Assessing the Impact of the REACTIVA Program: Credit, Debt, and Labor Demand Effects during the COVID-19 Pandemic in Peru*

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January, 2024

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Abstract

In the context of an economic shutdown due to the COVID-19 pandemic, the Peruvian government launched a Government-guaranteed loan program (REACTIVA) to enhance firms' private funding of working capital, necessary to meet their commitments with their employees and providers. Using a novel matched lender-borrower dataset of the Peruvian Financial System, we assess the impact of REACTIVA on credit and real outcomes of eligible firms. We find that borrowers' monthly average total debt increased by PEN S/269.5k (USD $67.4k) due to the program. However, excluding loans guaranteed by REACTIVA, we find a decrease of PEN S/79.5k (USD $19.9k), which suggests that eligible firms substituted more expensive unguaranteed credit for cheaper sponsored credit provided under REACTIVA. Finally, we find a positive causal effect on formal labor demand, allowing eligible firms to move up in the size distribution within their four-digit industry groups. This evidence implies that REACTIVA successfully allowed firms to access cheaper credit and to carry out more positive employment adjustments than non-eligible firms.

JEL Codes: E51, E58, G21, G28

Keywords: COVID-19, Government-guaranteed loans, Banks, Firms' debt

*We thank Costas Meghir and John Eric Humphries for their valuable suggestions for this paper. We also thank participants at the student seminars at The University of Texas at Austin for valuable comments and suggestions. This paper uses the borrower-lender dataset (*Reporte Crediticio de Deudores - RCD*), owned by the Peruvian Superintendence of Banking, Insurance, and Private Pensions Fund Administrators (SBS), and information from the Ministry of Economy and Finance of Peru (MEF). We thank SBS and MEF for providing authorization and Socorro Heysen, Edmundo Paredes, Antonio Usquiano, Alex Contreras, Juan Pichihua, and Roy Huarca for their valuable help when requesting the datasets. We take full responsibility for all the findings presented in this paper. These results do not reflect any involvement or endorsement by the SBS or MEF.

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1 Introduction

Crises have adverse effects on bank lending, particularly affecting small firms. During economic downturns, credit sources dry up more rapidly for small firms than for large companies. Moreover, according to the Organization for Economic Cooperation and Development (OECD), small and medium enterprises (SMEs) are more vulnerable and affected than larger corporations when bank lending decreases. Since late 2008, governments have taken extraordinary measures such as emergency and assistance programs, including government guarantees, to tackle these issues.

Government guarantees provided to SMEs via the financial system increased dramatically during 2009 - 2010. They were implemented again during the COVID-19 pandemic by countries such as the United States, United Kingdom, Sweden, Switzerland, Chile, and Peru. Among these cases, a common feature of the guarantee programs was the establishment of simple formulas for determining the program eligibility and loan and guarantee amounts. Although this simplicity aimed to ensure an expedited distribution of funds, in some cases, the government guarantees reached 100% of the credit or absorbed a significant proportion of credit risk, which could distort banks' incentives to screen borrowers properly.

This study explores the impact of government-guaranteed loan programs on firms' leverage and performance. We address this question by examining the Peruvian government's initiative (REACTIVA), designed to enhance firms' access to private credit for meeting obligations to employees and providers during the COVID-19 pandemic. With guarantees totaling USD $15 billion, equivalent to 7.3% of the GDP in 2020, we focus on empirical evidence. Mainly, we assess the causal effects of eligibility for the initial phase of the REACTIVA program.

Our findings reveal a positive effect of PEN S/269.5k (USD $67.4k) on total direct credits in a given month for an average eligible firm compared to a non-eligible counterpart. However, we also find adverse effects on net direct and net current credits of PEN S/79.5k (USD $19.9k) and PEN S/86.2k (USD $21.5k), respectively[1]. These first results imply that REACTIVA allowed firms to substitute more expensive unguaranteed credit for cheaper sponsored loans provided under the program. Moreover, estimates indicate that, although eligibility in the initial phase of REACTIVA did not boost firms' relative sales, it did foster their demand for formal relative employment compared to non-eligible counterparts. As opposed to the impact on sales, the effect on the demand for formal employment is robust to adding other controls.

With this evidence, we aim to incorporate the lender's capital structure decision and the exis-

[1]Direct credit corresponds to total credit, regardless of their performance. It gathers current or performing loans, restructured, refinanced, and non-performing loans. On the other hand, current credit corresponds to performing loans, which are being repaid according to schedule. We refer to Net direct and Net current credit as those net of REACTIVA loans.

tence of credit constraints into a heterogeneous firm model. In particular, we consider the possibility that banks optimally decide the share they will lend out of entrepreneurs' total funding needs, leading to optimal risk sharing. Moreover, based on Manova (2013), our model will incorporate firms' need for external capital and ability to pledge collateral depending on the industry in which they operate. The latter is important since, in informal economies, there is a wide dispersion in firms' productivity and industries' degree of financial development. These two features generate different levels of repayment capacity and credit enforcement. Given the model and the REACTIVA rules, we plan to perform counterfactual analyses, identifying the effects on financial and real outcomes of different percentages of government guarantees. This analysis is in a working process.

This paper contributes to the growing literature on the intersection of financial development and firms' dynamics. Relative to previous studies such as Acosta-Henao et al. (2023), Bazzi et al. (2023), Altavilla et al. (2022), we incorporate additional mechanisms through which government interventions in the credit markets can cause both intended and unintended consequences on firms' performance and demand for formal employment.

2 Institutional framework

In 2020, economies around the globe plummeted amid the devastating effects of the COVID-19 pandemic. Despite imposing one of the earliest and strictest lockdowns in Latin America, even before some European countries, Peru recorded among the highest pandemic-related mortality rates. It experienced among the largest economic contractions globally. In the context of an economic shutdown, authorities implemented unconventional monetary and liquidity policies on an unprecedented scale, reaching 18% of GDP. Nevertheless, their implementation dealt with operational difficulties, such as identifying vulnerable population groups in a context of prevalent informality and limited access to financial services.

Furthermore, according to the National Household Survey (ENAHO), the employed population in the country fell by 39.6% during the second quarter of 2020, equivalent to a loss of 6.7 million jobs. Likewise, micro-sized firms represent 95% of the country's business units that employ about two-thirds of the employed labor force who were the most affected during the pandemic[2].

Additionally, the impact of the pandemic during the second quarter was heterogeneous since this had been greater and more persistent among non-primary than primary activities such as

[2]For instance, during the second quarter of 2020, the employment in companies with less than ten workers fell by 66%, a higher percentage than those with eleven to fifty workers (-51%) and those with more than fifty workers (-37%).

agriculture, fishing, and mining[3]. For instance, the largest reduction in employment in percentage terms was recorded in the construction sector (-67.9%), followed by manufacturing (-58.2%), services (-56.6%), and commerce (-54.5%)[4].

