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

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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

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1 Introduction

Generally, crises have adverse effects on bank lending. According to OECD reports, small and medium enterprises (SMEs) tend to be more vulnerable and affected than larger corporations when bank lending is reduced. Also, credit sources tend to dry up more rapidly for small firms than for large companies during economic downturns. To tackle these issues, governments have taken extraordinary measures such as emergency and assistance programs, including government guarantees, since late 2008 or early 2009. Government guarantees provided to SMEs via the financial system increased dramatically during 2009 - 2010 and 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 the purpose for this simplicity was 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. In this paper, we study how the implementation of government-guaranteed loan programs affected firms' leverage and dynamics. We address this question by studying the case of REACTIVA, a government-guaranteed loan program implemented in Peru during 2020.

In this paper, we focus on empirical evidence. We determine the causal effects of being eligible for the first wave of the REACTIVA program. 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[1]. These first results imply that REACTIVA allowed firms to substitute more expensive unguaranteed credit for cheaper sponsored loans provided under REACTIVA. Moreover, estimates indicate that being eligible in the first wave of REACTIVA increases borrowers' chances to move up in the formal workers' distribution in their four-digit industry group. However, we do not find any significant effect on borrowers' chances to climb in the sales ranking within their corresponding distribution.

After this evidence, we are incorporating the lender's capital structure decision and credit constraints into a heterogeneous firm model to complement the empirical analysis. In the model, banks will decide the optimal capital structure they will accept. Moreover, based on Manova (2013), our model incorporates firms' need for external capital and ability to pledge collateral depending on the industry in which they are active. Contracts between entrepreneurs and investors are more

[1] Net direct and Net current credit refers to Direct and current credit net of non-performing loans.

likely to be enforced in regions with higher levels of financial development. Thus, based on this model, we will incorporate REACTIVA rules that may impact the optimal capital structure taken by banks. Finally, we plan to perform counterfactual analysis identifying the impact on the main 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 loan markets can cause both intended and unintended consequences on the allocation of credits.

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 and experienced among the largest economic contractions globally. In this context of an economic shutdown, government 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 high informality and low banking access.

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 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

[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%).

[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%)

companies stopped operating in 2020. However, this adverse situation was partially reversed by implementing government policies that aimed to prevent breaking the payment chain and provide the financial system liquidity. 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, aimed at enhancing 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 firm's loan to a Private Financial Institution (PFI). This percentage depended on the credit's amount and varied from 98% for small 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

[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.

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 of 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).

