some indicators that have not been tested before such as written-off credit, firm sales, and firm survival. Third, we focus on small and micro-businesses, which comprise the vast majority of firms populating the Peruvian economy.

3 Context and Data

3.1 Credit Support Programs

Owing to the increase in COVID-19 cases, Peru initiated a quarantine on March 15, 2020, which only permitted the operation of the essential sectors. This caused a sharp drop in employment between March and April. Thus, in May 2020, government-backed loan programs were implemented. The first RP, was a program of up to S/ 60 billion (initially S/ 30 billion), which offered guarantees between 80 and 98 percent, according to the amount of the debt. Thus, smaller loans with greater guarantees were aimed at riskier small businesses, and larger loans were aimed at large companies with a greater possibility of surviving the pandemic. Table 2 presents the debt amounts according to guarantee percentage.

Table 2: Loans per company (in soles).

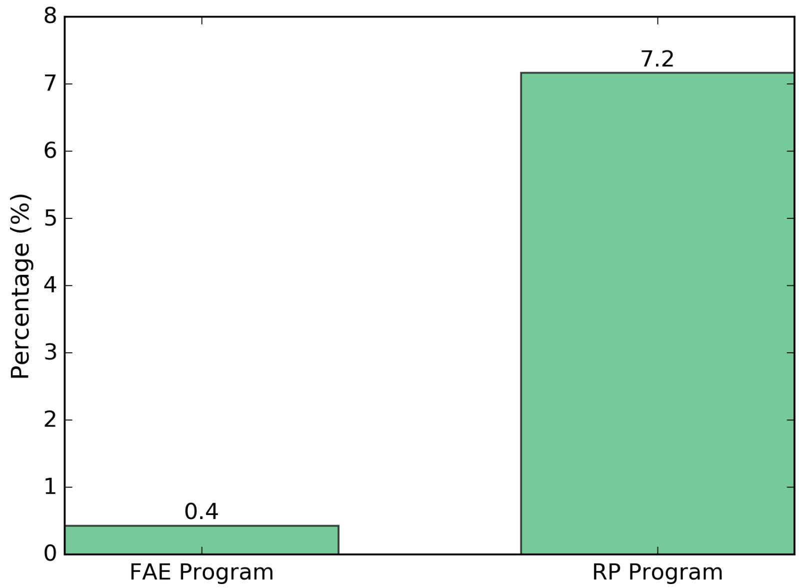
Guarantee percentage	RP 1 [1/]	RP 2 [2/]
98%	Up to 30,000	Up to 90,000
95%	From 30,001 to 300,000	From 90,001 to 750,000
90%	From 300,001 to 5,000,000	From 750,001 to 7,500,000
80%	From 5,000,001 to 10,000,000	From 7,500,001 to 10,000,000

[1/] Guaranteed loans before June 1, 2020. [2/] Guaranteed loans after June 1, 2020.

A crucial difference between the RP program and those programs implemented by other countries in the region was the way in which the interest rates were set, and the degree of participation by the Central Bank (BCRP). Thus, the BCRP implemented an auction system in which companies in the financial system competed with each other to set the interest rates that the borrowing companies would pay. This was important because interest rates were also set in other countries of the region.

The second type of program was the FAE. Unlike the RP program, the BCRP did not participate in the FAE program. In addition, this program was more focused and loans were mainly given to the companies that were most affected by the implementation of confinement measures during the pandemic. However, as Figure 1 shows, the total amount of loans disbursed through the RP

Figure 1: Credit Support Programs as a Percentage of 2020 GDP



program was 18 times higher than those through the FAE program. This shows the importance of the RP program, which was implemented from a macro perspective, to avoid the breakdown of the payment chain in the Peruvian economy.

However, these were not the only differences between the programs. The fact that the FAE program aimed to provide credit to smaller companies that were most affected by the pandemic necessitated easier credit terms and better access to financing. Similarly, the group of companies in the financial system that participated in the FAE program was broader and better linked to the informal sector (cooperatives and development entities for small and microenterprises). Table 3 lists the requirements that the companies had to meet. The RP program stands out because it has two rules that differentiate it from the FAE program: no outstanding tax debt, and the requirement that borrowers should have at least 90 percent of their debt in the Normal (best credit score) or CPP (second-best credit score) categories, by February 2020, that is one month before the start of the pandemic in Peru.