At the same time, according to the Ministry of Production (PRODUCE), around 859,616 formal companies stopped operating in 2020. However, this adverse situation was partially reversed by implementing government policies to prevent breaking the payment chain and provide liquidity to the financial system. Some examples of the policies adopted were the postponement of tax payments, cash transfers, and government-guaranteed loan programs, which promote the reduction of interest rates.

2.1 REACTIVA program

In April 2020, the Peruvian Government launched the REACTIVA program to enhance firms' access to private credit to meet firms' commitments with their employees and providers during the COVID-19 pandemic. The program offered National Government (NG) guarantees to private loans funding firms' working capital. In total, NG guarantees amounted to USD $15 billion, which represents 21.9% of total domestic credit to the private sector in 2019 or 7.3% of GDP in 2020[5].

REACTIVA was launched in two stages. During the first stage, it targeted two types of firms: (i) those with at least 90% of their liabilities classified with "Normal" or "With potential problems" credit rating, and (ii) those appointed with "Normal" credit rating during the last 12 months. In this stage, under the program, eligible firms could borrow for up to the maximum between the firm's monthly average sales declared to the National Tax Authority in 2019 and three times the firm's total contribution to the Social Health Insurance System (ESSalud).

During the second stage, REACTIVA relaxed both the eligibility criteria and firms' credit limit under the program, primarily favoring the inclusion of smaller companies. In addition to the already eligible firms, REACTIVA included all new borrowers with no credit rating during the last 12 months. Moreover, the firm's upper limit was increased to three times the firm's average monthly sales reported in 2019, with a cap of USD $10,000[6] for micro-sized firms.

REACTIVA offered a guarantee over a percentage of a firm's loan to a Private Financial Institution (PFI). This percentage depended on the credit's amount and varied from 98% for small

[3] ILO Report published on November 2020

[4] Sales of micro, small and medium-sized firms are concentrated on commerce (44.2%), services (35.1%) and manufacturing (10.9%)

[5] In PEN soles, the guarantees amount to PEN S/60 billion.

[6] In the second stage, micro firms can borrow for up to two average months of its debt in the financial system in 2019, with a maximum of S/40 000.

loans for less than USD $10,000 or USD $30,000 in the first and second stages, respectively, to 80% for larger loans for more than USD $1.7 million.

REACTIVA was implemented through liquidity auctions organized by the Central Bank of Peru (BCRP). The process had four steps. First, firms applied for loans under REACTIVA program in a given PFI. Second, the PFI assessed and approved some firms' borrowing requests, with a maximum term of 36 months, including a grace period of 12 months. Third, the PFI participates in a liquidity auction for the total amount of its approved portfolio. The money was awarded to the PFI that committed to charging the lowest interest rate to firms. Fourth, the BCRP provided liquidity to the winner in exchange for an annual cost of 0.5% and a collateral asset subject to a repurchase agreement (REPO), due in 36 months. Importantly, the NG guarantee applied to this collateral asset. Therefore, if the awarded PFI's loans defaulted, it at least got the percentage guaranteed by REACTIVA.

Table 1 exhibits the reduction of interest rates before and after the REACTIVA program, where the reduction of micro, small, and medium-sized firms were the most prominent. Furthermore, Figure 1 shows an increase in average debt months after REACTIVA implementation and, afterward, a consistent decline due to, partially, the increase in the number of debtors in the formal financial system who were included in the second stage of REACTIVA as "normal" borrowers even though they didn't register any credit in the formal financial system at that point of time.

Table 1: **Average interest rate by type of credit**

Type of credit	**Currency**	**Mar-20**	**Jun-20**	**Sep-20**	**Change** (in bps)
Corporate	Domestic	3.75	3.15	2.31	-102.0
Large-sized firms	Domestic	5.79	3.23	4.40	-197.5
Medium-sized firms	Domestic	8.87	4.70	4.38	-433.0
Small-sized firms	Domestic	26.02	7.80	10.10	-1707.0
Micro-sized firms	Domestic	46.84	18.19	22.59	-2645.0
Consumer credit	Domestic	44.97	41.78	41.47	-334.5
Mortgages	Domestic	6.73	6.88	6.75	8.5
Corporate	Foreign	2.64	2.64	1.95	-34.5
Large-sized firms	Foreign	4.64	5.13	4.60	22.5
Mortgages	Foreign	5.69	6.21	5.87	35.0

Note: The last column corresponds to the difference between the interest rate in the first quarter of 2020 and the average interest rate during the second and third quarters of 2020. The difference is expressed in basic points.
Source: Report in March, June, and September 2020 published by the Superintendence of Banking, Insurance and Private Pensions Fund Administrators (SBS).

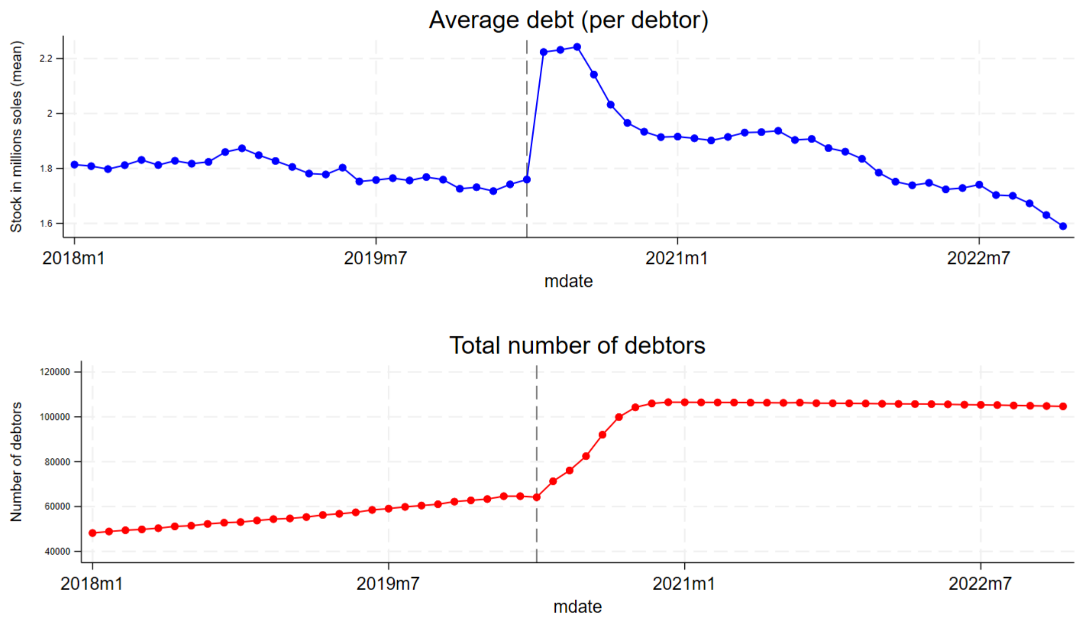


Figure 1: Average debt stock vs number of debtors

2.2 Other credit policies

According to Law No. 31050 published in October 2020, financial institutions can grant payment facilities to their clients with consumer loans, mortgages, and MYPEs through the so-called COVID-19 Guarantee Program that allows entities to reschedule debts, reducing the cost of the interest rate associated with the credit, due to the effect of the partial guarantee granted by the government.