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-

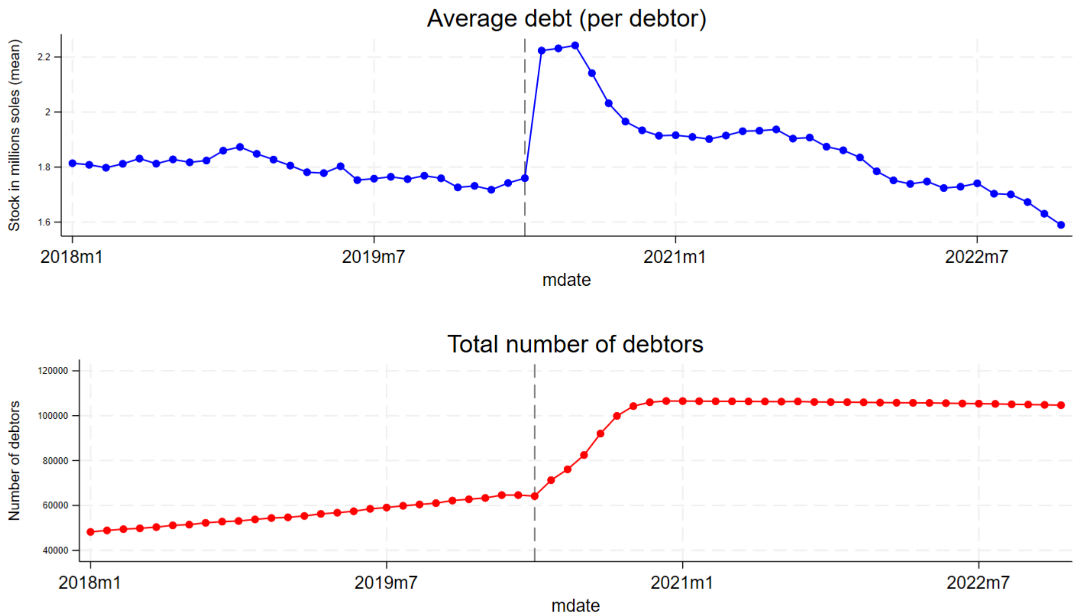


Figure 1: Average debt stock vs number of debtors

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 analysis period. Table 2 presents the most relevant descriptive statistics of our dataset, which exhibits a rise of 80% in the number of firms that are borrowers in the formal financial sector in 2022 with respect to 2019. Moreover, the average monthly total stock of debt per borrower increased 13.6% in the same period, whereas the monthly stock of debt excluding REACTIVA decreased 10.5%. Notably, this leverage's composition across different firm's sizes has also changed. For instance, an average large-sized firm had 425.7x and 180.7x of the monthly average debt stock of a micro-sized firm in 2019 and 2022, respectively. Furthermore, there had been an important deterioration in the composition of debt by credit rating since the doubtful and loss categories have increased by 287.1% and 258.2%, respectively, from 2019 to 2022.

Regarding the distribution of sales and workers, the average sales across industries show a decline in average sales in the 10th percentile from PEN S/ 1.238mm ($309,378.8) in 2019 to PEN S/ 0.985mm ($246,275.8) in 2022 (-20.4%). In contrast, the 50th and 90th percentile increased by 20.5% and 50.8%, respectively. Finally, the average formal employment fell in the 10th, 50th, and 90th percentile 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 financial outcomes such as total and net direct credits and net[7] current credits. According to the SBS, direct credits correspond to the sum of current, restructured, refinanced, past due, and in-judicial collection credits. In comparison, current credits are loans granted in different modalities whose payments are up to date, as agreed. We also determine its impact on firms' mobility in sales and formal employment distribution. We compare firms eligible to REACTIVA against those not, identifying the intention to treat effect of the program.

Our empirical difference-in-difference design has two control groups: eligible cohort in first stage

[7]Excluding REACTIVA credits

Table 2: **Descriptive statistics** (In PEN S/.)

	2018	**2019**	**2020**	**2021**	**2022**
Number of firms	50,074	57,433	84,312	104,125	103,325
Stock of debt	512,281	511,014	632,819	651,423	580,618
Reactiva loan			272,538	307,533	123,032
By size					
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					
Normal	505,523	504,872	622,104	644,642	597,486
CPP	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 sales (In million PEN S/.)					
P10	1.084	1.238	11.398	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					
P10	218	237	232	225	220
P50	917	993	965	974	974
P90	21,049	23,408	21,147	22,109	23,085

and second stage of REACTIVA. First, we analyzed the causal effect on the first eligible cohort and thereafter, we implemented the staggered difference-in-difference according to Callaway and Sant'Anna (2021).

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 and real variables. Moreover, eligible$_i$ is an indicator variable equal to one if a firm i is eligible to receive REACTIVA loans using the first stage's eligibility criteria, post$_t$ is an indicator variable equal to 1 from May 2020 onward and zero otherwise. $X_{i,t}$ 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 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, $\beta_1 > 0$ implies that the dependent variable increases for eligible firms after REACTIVA relative to non-eligible firms after REACTIVA. Moreover, to identify our coefficient of interest, we checked the standard assumption of parallel trends between the control and treatment group exhibits in Figures 2, 3 and 4.