This 90 percent rule allowed us to evaluate the impact of the RP program based on the discontinuities generated by the implementation of this requirement. Thus, this study evaluates the effectiveness of the RP program around the discontinuity threshold, using real and credit variables.

It is worth mentioning that credit score in Peru is a categorical variable with five scores (from 0, the best, to 4, the worst)[2], and to be classified as Normal (0) or CPP (1), the firm needs to have at least 80 percent of total outstanding loans in those categories. In other words, the 90 percent rule is, *per se* meaningless except as an eligibility rule for *Reactiva*; if, for instance, we consider one firm with a 91 percent share of Normal loans and another with 89 percent, they both have the same overall score (0), but only the former would be eligible for *Reactiva*.

[2] See Garmaise and Natividad (2017) for an empirical application of credit score rules in Peru.

Table 3: Conditions for each program (in soles)

Program	Conditions
Reactiva Per	– Not have a tax debt greater than S/ 4 300. – As of February 2020, 90 percent or more of its credit operations in the financial system should have Normal or CPP ratings. – Those who do not have a classification should have been in the Normal category in the 12 months prior to the granting of the loan.
FAE Mype	– As of February 2020, have a Normal or CPP classification. – Those who do not have a classification should have been in the Normal category in the 12 months prior to the granting of the loan. – For those without a classification, the financial institution must indicate an internal classification equivalent to Normal or CPP.
FAE Tourism	– Operate in the tourism sector. – As of February 2020, 90 percent or more of its credit operations in the financial system should have Normal or CPP rating. – Those who do not have a classification should have been in the Normal category in the 12 months prior to the granting of the loan.
FAE Agro	– Operate in the agricultural sector. – Affidavit accredited by the financial institution.

3.2 Data and Descriptive Statistics

We used credit information, that is obtained from the credit register and reported to the Peruvian Bank Regulator (SBS). This report records the loan-level information of all individuals and firms on a monthly basis. In particular, we used monthly information on all loans issued to non-financial firms in the Peruvian financial system. We also worked with the employment data set of the National Superintendency of Customs and Tax Administration. This report records the monthly evolution of the number of employees in approximately 400,000 companies. In addition, we used Padron RUC[3] to obtain information on the economic sector and location of the firm. The universe of firms was defined as the set of all firms with some credit record between January 2019 and February 2020.

Table 4 presents the descriptive statistics of the dependent variables from the sample that is less than 10 percent away from the limit, considering the 90 percent rule. As can be seen, there is no information on workers or sales for all companies. For workers, a drop in the level of employment can be observed between 2020 and 2023, and both the average and other statistics are reduced. No conclusions can be drawn regarding sales because information is only available for 2021 due to data limitations.

Table 4: Descriptive statistics.

Variable	Mean	Median	Std. Dev.	Min	Max	N. Obs.
End of Year Labor:						
December 2020	8.1	2.0	48.7	0.0	1 436	1 804
December 2021	7.6	2.0	45.6	0.0	1 362	1 775
December 2022	7.5	2.0	44.7	0.0	1 393	1 736
December 2023	7.2	2.0	43.9	0.0	1 311	1 617
Average Year Labor:						
Year 2020	7.0	2.0	45.6	0.0	1 543	2 293
Year 2021	6.6	2.0	42.2	0.0	1 362	2 197
Year 2022	6.5	2.0	40.9	0.0	1 378	2 116
Year 2023	6.3	1.9	39.5	0.0	1 343	2 004
Average Year Sales (in thousands):						
Year 2021	161.8	4.4	1 838.9	0.0	89 100	15 746

[3] It is the register that contains the identification data of the economic activities and other relevant information for the registered companies.

4 Methodology

4.1 Fuzzy RD Design

We use the fuzzy RDD (FRDD) which is an extension of the sharp RDD that accommodates situations where compliance with the treatment assignment is imperfect. This methodology section is based on the seminal works of Imbens and Lemieux (2008), Calonico et al. (2014), and Calonico et al. (2019)[4].