However, as of September 2021, 12 entities (including banks, finance companies, and municipal savings banks) have rescheduled credits for S/113 million within the framework of this program. 95% of this portfolio is made up of consumer loans. For this reason, this project does not analyze the effect of this Law since our dataset comprises firm credits.

3 Data and Empirical strategy

3.1 Data

In this paper, we mainly use the novel administrative borrower-lender dataset (Reporte Crediticio de Deudores, RCD), collected by the Peruvian Superintendence of Banking, Insurance, and Private Pensions Fund Administrators (SBS). This dataset contains the universe of credit operations between households and firms with all financial institutions under the supervision of SBS. RCD gathers monthly information on borrowers' credit, including different categories such as size (large, medium, small, and micro-sized credits); and credit performance (current and non-performing loans). RCD also contains borrowers' industry, city, and credit rating, among other variables.

We combine the RCD with the Peruvian Tax Authority dataset (SUNAT) to obtain monthly information on firms' deciles of sales and formal labor employment within four-digit industry groups. These variables allow us to analyze the firms' sales and labor demand mobility after the implementation of REACTIVA program.

We have monthly information available from January 2018 to December 2022, which constitutes our period of analysis. Table 2 presents the most relevant descriptive statistics of our dataset. It shows that the number of borrowers in the formal financial sector increased by 80% between 2019 and 2022. Moreover, the average monthly stock of debt per borrower increased 13.6% in the same period, whereas the monthly stock of debt excluding REACTIVA decreased 10.5%. Notably, the average amount of debt by size of credit significantly changed between 2019 and 2022. For instance, an average micro-credit increased from PEN S/4.7k to PEN S/10.7k in 2022. This contrasts with the case of an average large credit, which decreased from PEN S/1,999k to PEN S/1,939k. Furthermore, there has been a significant worsening in the debt composition based on credit ratings. Specifically, the doubtful and loss categories have witnessed respective increases of 287.1% and 258.2% from 2019 to 2022.

Regarding the distribution of sales and workers, during the same period, the average total sales in the 10th percentile shows a decline of 20.4%, going from PEN S/1.238 MM (USD $309,378.8) to PEN S/0.985 MM (USD $246,275.8). In contrast, total sales in the 50th and 90th percentiles increased by 20.5% and 50.8%, respectively. Finally, the average number of formal employees fell in the 10th, 50th, and 90th percentiles by 7.4%, 1.9%, and 1.4%, respectively.

For the purpose of this study, we focus on firms. We consider those with total average debt between 1% and 99% of the distribution, and that can be observed for more than eight months during the period of analysis. Finally, we temporarily drop the new borrowers who have begun to be observed since REACTIVA implementation.

3.2 Empirical specification

In this paper, we assess the effect of the REACTIVA program on firms' financial and real outcomes. Regarding the first group, we identify the impact on total and direct and current debt net of REACTIVA loans[7]. According to the SBS, direct credits correspond to the sum of current or

[7]In particular, We refer to net direct and net current credits as those excluding REACTIVA loans.

Table 2: **Descriptive statistics**

	2018	**2019**	**2020**	**2021**	**2022**
Number of firms	50,074	57,433	84,312	104,125	103,325
Average Stock of debt (PEN S/)	512,281	511,014	632,819	651,423	580,618
Average Reactiva loan (PEN S/)			272,538	307,533	123,032
By size (PEN S/)					
Micro	4,472	4,696	7,709	13,860	10,736
Small	115,793	117,664	120,231	119,551	118,645
Medium	388,021	387,569	388,445	388,642	387,934
Large	2,064,142	1,999,464	2,055,264	2,008,259	1,939,443
By credit rating (PEN S/)					
Normal	505,523	504,872	622,104	644,642	597,486
With potential issues	884,221	802,526	975,918	948,324	782,143
Deficient	532,743	513,601	615,565	745,032	700,421
Doubtful	187,778	145,247	312,896	527,040	562,243
Loss	50,892	76,585	258,804	280,932	274,390
Average total sales (million PEN S/)					
P10	1.084	1.238	1.139	0.992	0.985
P50	16.523	17.367	11.094	19.881	20.925
P90	517.410	469.091	81.206	659.909	707.191
Average formal employment (number of employees)					
P10	218	237	232	225	220
P50	917	993	965	974	974
P90	21,049	23,408	21,147	22,109	23,085

performing loans, restructured, refinanced, and non-performing credit. In comparison, current credits are performing loans. Regarding the second group, We also determine the impact of REACTIVA on firms' ranking in the sales and formal employment distributions. When assessing both groups of outcomes, we compare firms eligible to REACTIVA against those not, identifying the intention to treat the effect of the program.

Our empirical difference-in-difference design has two control groups: the non-eligible cohort in the first stage of REACTIVA; and the non-eligible cohort in the second stage. This paper focuses on determining the causal effect on the first eligible cohort. In the Appendix, we report the results when considering the two stages. We assess the program using a staggered difference-in-difference (Callaway and Sant'Anna (2021)) and find similar but less significant results.

To identify the causal effect of the first stage of REACTIVA, we estimate the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 \text{eligible}_i \times \text{post}_t + X_{i,t}\Gamma + \alpha_i + \theta_t + \epsilon_{i,t} \tag{1}$$

where i denotes a firm, t denotes a month-year date, and $Y_{i,t}$ is the outcome variable of interest consisting of financial or real variables. Moreover, eligible_i is an indicator variable equal to one if a firm i is eligible to receive REACTIVA loans under the eligibility criteria in the first stage, post_t is an indicator variable equal to 1 from May 2020 onward and zero otherwise. In addition, $X_{i,t}$ consists of a vector of controls such as lagged credit rating, industry, main lender of REACTIVA loans, etc. Also, we add two-way fixed effects (TWFE) to remove the effect of potential time-invariant unobservable characteristics of firms and to control for macro-level shocks such as COVID-19 pandemic. Importantly, our coefficient of interest is β_1, which captures the causal effect of the program. It represents the average differential change in $Y_{i,t}$ for the eligible firms relative to that for the non-eligible ones after the first stage of the REACTIVA program. For example, $\beta_1 > 0$ would imply that, considering the first stage of the program, the dependent variable increases for eligible firms relative to non-eligible firms due to REACTIVA. Moreover, to identify our coefficient of interest, we checked the standard assumption of parallel trends between the control and treatment group (see Figures 2, 8 and 3).

In the following section, we show regression results when controlling for aggregate fluctuations, borrower, and main lender FE. Additionally, in the Appendix, we show alternative specifications, adding controls for robustness. Results are proven to be robust to different specifications.