In the following section, we show regression's 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 proved 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:

$$Y_{i,t} = \beta_0 + \beta_1 \text{eligible}_i \times \text{post}_t \times h_i + \beta_2 \text{eligible}_i \times \text{post}_t + \beta_3 \text{post}_t \times h_i + \beta_4 \text{eligible}_i \times h_i \\ + X'_{i,t}\Gamma + \alpha_i + \theta_t + \epsilon_{i,t} \quad (2)$$

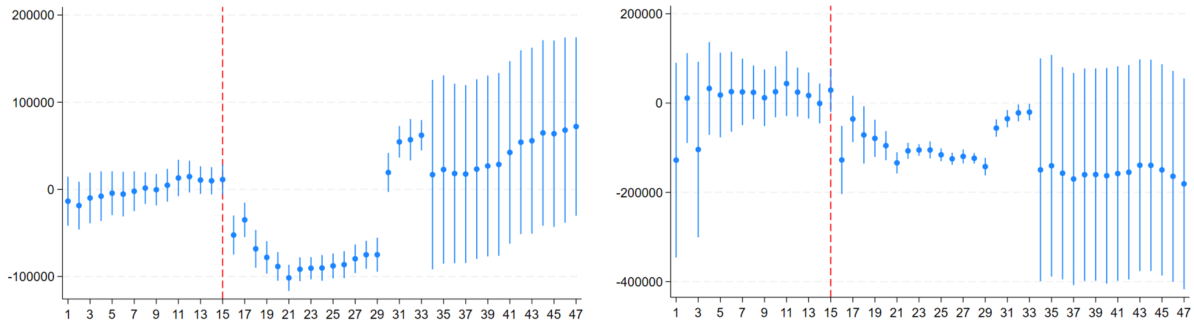
where h_i is an indicator variable equal to one if before the introduction of REACTIVA, a firm i exhibited a total direct credit stock above the median in the sample and zero otherwise. Thus, the inclusion of h_i allows us to analyze the heterogeneous effect on high versus low-leveraged firms. In this 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 of 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 to 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

[8] These effects amount to USD 19,9k and USD 21.5k, respectively.

Figure 2: **Study Event: 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 REACTIVA beginning and being eligible. 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.

cheaper sponsored loans provided under REACTIVA. Furthermore, when we combine these results with study events in Figure 2 we confirm that an eligible average borrower substituted preexisted direct and current credits since the beginning of REACTIVA implementation. Also, consistent with the absence of differential pre-trends, we see that there is no effect of being eligible in the first stage before REACTIVA took place.

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	Borrower	Borrower
	Time	Time	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. The estimates indicate that being a high-leveraged eligible firm in the first stage of REACTIVA has a significant effect on the total direct credits relative to a high-leveraged non-eligible firm equivalent to PEN S/ 340.1k ($ 85,019) (Column 1). Moreover, there is a monthly negative effect of PEN S/ 479.1k ($ 119,775) and PEN S/ 74.2k ($ 18,540) on the net direct credits and net current credits, excluding REACTIVA loans, respectively (Column 2 and 3).