In a standard sharp RDD, treatment is assigned based on whether the observed running variable Y_i exceeds the cutoff c. However, in the fuzzy RD (FRD), not all individuals comply perfectly with the treatment assignment rule. We estimate Equation 1 as follows:

$$Y_i = g(C_i - c_0) + \tau R_i + \eta X_i + \varepsilon_i, \tag{1}$$

where R_i is 1 if firm i benefits from RP ($R_i = 1$), or 0 ($R_i = 0$) otherwise. C_i indicates the percentage of debt that is in a Normal or CPP rating for firm i and c_0 is the threshold value. X_i denotes the set of control variables included in the study. Finally, Y_i denotes the set of tested output variables.

To estimate Equation 1, we estimate the first-stage of Equation 2: We consider $Z_i = 1\{(Y_i - y_0) \geq 0\}$ as the excluded instrument for R_i.

$$R_i = g(C_i - c_0) + \kappa Z_i + \eta X_i + \omega_i, \tag{2}$$

where, $g(C_i - c_0)$ is approximated with a fourth-order polynomial in $(C_i - c_0)$.

The FRD design estimates the treatment effect τ using a two-stage least squares (2SLS) approach. The first stage involves estimating the probability of treatment receipt R_i as a function of the running variable C_i. The second stage regresses the outcome Y_i on the predicted treatment values from the first stage. The local average treatment effect (LATE) is identified at the cutoff c:

[4] See also Calonico et al. (2018) and Calonico et al. (2020)

$$\tau = \frac{\lim_{C\downarrow c_0} \mathbb{E}[Y_i \mid C_i = c] - \lim_{C\uparrow c_0} \mathbb{E}[Y_i \mid C_i = c]}{\lim_{C\downarrow c_0} \mathbb{E}[R_i \mid C_i = c] - \lim_{C\uparrow c_0} \mathbb{E}[R_i \mid C_i = c]}. \tag{3}$$

4.2 Testing FRD Assumptions

In this section, we test two crucial assumptions for applying the FRDD design. In particular, we can test whether (1) there is a manipulation in the density of the running variable around the threshold, and (2) if covariates, such as pre-treatment variables, are continuous around the cutoff.

The first test pertains to the non-manipulation of the 90 percent rule. While the share of high quality outstanding loans is a variable that can be strategically selected and manipulated by the firm, it is important to remark that this rule considers the company's rating in February 2020; that is, several months before the implementation of *Reactiva* and one month before the announcement of the State of Emergency.

Moreover, as mentioned in the previous section, there is no incentive to manipulate around the 90 percent threshold since the credit score is a categorical variable and transitions (e.g. downgrades) depend on crossing a different threshold[5].

Figure 2 shows the continuity of density (Calonico, Cattaneo and Titiunik (2015a))[6] around the threshold for all companies less than 10 percent away from it. There is no significant discontinuity, suggesting that there is no manipulation of the running variable.

The second assumption is that there are no discontinuities in the dependent variables prior to the intervention. Table 5 presents the estimated coefficients of the pre-intervention variables. As can be seen, the coefficients are not significant for any of the variables, which shows that prior to the intervention, there is no discontinuity for the employment and credit variables among the companies that are around the threshold. Similarly, Figure 3 shows the four pre-intervention variables, where no significant jump around the cutoff is observed.

[5]We also tested whether there was manipulation around the 80-percent rule (i.e. the rule that deterministically affects the credit score). We cannot reject the hypothesis that there is a density discontinuity around the cutoff value.

[6]The McCrary (2008) test delivers similar results.