Additionally, we estimate the following equation in order to identify a potential heterogeneity in the impact of the program, based on the amount of leverage before REACTIVA:

$$Y_{i,t} = \beta_0 + \beta_1 \text{eligible}_i \times \text{post}_t \times h_i + \beta_2 \text{eligible}_i \times \text{post}_t + \beta_3 \text{post}_t \times h_i + \beta_4 \text{eligible}_i \times h_i + X_{i,t}\Gamma + \alpha_i + \theta_t + \epsilon_{i,t} \quad (2)$$

In this specification, h_i is an indicator variable equal to one if, before the introduction of REACTIVA, a firm i exhibited a total direct credit stock above the median in the sample and zero otherwise. Thus, the inclusion of h_i allows us to analyze the heterogeneous effect on high versus low-leveraged firms. In this specification, our coefficient of interest is β_1, which captures the average differential change in $Y_{i,t}$ of the high-leveraged eligible firms compared to low-leveraged firms before and after REACTIVA, relative to the same change for the non-eligible firms.

3.3 Effect on financial outcomes

Table 3 reports the coefficient of interest of Equation 1. Columns 1-3 show the estimated causal effects of being eligible for the first stage of REACTIVA on (i) total direct credits, (ii) direct credits net of REACTIVA loans, and (iii) current credits net of REACTIVA loans. The estimates indicate a monthly positive effect of PEN S/269.5k (USD 67.4k) on the total direct credits for an average eligible firm relative to a non-eligible one. However, there are monthly negative effects on net direct and net current credits of PEN S/79.5k and PEN S/86.2k, respectively[8]. These first results imply that REACTIVA allowed firms to substitute more expensive unguaranteed credit for cheaper sponsored loans provided under REACTIVA. These results are supported by the event studies in Figure 2, which show significant reductions in the stock of debt after the beginning of the program. Moreover, the event studies also show that, before REACTIVA, there was no effect of being eligible for the program, which is consistent with the absence of differential pre-trends.

Table 3: **Effect of the intention to treat on financial outcomes**

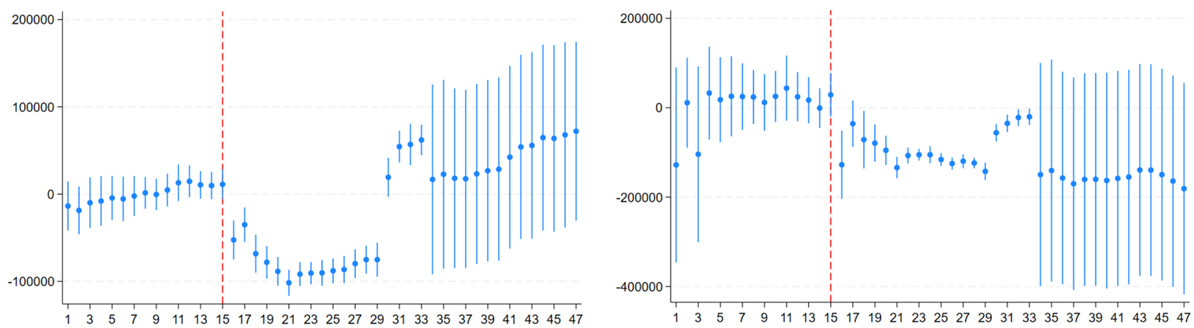
	(1) Direct credits	(2) Net direct credits	(3) Net current credits
$\text{eligible}_i \times \text{post}_t$	269491.9	-79542.5	-86190.1
	(27130.3)	(11284.9)	(12632.8)
$\text{Credit Rating}_{t-2}$	-56176.3	-6808.3	-61512.5
	(7737.4)	(2761.6)	(6716.6)
Borrower FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower and Time	Borrower and Time	Borrower and Time
Observations	1507229	1507229	1507229

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses
The sample period is April 2019 to April 2021. Direct credits correspond to the sum of current and non-performing credits.

Table 4 reports the estimated parameters of Equation 2. Focusing on high-leveraged firms, the estimates indicate that REACTIVA triggered a significant increase in total direct credits in eligible relative to non-eligible firms (Column 1). The impact is equivalent to PEN S/363.5k (USD $90.9k). However, this increase is mainly explained by borrowing from REACTIVA credit since the effect on the direct and current debt net of the program's loans is negative: PEN S/ - 434.5k (USD $ -108.6k) and PEN S/ - 95.7k (USD $ -23.9k), respectively (Columns 2 and 3). Similar to

[8]These effects amount to USD $19.9k and USD $21.5k, respectively.

Figure 2: **Event Study: Effect on net direct and current credits**



Note: REACTIVA took place on the 16th month (the 15th month is the base). Each dot is the coefficient on the interaction between being observed t months after the beginning of the program and being eligible for the program. The graph on the left exhibits the effect of being eligible to REACTIVA in the first stage on the net direct debt stock. The graph on the right exhibits the effect of being eligible to REACTIVA in the first stage on the net current debt stock.

the baseline results, these impacts suggest that high-leveraged firms benefited from REACTIVA, substituting preexisting debt for new, cheaper REACTIVA loans.

The table also shows the results for firms with a preexisting debt below the median. We do not observe a significant increase in direct credits due to the program. However, we find a significant increase in direct credits net of REACTIVA (PEN S/44.6k or USD $11.1k). Importantly, this increase does not correspond to a rise in current loans net of REACTIVA. Instead, it corresponds to a boost in net non-performing loans. Column 3 shows that the program triggered a reduction in the net current credit of PEN S/21.5k (USD $5.4k). Considering that net direct credits equal the sum of net current and net non-performing loans, this result implies that REACTIVA increased non-performing loans for low-leveraged firms.

Notably, the results in Tables 3 and 4 reveal substantial heterogeneity in the program's impact, according to the preexisting level of firms' indebtedness. We find evidence that, while more indebted firms benefited from REACTIVA, the less leveraged firms took more unwarranted debt due to the program, most of which corresponded to non-performing loans.

Table 4: **Heterogeneous effects of the intention to treat on financial outcomes**

	(1) Direct credits	(2) Net direct credits	(3) Net current credits
$\text{eligible}_i \times \text{post}_t \times h_i$	340077.7	-479100.2	-74162.5
	(47929.5)	(228037.5)	(25600.2)
$\text{eligible}_i \times \text{post}_t$	23446.1	44593.9	-21518.5
	(30328.9)	(15806.7)	(10098.8)
$\text{post}_t \times h_i$	39476.3	341279.5	-57313.9
	(46067.9)	(228175.9)	(20162.5)
$\text{Credit Rating}_{t-2}$	-66825.4	27918.4	-58423.8
	(7502.8)	(14812.3)	(6796.2)
Effect on $h_i = 1$	363523.8	-434506.3°	-95681.0
	(39124.5)	(227773.0)	(23641.0)
Borrower FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower and Time	Borrower and Time	Borrower and Time
Observations	1488895	1488895	1488895

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$, $^{\circ}$ (p<0.10). Standard errors in parentheses. The sample period is April 2019 to April 2021. Direct credits correspond to the sum of current and non-performing credits.