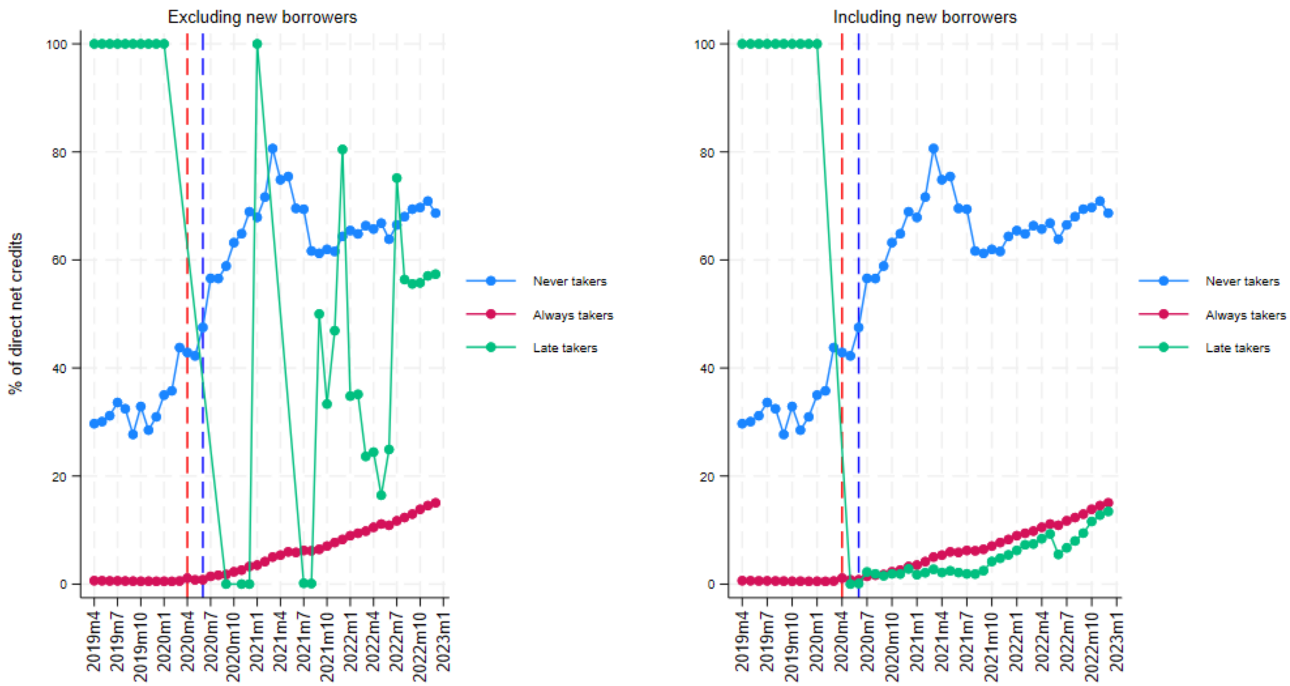
Notably, results in Tables 3 and 4 suggest that there was an important change on non-performing loans. Given that $E[Y|X] = E[Y_1 + Y_2|X] = E[Y_1|X] + E[Y_2|X]$ where Y,Y_1 and Y_2 represent net direct, net current and net non-performing loans, respectively, we can calculate the effect on net non-performing loans which based on Table 3 is PEN S/ 6.6k ($1.65k) and based on Table 4 is - PEN S/404.9k (-$101.2k). This last result implies there is an important heterogeneous effect on non-performing loans when the borrower is high-leveraged relative to when it is not. Complementary, Figure 3 shows that there is no unconditional parallel trend but there is an increasing trend in non-performing credits measured as a share of net direct credits in the control and treatment group.

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)
Borrower FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Clustered SE	Borrower Time	Borrower Time	Borrower Time
Observations	1488895	1488895	1488895

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.

Figure 3: **Net non-performing and punished credits**



3.4 Effect on real outcomes

In this section, the dependent variable is a categorical variable that reflects the percentile where the borrower belongs each month from the distribution of sales and workers of its respective industry. 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 to the first stage of REACTIVA on sales' distribution percentile. Moreover, the results in Table 5 include additional controls. To remove the effect of production inputs, we include the average number of workers in the industry where each borrower belongs lagged by four months. Also, to remove any contemporaneous effect of lagged sales, we include the average sales in the industry where each borrower belongs.

The estimates indicate that being eligible in the first stage of REACTIVA has a monthly negative effect of 0.397 on the percentile of sales of an average eligible firm relative to a non-eligible firm (Column 2). In short, this point estimate implies that an eligible firm jumps 0.397 deciles within the monthly sales distribution in its respective industry. Similar results come from

Column 3 when we control by the interaction of industry-time FE; however, if we remove the effect of lagged average number of workers in each industry, this effect loses significance (Column 4).