Figure 2: Manipulation Test

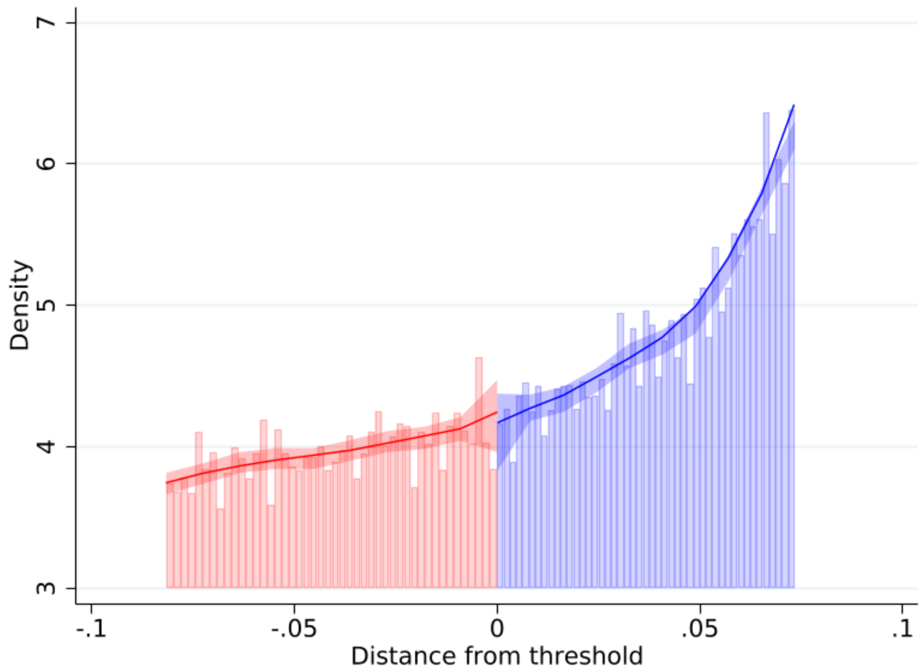
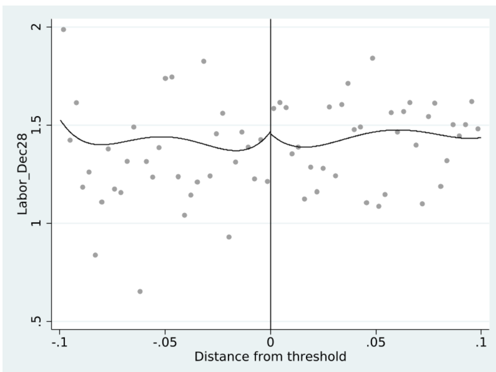


Table 5: Pre-intervation variables

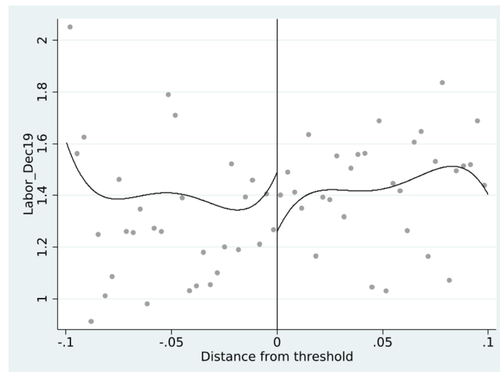
	Dependent Variable			
	Labor December 2018	**Labor December 2019**	**Credit December 2018**	**Credit December 2019**
D(Reactiva)	0.050	-0.214	0.254	-0.849
	(0.244)	(0.299)	(9.661)	(8.576)
Observations	1 793	1 552	2 147	2 147
Sector Control	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Region Control	Yes	Yes	Yes	Yes
Labor 2017 Control	Yes	Yes	Yes	Yes

This evidence shows that the FRD assumptions are satisfied, and that there is no perfect manipulation of the 90 percent rule (Figure 2) around the discontinuity. In addition, there is no significant increase in the pre-intervention variables (Table 5 and Figure 3). These results suggest that the RP program is quasi-experimentally assigned around the selected threshold.

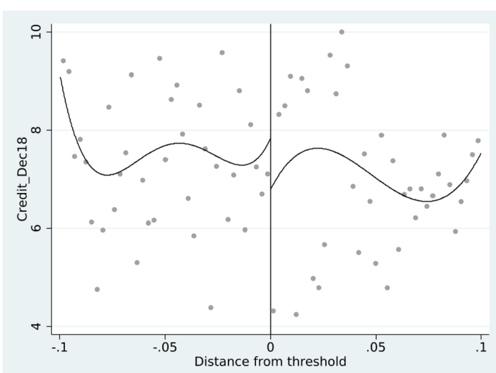
Figure 3: RD Plots on Pre-Intervention Variables



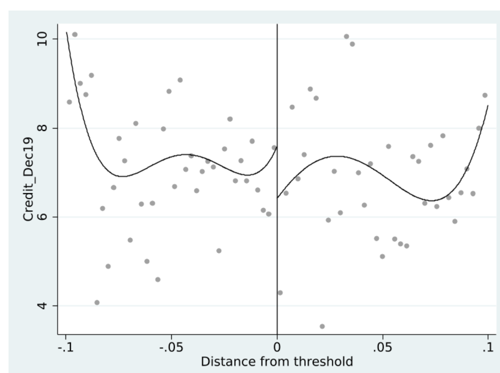
(a) Labor December 2018



(b) Labor December 2019



(c) Total Credit December 2018



(d) Total Credit December 2019

5 Results

This section presents the results of the first stage estimation and the (causal) impact of Reactiva on the outcome variables.