3.4 Effect on real outcomes

In this section, the dependent variable is a categorical variable that captures the borrowers' rank in the distribution of sales and workers of its respective four-digit industry. The rank is determined in two steps. First, borrowers are categorized according to the decile they belong in their corresponding distribution. Second, firms are assigned to a position, which inversely runs to the number of decile they belong. Therefore, this rank takes values from ten to one, where ten corresponds to firms that belong to the bottom 10% of their corresponding distribution, and one is reserved for those in the top 10%.

Since the data sample contains as many distributions as industries, we control all regressions in this section by time, industry, and industry-time FE. This latter interaction is important because the COVID-19 shock might have produced heterogeneous effects across industries.

Columns 1-4 in Table 5 show the estimated causal effects of being eligible for the first stage of REACTIVA on sales' rank, following different specifications. To control for the effect of production inputs, we include the total number of workers in the industry-decile group to which each borrower belongs, lagged by four months. Also, to control for potential dynamics in sales rank, we include the one-month-lagged average total sales in the industry-decile group where each borrower belongs.

The estimates suggest a significant causal effect of REACTIVA on firms' sales rank. Column 2 indicates that the program reduced the sales rank of eligible firms by 0.397 relative to a non-eligible firm. This point estimate means an eligible firm climbs up 0.397 deciles in the sales ranking within its four-digit industry distribution. This would imply that the program helped eligible firms increase their sales, relative to non-eligible firms. Although this result remains significant to the inclusion of industry-time FE, it loses statistical significance when we control for a lagged average number of workers (Column 4). This weakens the evidence favoring a positive impact on firms' sales. Therefore, we conclude that REACTIVA did not positively affect firms' sales.

Table 5: **Effect of the program on sales rank**

	(1) Sales rank	(2) Sales rank	(3) Sales rank	(4) Sales rank
$\text{eligible}_i \times \text{post}_t$	-0.303	-0.397	-0.373	-0.239
	(0.134)	(0.160)	(0.161)	(0.188)
Sales_{t-1} (per 100 MM)		-0.0435	-0.0448	
		(0.00252)	(0.00259)	
Workers_{t-4} (per 1 MM)				-6.54
				(1.34)
Borrower FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry Time	No	No	Yes	Yes
Clustered SE	Borrower and Time	Borrower and Time	Borrower and Time	Borrower and Time
Observations	1442655	1276009	1275989	1162644

Source: RCD, MEF Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses. The sample period is April 2019 to April 2021.

Similarly to the previous analysis, Columns 1-4 in Table 6 show the estimated causal effects of being eligible to REACTIVA on workers' rank. The estimates indicate that being eligible in the first stage of REACTIVA reduces firms' rank by 0.587 relative to non-eligible firms (Column 2). This point estimate means that an eligible firm climbs up the formal employment ranking by 0.587 deciles. This result is robust to the inclusion of industry-time fixed effects, and becomes even stronger when we control for lagged sales in each industry (Column 4).

Overall, the previous results imply that the program did not improve eligible firms' relative position in the sales distribution. However, it did help firms to climb up in the distribution of formal employment. This result indicates that REACTIVA allowed firms to increase their demand for formal employment relative to non-eligible firms.

Finally, the Appendix includes the results from the triple DiD. They show that there is no heterogeneous effect across different groups of leverage before the program.

Table 6: **Effect of the program on formal employment rank**

	(1) Workers rank	(2) Workers rank	(3) Workers rank	(4) Workers rank
$\text{eligible}_i \times \text{post}_t$	-0.615	-0.587	-0.581	-0.643
	(0.175)	(0.174)	(0.173)	(0.222)
Workers_{t-1} (per 1000)		-0.0364	-0.0365	
		(0.00153)	(0.00152)	
Sales_{t-4} (per 100 MM)				-0.0109
				(0.00172)
Borrower FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry Time	No	No	Yes	Yes
Clustered SE	Borrower and Time	Borrower and Time	Borrower and Time	Borrower and Time
Observations	1387275	1334338	1334321	1133245

Source: RCD, MEF Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses. The sample period is April 2019 to April 2021.

4 Conclusions

In the context of an economic shutdown due to the COVID-19 pandemic, the Peruvian government launched a Government-guaranteed loan program (REACTIVA) to enhance firms' private funding of working capital necessary to meet their commitments with their employees and providers. The program guaranteed a total of USD $15 billion (7.3% of GDP in 2020).

Using a novel matched lender-borrower dataset of the Peruvian Financial System, we assess the impact of REACTIVA on the financial and real outcomes of eligible firms.

We find that borrowers' monthly average total debt increased by PEN S/269.5k (USD $67.4k) due to the program. However, excluding loans guaranteed by REACTIVA, we find a decrease of PEN S/79.5k (USD $19.9k), which suggests that eligible firms substituted more expensive unwarranted credit for cheaper sponsored credit provided under REACTIVA. However, when distinguishing between firms that were highly indebted before the pandemic and those that were not, we observe that, while more indebted firms benefited from REACTIVA, the less leveraged firms took more unwarranted debt due to the program, which corresponds to non-performing loans.

Finally, we find that REACTIVA did not affect the sales of firms eligible for the program. However, it fostered firms' demand for formal employment. This result allowed eligible firms to grow larger compared to their non-eligible counterparts.

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Appendix

Table 7: **Effects of the intention to treat on direct credits**

	(1)	(2)	(3)
	Direct credit	Direct credit	Direct credit
$\text{eligible}_i \times \text{post}_t$	261315.5	328626.7	269491.9
	(3947.2)	(22850.4)	(27130.3)
Credit Rating_{t-2}		-58248.3	-56176.3
		(7506.2)	(7737.4)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1630465	1549986	1507229

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 8: **Heterogeneous effects of the intention to treat on direct credits**

	(1)	(2)	(3)
	Direct credit	Direct credit	Direct credit
$\text{eligible}_i \times \text{post}_t \times h_i$	-222871.2	363079.8	340077.7
	(278074.3)	(38186.5)	(47929.5)
Credit Rating_{t-2}		-66485.3	-66825.4
		(7028.5)	(7502.8)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1609083	1530868	1488895

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 9: **Effect on direct credits** (Staggered Difference-in-Difference)

	(1)	(2)	(3)	(4)	(5)
	TWFE	Staggered DiD - Direct credits			
$\text{eligible}_{1i} \times \text{post}_{1t}$	234630.6	328323.3	269254.3		
	(4475.4)	(22802.5)	(27082.9)		
$\text{eligible}_{2i} \times \text{post}_{2t}$	143930.8			-46158.9	-51459.6
	(114730.0)			(39500.7)	(35884.7)
Credit Rating_{t-2}		-56927.1	-55110.7		
		(7379.5)	(7653.1)		
Borrower FE	No	Yes	Yes	Yes	Yes
Lender FE	No	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Borrower	Borrower Time			
Observations	1674766	1583293	1539016	1674757	1627360