Table 5: **Effect of the intention to treat on sales decile mobility**

	(1)	(2)	(3)	(4)
	Sales pctile	Sales pctile	Sales pctile	Sales pctile
$\text{eligible}_i \times \text{post}_t$	-0.303*	-0.397*	-0.373*	-0.239
	(0.134)	(0.160)	(0.161)	(0.188)
Sales_{t-1} (per 100mm)		-0.0435***	-0.0448***	
		(0.00252)	(0.00259)	
Workers_{t-4} (per 1mm)				-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	Borrower	Borrower	Borrower
	Time	Time	Time	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 the first stage of REACTIVA on workers' distribution percentile. The results in Table 6 include additional controls. To remove the effect of lagged sales that can have a contemporaneous effect on workers' decile mobility, we include the average sales in the industry where each borrower belongs lagged by four months. Also, to remove any contemporaneous effect of the lagged number of workers, we include the average number of workers in the industry where each borrower belongs.

Notably, the estimates indicate that being eligible in the first stage of REACTIVA has a monthly negative effect of 0.587 on the percentile of workers of an average eligible firm relative to a non-eligible firm (Column 2). This point estimate implies that an eligible firm jumps 0.587 deciles within its respective industry's monthly workers' distribution. Similar results come from Column 3 when we control by the interaction of industry-time FE, and this negative effect increases to 0.643 deciles even when we remove the effect of lagged average sales in each industry (Column 4).

Overall, results from Table 6 show robust results that imply being eligible in the first stage of REACTIVA increase borrower's chances to move up within workers' distribution in their respective industry; however, after controlling by the larger size of workers in each industry, there is no significant effect of being eligible of REACTIVA on the borrower's decile mobility within the sales distribution of their respective industry.

Finally, the Appendix includes the results from the triple DiD and they show that there is no heterogeneous effect of being elegible and high-levered.

Table 6: **Effect of the intention to treat on workers decile mobility**

	(1) Workers pctile	(2) Workers pctile	(3) Workers pctile	(4) Workers pctile
$\text{eligible}_i \times \text{post}_t$	-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 100mm)				-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 Time	Borrower Time	Borrower Time	Borrower 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.

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Appendix

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

	(1) Direct credit	(2) Direct credit	(3) 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) Direct credit	(2) Direct credit	(3) 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)	(2)	(3)
	Net direct credits	Net direct credits	Net direct credits
$\text{eligible}_i \times \text{post}_t$	-103888.4***	-70837.7***	-79542.5***
	(8389.8)	(10580.5)	(11284.9)
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)	(2)	(3)
	Net direct credits	Net direct credits	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)
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)
$\text{Credit Rating}_{t-2}$		-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)
$\text{Credit Rating}_{t-2}$		-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)
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)
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 100mm)		-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 100mm)			-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.