5.1 First Stage

The first stage estimation evaluates whether crossing the 90 percent threshold has a positive effect on the probability of receiving a *Reactiva* loan. Table 6 presents the results and shows that the coefficient for this dummy variable is positive and significant. As expected, if a firm is above the 90 percent threshold, it is more likely to receive government-backed *Reactiva* loans.

Table 6: Results for first stage

	Reactiva Beneficiary
	(1)
RD_Estimate	0.006***
	(0.001)
Observations	121,110
Sector Control	Yes
Size Control	Yes
Region Control	Yes
Credit 2019 Control	Yes

5.2 On Outcomes

Table 7 shows the results for the average number of employees in each year, the results are positive and significant in all cases. An important fact is that these variables show a growing effect of the impact of the RP program on employment, which lasts until 2022; by 2023, a smaller effect is observed than in the previous year. In particular, companies that received RP credit have, on average, 9, 20, and 3 more annual workers than those that did not in 2021, 2022, and 2023, respectively.

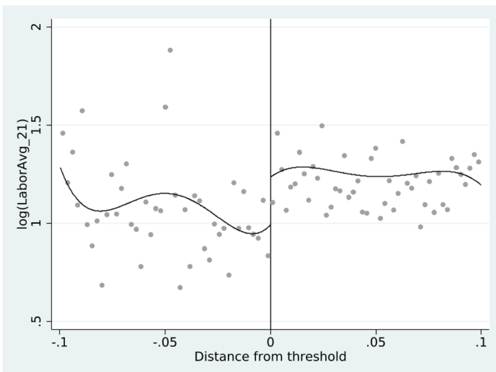
Table 7: Results for average labor

	Dependent Variable		
	Labor Avg. 2021	**Labor Avg. 2022**	**Labor Avg. 2023**
D(Reactiva)	2.221**	2.998**	1.223***
	(1.014)	(1.384)	(0.351)
Observations	2 633	2 571	2 481
Robust 95% CI	[.118 ; 4.916]	[.239 ; 6.757]	[.275 ; 1.959]
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
Sector Control	Yes	Yes	Yes
Size Control	Yes	Yes	Yes
Region Control	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes

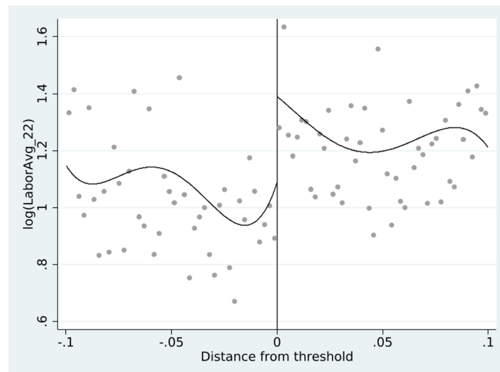
Figure 7 shows a discontinuity graph for the same variables: a significant jump is observed around the limit for all cases, confirming the positive effect of the program.

Table 8 and Figure 5 show the estimates for the level of employment in December from 2020 to 2023. Thus, firms that received RP credit had, on average, 12, 4, and 3 more workers than those that did not by the end of the years 2021, 2022, and 2023, respectively. The estimates reveal that the impact of the RP program is significant and positive, although the coefficient is lower than that observed at the average level of employment. In this case, geographical, company size, and economic sector controls are included as covariates, as are outstanding business loans as of December 2019.