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 10: **Heterogeneous effects of the intention to treat on direct credit** (Cohort 1)

	(1)	(2)	(3)
	Direct credit	Direct credit	Direct credit
$\text{eligible}_{1i} \times \text{post}_{1t} \times h_i$	-216912.6	363761.0	340813.4
	(277479.5)	(38142.7)	(47901.2)
$\text{eligible}_{1i} \times \text{post}_{1t}$	296587.4	66829.1	23210.8
	(104228.8)	(22159.6)	(30315.8)
Credit Rating_{t-2}		-65643.8	-66227.6
		(6914.7)	(7429.9)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1651147	1562464	1519043

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 11: **Effects of the intention to treat on net direct credits**

	(1) Net direct credits	(2) Net direct credits	(3) Net direct credits
$\text{eligible}_i \times \text{post}_t$	-103888.4	-70837.7	-79542.5
	(8389.8)	(10580.5)	(11284.9)
$\text{Credit Rating}_{t-2}$		-4886.5	-6808.3
		(2467.4)	(2761.6)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1630465	1549986	1507229

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 12: **Heterogeneous effects of the intention to treat on net direct credits**

	(1) Net direct credits	(2) Net direct credits	(3) Net direct credits
$\text{eligible}_i \times \text{post}_t \times h_i$	-738138.4	-108897.1	-479100.2
	(264931.2)	(24552.5)	(228037.5)
$\text{eligible}_i \times h_i$	765549.5	0	751581.8
	(8887.5)	(0.0000967)	(8952.3)
$\text{eligible}_i \times \text{post}_t$	10664.4	1608.1	44593.9
	(5150.5)	(4789.7)	(15806.7)
$\text{Credit Rating}_{t-2}$		-2706.5	27918.4
		(2420.8)	(14812.3)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1609083	1530868	1488895

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 13: **Effect on net direct credits** (Staggered Difference-in-Difference)

	(1)	(2)	(3)	(4)	(5)
	TWFE	Staggered DiD - Net direct credits			
$\text{eligible}_{1i} \times \text{post}_{1t}$	-116864.7	-70649.4	-79369.0		
	(8347.4)	(10576.5)	(11279.5)		
$\text{eligible}_{2i} \times \text{post}_{2t}$	23886.7			-1804.6	-960.5
	(11477.4)			(21089.0)	(20757.0)
Credit Rating_{t-2}		-4958.3	-6876.2		
		(2447.0)	(2745.9)		
Borrower FE	No	Yes	Yes	Yes	Yes
Lender FE	No	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Borrower Time				
Observations	1674766	1583293	1539016	1674757	1627360

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 14: **Heterogeneous effects of the intention to treat on direct credit** (Cohort 1)

	(1)	(2)	(3)
	Net direct credits	Net direct credits	Net direct credits
$\text{eligible}_{1i} \times \text{post}_{1t} \times h_i$	-738623.7	-108779.7	-92520.4
	(265043.4)	(24523.7)	(26422.6)
$\text{post}_{1t} \times h_i$	606930.7	-13278.3	-31067.5
	(264717.6)	(20497.9)	(22689.8)
$\text{eligible}_{1i} \times \text{post}_{1t}$	223912.8	1575.2	-9458.0
	(101225.4)	(4771.7)	(6279.6)
Credit Rating_{t-2}		-2678.5	-3824.6
		(2401.3)	(2724.9)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1651147	1562464	1519043

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 15: **Effects of the intention to treat on net current credits**

	(1) Net current credits	(2) Net current credits	(3) Net current credits
$\text{eligible}_i \times \text{post}_t$	-105748.5	-81699.1	-86190.1
	(9308.2)	(10130.8)	(12632.8)
$\text{Credit Rating}_{t-2}$		-55135.2	-61512.5
		(5698.9)	(6716.6)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1630465	1549986	1507229

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 16: **Heterogeneous effects of the intention to treat on net current credits**

	(1) Net current credit	(2) Net current credit	(3) Net current credit
$\text{eligible}_i \times \text{post}_t \times h_i$	-175102.5	-94688.1	-74162.5
	(16268.6)	(20220.1)	(25600.2)
$\text{post}_t \times h_i$	35541.2	-35449.2	-57313.9
	(12298.6)	(12269.6)	(20162.5)
$\text{eligible}_i \times \text{post}_t$	44904.0	-14555.9	-21518.5
	(9130.8)	(7385.3)	(10098.8)
$\text{Credit Rating}_{t-2}$		-52890.6	-58423.8
		(5844.4)	(6796.2)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1609083	1530868	1488895

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 17: **Effect on net current credits** (Staggered Difference-in-Difference)

	(1)	(2)	(3)	(4)	(5)
	TWFE	Staggered DiD - Net current credits			
$\text{eligible}_{1i} \times \text{post}_{1t}$	-118305.1	-81234.8	-85744.8		
	(11087.4)	(10079.0)	(12580.4)		
$\text{eligible}_{2i} \times \text{post}_{2t}$	48836.7			2693.7	3553.7
	(13363.7)			(21768.7)	(21446.3)
Credit Rating_{t-2}		-54812.3	-61253.2		
		(5643.9)	(6666.8)		
Borrower FE	No	Yes	Yes	Yes	Yes
Lender FE	No	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Clustered SE	Borrower Time				
Observations	1674766	1583293	1539016	1674757	1627360

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 18: **Heterogeneous effects of the intention to treat on net current credits** (Cohort 1)

	(1)	(2)	(3)
	Net current credit	Net current credit	Net current credit
$\text{eligible}_{1i} \times \text{post}_{1t} \times h_i$	-175776.4	-94356.3	-73843.7
	(16022.7)	(20132.6)	(25500.6)
$\text{post}_{1t} \times h_i$	35415.8	-35660.2	-57537.0
	(12248.8)	(12233.3)	(20112.1)
$\text{eligible}_{1i} \times \text{post}_{1t}$	43529.0	-14396.9	-21397.7
	(8948.6)	(7322.4)	(10045.0)
Credit Rating_{t-2}		-52518.5	-58145.2
		(5784.9)	(6749.7)
Borrower FE	No	Yes	Yes
Lender FE	No	No	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1651147	1562464	1519043

Source: RCD, Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 19: **Effect of intention to treat on sales percentiles**

	(1) Sales percentile	(2) Sales percentile	(3) Sales percentile
$\text{eligible}_{1i} \times \text{post}_{1t} \times h_i$	-0.296	-0.499	-0.449
	(0.272)	(0.306)	(0.340)
$\text{post}_{1t} \times h_i$	0.430	0.620	0.544
	(0.263)	(0.298)	(0.334)
Sales*_{t-1} (per 100 MM)		-0.044	
		(0.00272)	
Workers**_{t-4} (per 10000)			-0.0649
			(0.0133)
Borrower FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Industry Time	No	No	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1424797	1260863	1149118