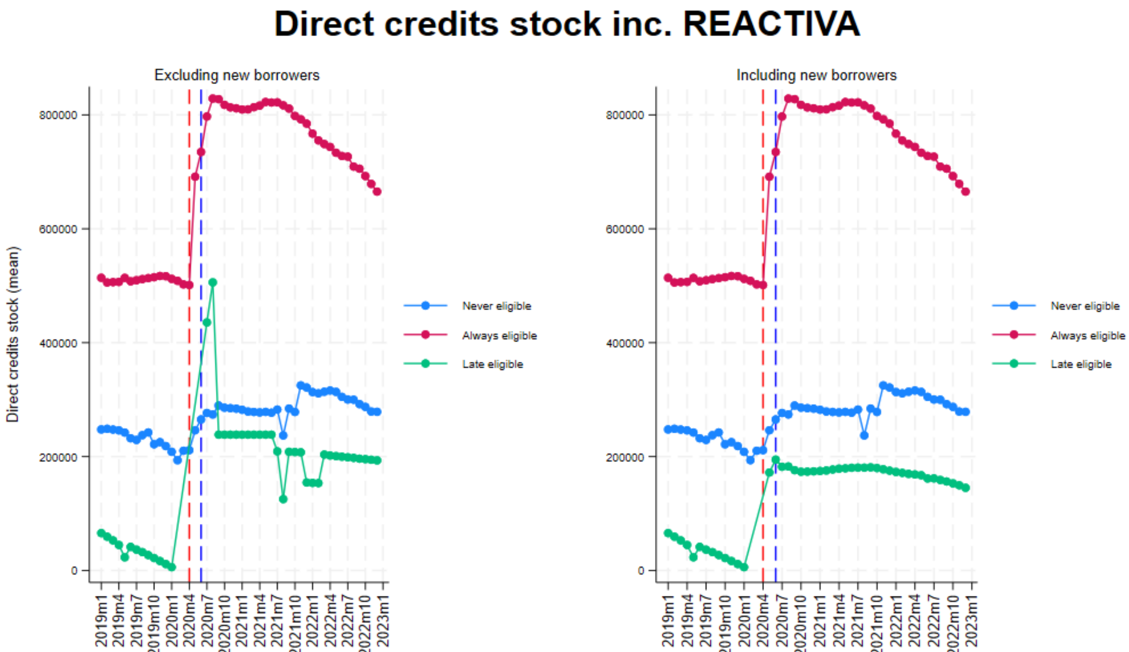

Figure 4: Parallel trend: Direct credits

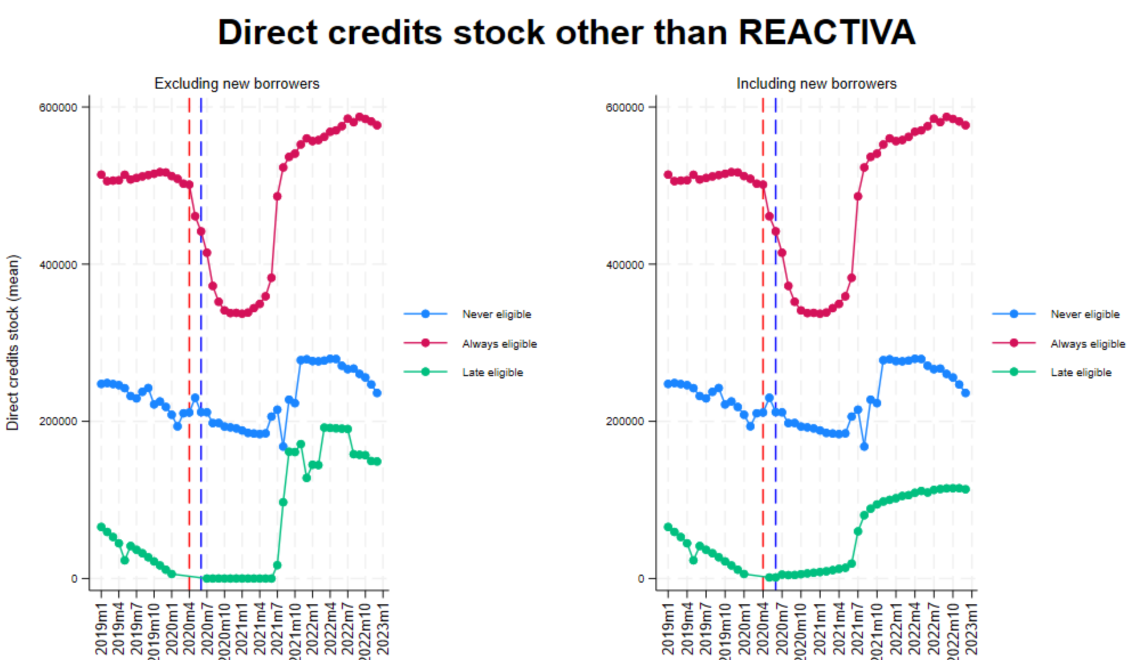

Figure 5: Parallel trend: Direct credits excluding REACTIVA