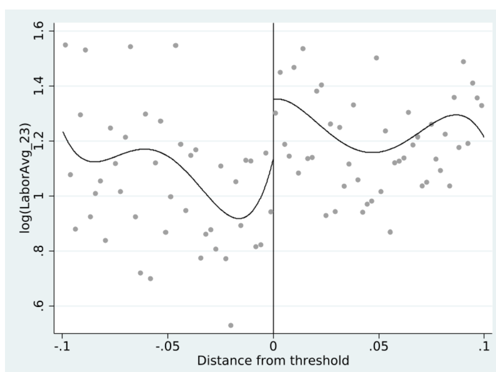
Figure 4: RD Plots on Avg. Labor



(a) Average Labor 2021

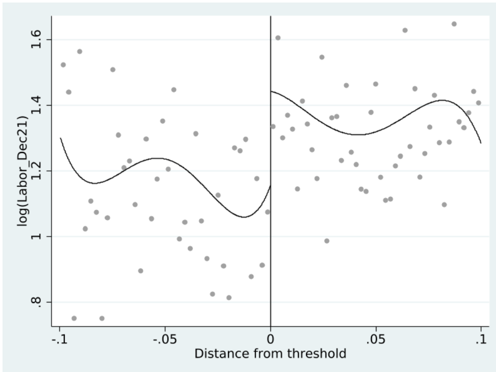


(b) Average Labor 2022

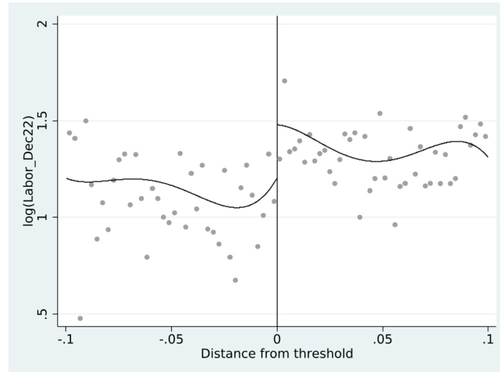


(c) Average Labor 2023

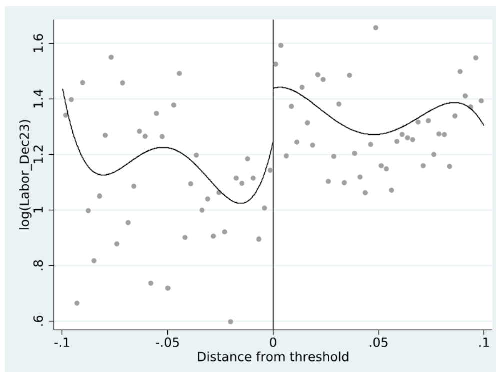
Figure 5: RD Plots on Avg. Labor



(a) Average December 2021



(b) Average December 2022



(c) Average December 2023

Table 8: Results for average labor

	Dependent Variable			
	Labor Dec. 2021	**Labor Dec. 2022**	**Labor Dec. 2023**	
D(Reactiva)	2.512**	1.323***	1.252***	
	(1.077)	(0.406)	(0.412)	
Observations	2,248	2,228	2,123	
Robust 95% CI	[.32 ; 5.559]	[.409 ; 2.286]	[.231 ; 2.167]	
Order Loc. Poly. (p)	1	1	1	
Order Bias (q)	2	2	2	
Sector Control	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes
Region Control	Yes	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes	Yes

Figure 6: RD Plots on Average Sales 2021

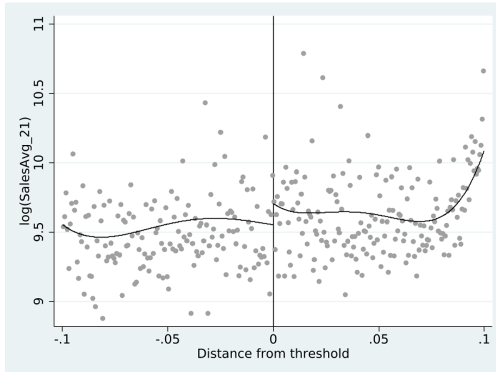


Table 9 shows the results for average sales in 2021. The impact of RP was positive, but not significant. A possible reason for this is that in 2021, confinement measures had not yet been fully relaxed. Therefore, it would be important to evaluate the program's impact in subsequent years. Figure 6 shows the RD plot for the same variable, which suggest that there was no significant jump.