Source: RCD, MEF Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Table 20: **Effect of intention to treat on workers percentiles**

	(1) Workers percentile	(2) Workers percentile	(3) Workers percentile
$\text{eligible}_{1i} \times \text{post}_{1t} \times h_i$	-0.181	-0.175	-0.236
	(0.331)	(0.328)	(0.403)
$\text{eligible}_{1i} \times \text{post}_{1t}$	-0.529	-0.527	-0.589
	(0.254)	(0.253)	(0.353)
Workers $_{t-1}$ (per 1000)	-0.0363	-0.0364	
	(0.00153)	(0.00152)	
Sales**_{t-1} (per 100 MM)			-0.0168
			(0.00148)
Borrower FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Industry Time	No	No	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1316796	1316779	1170431

Source: RCD, MEF Peru. Notes: $p < 0.001$, $p < 0.01$, $p < 0.05$. Standard errors in parentheses.

Figure 3: Parallel trend: Direct credits

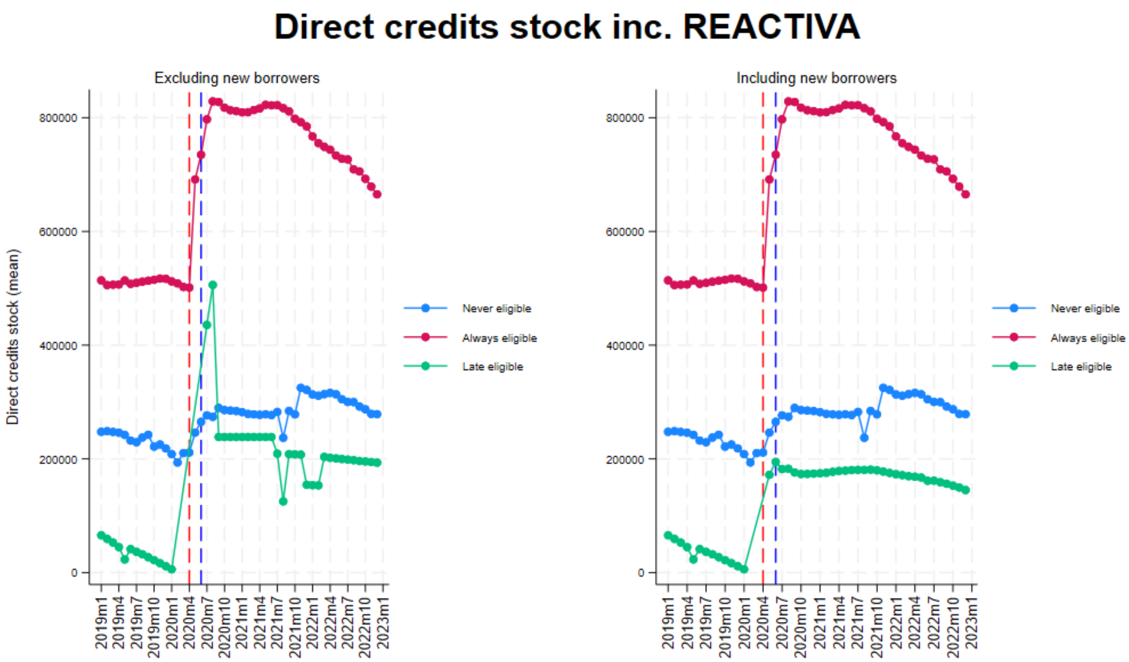

Figure 4: Parallel trend: Direct credits excluding REACTIVA

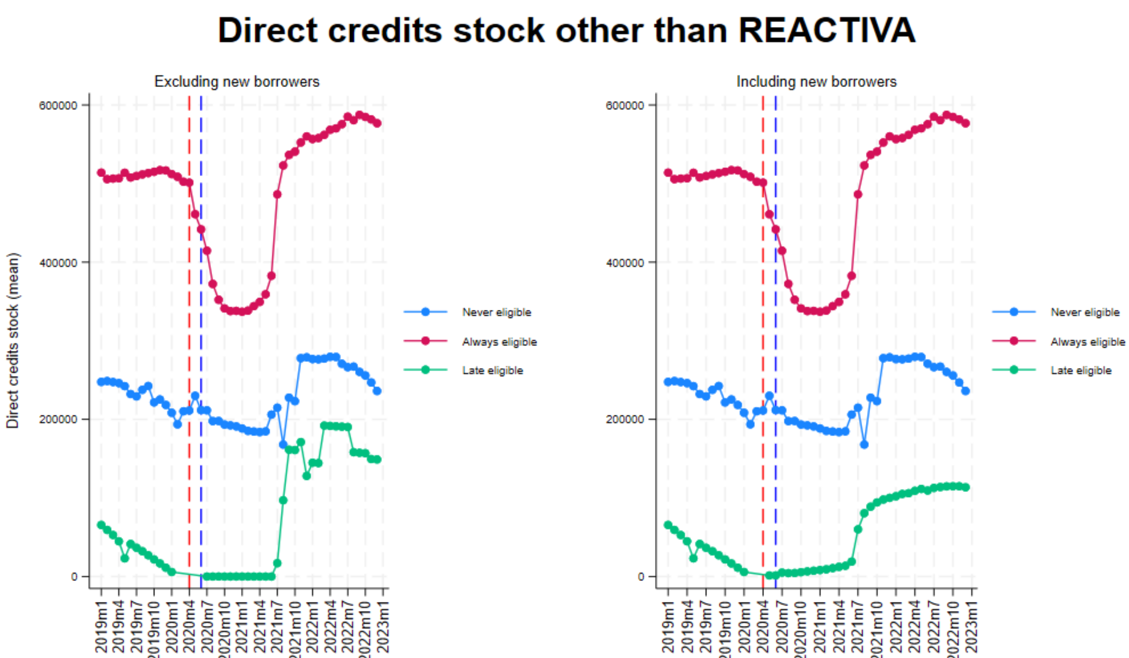

Figure 5: Parallel trend: Current credits excluding REACTIVA

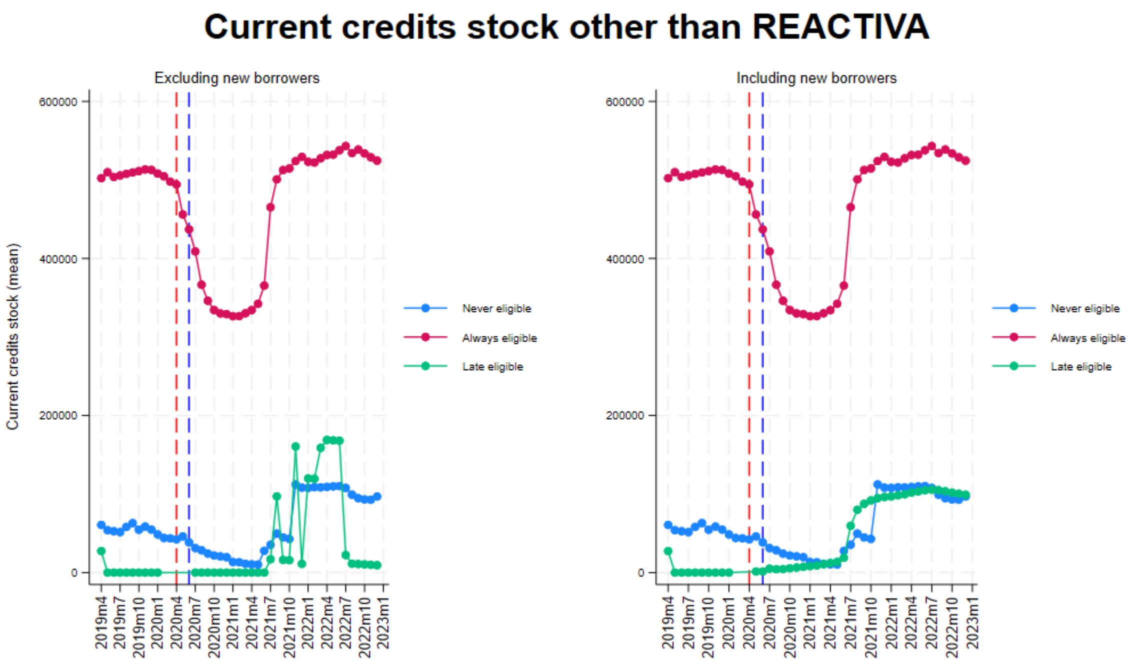

Figure 6: Parallel trend: Sales distribution in percentiles

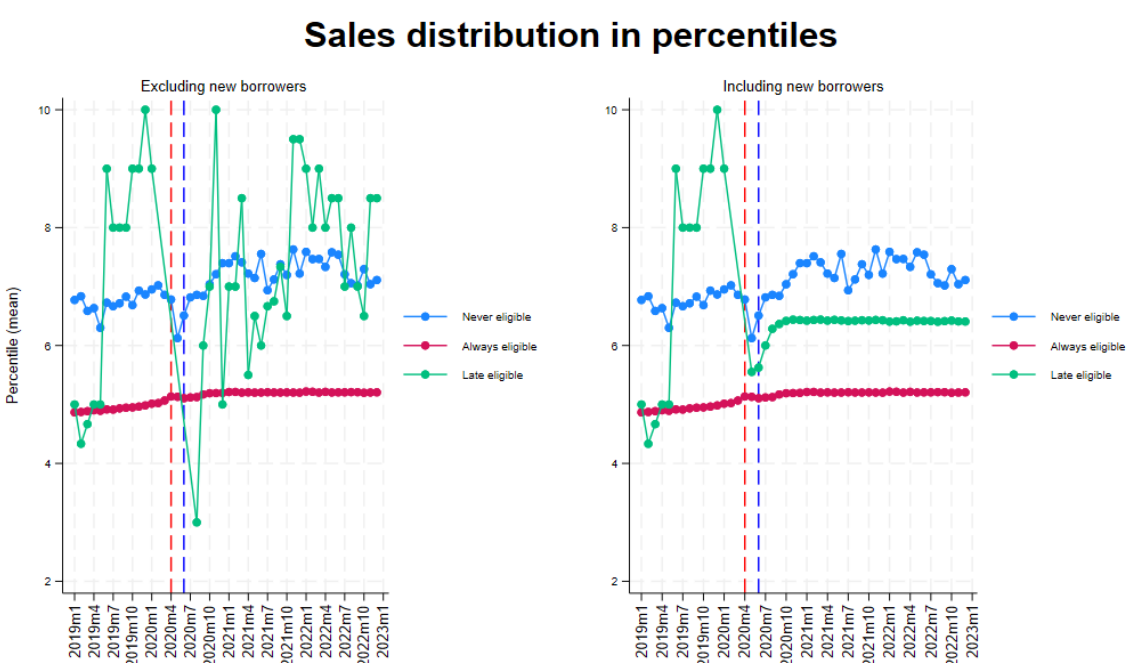

Figure 7: Parallel trend: Worker distribution in percentile

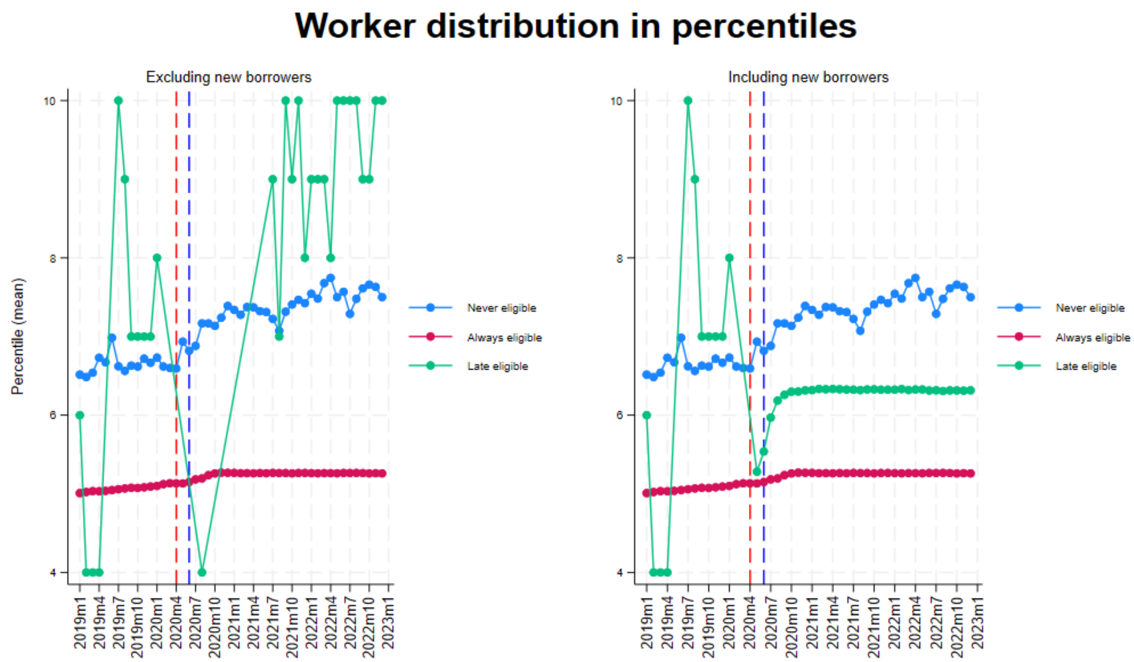

Figure 8: **Net non-performing and punished credits**
(as % of net direct credits)