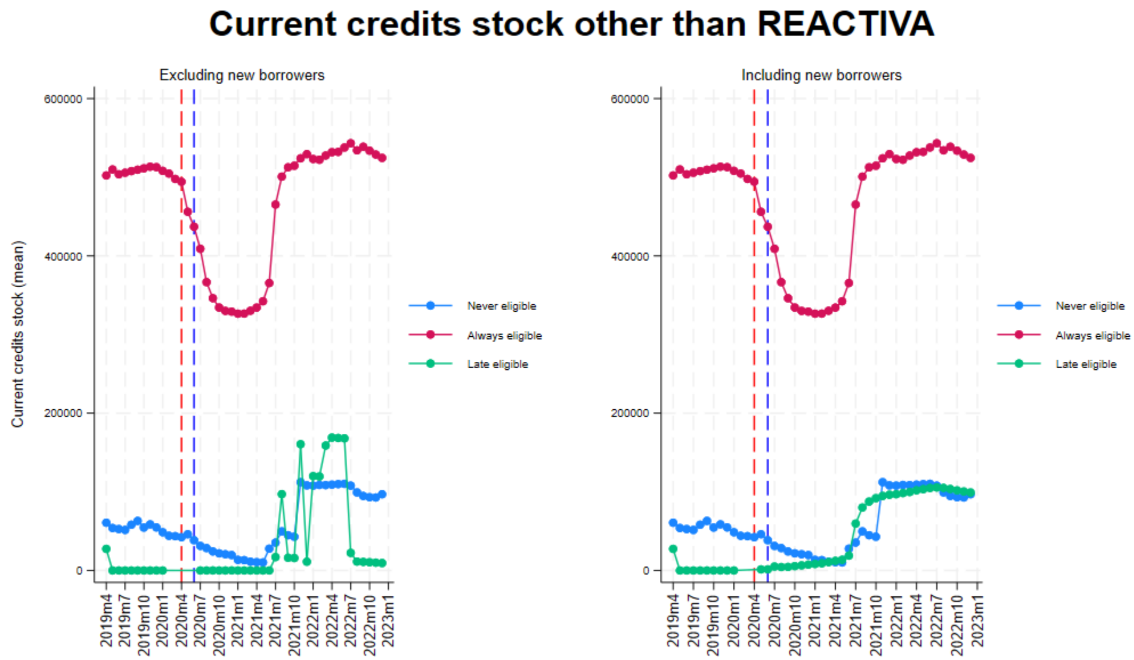

Figure 6: Parallel trend: Current credits excluding REACTIVA

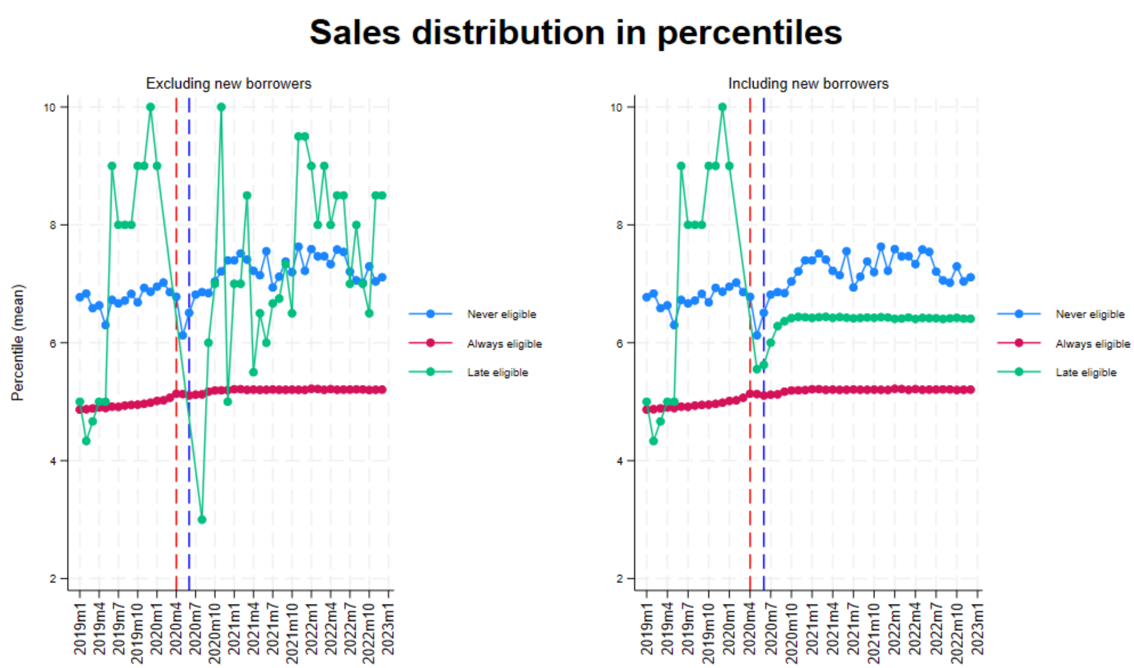