The effects on the credit level between 2020 and 2024 were also estimated. Although this effect was positive, the difference was not statistically significant. Similarly, the impact of the program on variables such as exit from the market, and written-off loans, which would serve as proxies for company bankruptcy, was estimated. Here, the impact of the program was also as expected, but the coefficients were not significant.

Table 9: Results for average sales 2021

	Dependent Variable
	Labor Dec. 2021
D(Reactiva)	9.079
	(14.284)
Observations	13,548
Robust 95% CI	[-22.471 ; 39.604]
Order Loc. Poly. (p)	1
Order Bias (q)	2
Sector Control	Yes
Size Control	Yes
Region Control	Yes
Credit 2019 Control	Yes

6 Heterogeneity

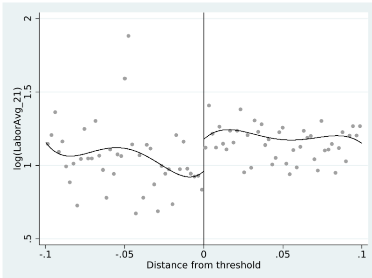
As mentioned in the introduction, small businesses are important for the Peruvian economy because they represent more than two-thirds of all companies and generate more than one-third of the country's formal employment. In this section, we present the results, limiting ourselves only to small companies.

Tables 10 and 11 present the results for average employment and employment in December for 2020 and 2023, respectively. The results are positive and significant, and similar to those found for all companies. Similarly, they also increase over time until 2022, which would confirm what was observed in the previous section. It is important to mention that although the RP program did not focus on them, mostly small companies benefitted from it.

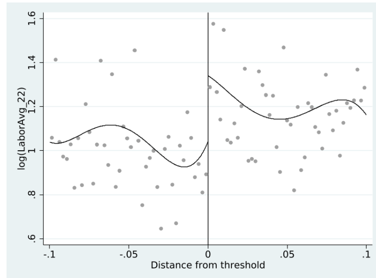
Table 10: Results for average labor

	Dependent Variable		
	Labor Avg. 2021	**Labor Avg. 2022**	**Labor Avg. 2023**
D(Reactiva)	2.214**	2.255***	1.296***
	(1.053)	(0.837)	(0.385)
Observations	2,586	2,526	2,437
Robust 95% CI	[.024 ; 5.049]	[.609 ; 4.679]	[.303 ; 2.156]
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
Sector Control	Yes	Yes	Yes
Size Control	Yes	Yes	Yes
Region Control	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes

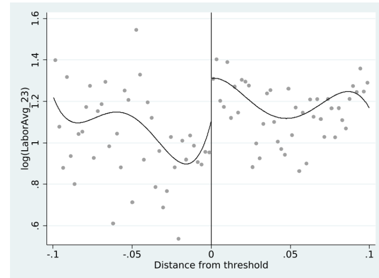
Figure 7: RD Plots on Avg. Labor



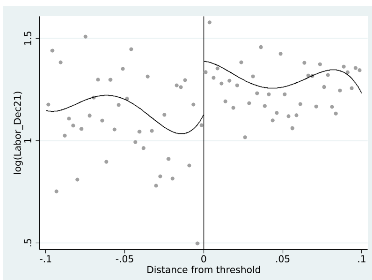
(a) Average Labor 2021



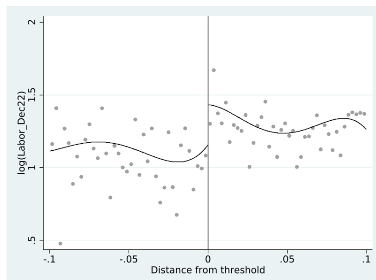
(b) Average Labor 2022



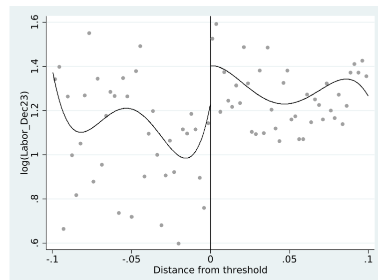
(c) Average Labor 2023



(d) Labor December 2021



(e) Labor December 2022



(f) Labor December 2023

Table 11: Results for labor

	Dependent Variable		
	Labor Dec. 2021	**Labor Dec. 2022**	**Labor Dec. 2023**
D(Reactiva)	2.375**	1.472***	1.109***
	(1.005)	(0.454)	(0.329)
Observations	2,202	2,183	2,082
Robust 95% CI	[.343 ; 5.301]	[.454 ; 2.604]	[.27 ; 1.875]
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
Sector Control	Yes	Yes	Yes
Size Control	Yes	Yes	Yes
Region Control	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes

7 Conclusion

Developing countries are generally characterized by a high degree of informality, low productivity, incomplete financial inclusion, and an inefficiently large number of small firms. These features, among others, suggest a higher level of vulnerability to (negative) aggregate shocks compared with developed economies. Accordingly, policy-makers should be careful when taking action to mitigate the effects of downturns, because policies that are effective in rich economies, may not be beneficial in these countries. This research attempts to study the causal effect of a huge policy intervention to mitigate the effects of pandemics in Peru, such as the government-backed business loan program, RP. Our preliminary results suggest a positive causal impact of *Reactiva* on employment variables (2021-2023) for the treated firms, and no impact on sales or survival rates.

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A Appendix A

Table 12: Reduced Form

	Labor Avg. 21	Labor Avg. 22	Labor Avg. 23	Labor Dec. 21	Labor Dec. 22	Labor Dec. 23	Sales Avg. 21
Above Threshold	0.180**	0.176**	0.267***	0.211**	0.266**	0.298***	0.010
	(0.08)	(0.09)	(0.07)	(0.10)	(0.08)	(0.09)	(0.01)
N	2 633	2 571	2 481	2 248	2 228	2 123	13 548
Sector Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13: Results for Survival

	Survive 2020	Survive 2021	Survive 2022	Survive 2023	Survive 2024	Survive 2020-2024
	(1)	(2)	(3)	(4)	(5)	(6)
RD_Estimate	-0.663	0.410	1.362	0.625	-0.100	-1.650
	(0.590)	(0.656)	(1.272)	(1.118)	(0.148)	(1.648)
Observations	80,325	80,216	80,548	80,828	79,252	84,245
Robust 95% CI	[-2.25 ; .573]	[-.861 ; 2.033]	[-1.118 ; 4.213]	[-2.027 ; 3.042]	[-.446 ; .225]	[-5.579 ; 1.757]
Order Loc. Poly. (p)	1	1	1	1	1	1
Order Bias (q)	2	2	2	2	2	2
Sector Control	Yes	Yes	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes	Yes	Yes
Region Control	Yes	Yes	Yes	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes	Yes	Yes	Yes

Table 14: Results for Written-off Credits

	Written-off 2020	Written-off 2021	Written-off 2022	Written-off 2023	Written-off 2020-2024
	(1)	(2)	(3)	(4)	(5)
RD_Estimate	1.027*	-0.574	-1.006*	0.413	0.103
	(0.587)	(0.891)	(0.520)	(0.662)	(1.256)
Observations	57,613	57,613	57,613	57,613	57,613
Robust 95% CI	[.168 ; 2.792]	[-2.477 ; 1.438]	[-2.651 ; .124]	[-1.039 ; 2.096]	[-2.406 ; 3.406]
Order Loc. Poly. (p)	1	1	1	1	1
Order Bias (q)	2	2	2	2	2
Sector Control	Yes	Yes	Yes	Yes	Yes
Size Control	Yes	Yes	Yes	Yes	Yes
Region Control	Yes	Yes	Yes	Yes	Yes
Credit 2019 Control	Yes	Yes	Yes	Yes	Yes

Table 15: Results for Score

	Score Dec20	Score Dec21	Score Dec22	Score Dec23
	(1)	(2)	(3)	(4)
RD_Estimate	2.555	-4.254	-3.513	-5.049
	(5.259)	(5.201)	(4.528)	(7.433)
Observations	36,742	27,420	25,065	22,169
Robust 95% CI	[-9.329 ; 15.01]	[-17.99 ; 6.224]	[-13.844 ; 5.606]	[-22.715 ; 9.126]
Order Loc. Poly. (p)	1	1	1	1
Order Bias (q)	2	2	2	2
Sector Control	Yes	Yes	Yes	Yes
Yes				
Size Control	Yes	Yes	Yes	Yes
Yes				
Region Control	Yes	Yes	Yes	Yes
Yes				
Credit 2019 Control	Yes	Yes	Yes	Yes
Yes				