Figure 7: Parallel trend: Sales distribution in percentiles

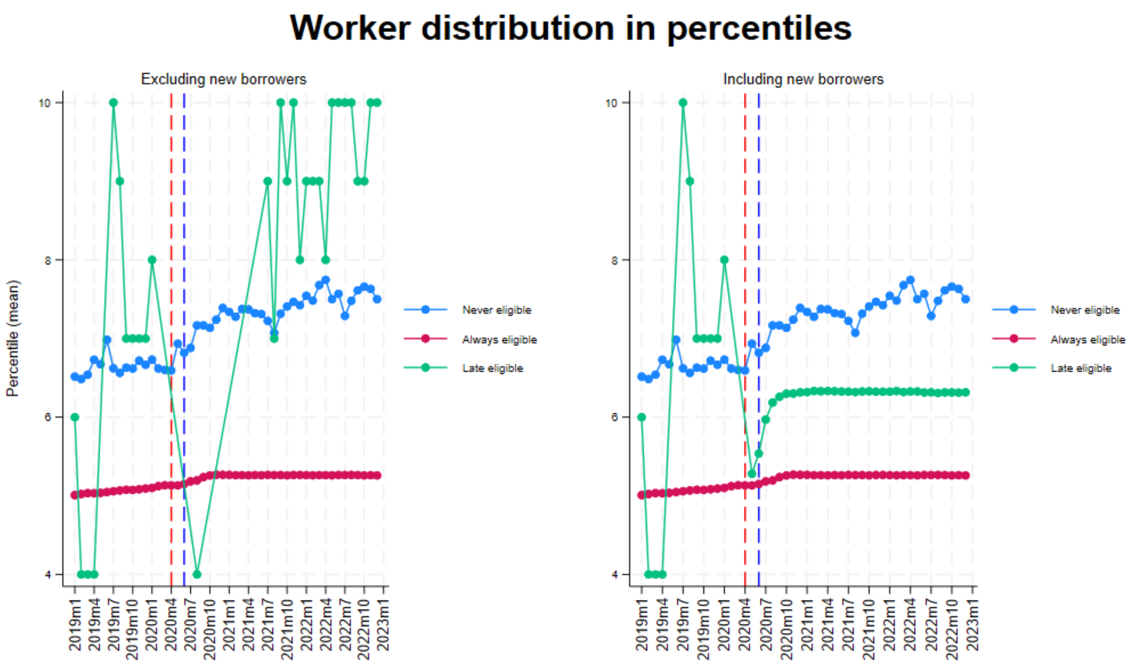

Figure 8: Parallel trend: Worker distribution in percentile