BANCO CENTRAL DE RESERVA DEL PERÚ

The Impact of REACTIVA on the Real Economy and on Bank Risk-Taking

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DT. N°. 2023-005
Serie de Documentos de Trabajo
Working Paper series
Octubre 2023

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1 Summary

We analyze empirically the impact on the credit market, including bank risk-taking, as well as the associated real effects of REACTIVA Peru, a Peruvian public credit guaranteed program oriented to avoid a severe reduction in the economic activity and the credit market. We use matched administrative datasets: the exhaustive credit register and firm-level monthly employment data.

Our results suggest that REACTIVA reduces bank risk (defaults) of the total credit portfolio, as well as it has a positive impact on the real economy – firm employment–, both at the intensive and extensive margins. In addition, our results suggest that in normal times there could be a trade-off between bank risk-taking and economic activity: REACTIVA avoids a stronger contraction of the real economy, due to a positive impact on employment, and increases bank willingness to take risk, captured by an increase of the risk of the non-REACTIVA credit portfolio. However, during the Covid-19 shock, this finding is associated with the desired impact of REACTIVA in diminishing any excessive increment of bank risk aversion.

2 Introduction

The Covid-19 pandemic has produced a strong negative impact on the economy. This challenging environment, in turn, forced Central Banks to implement both conventional

*The views expressed in this paper do not necessarily represent those of the Central Reserve Bank of Peru. We thank Carlos Montoro and the participants of the Virtual Research Seminars at the Central Reserve Bank of Peru.

and unconventional policies. These latter are due to the already low interest rate environment.

As in several emerging and developed countries, in Peru in April 2020, the fiscal and monetary authorities implemented the REACTIVA program. It consists of a Central Bank giving liquidity to banks so the latter can issue cheap government-guaranteed domestic currency loans to firms, with the purpose of avoiding the disruption of the payment chain. In that sense, REACTIVA also aimed to encourage bank lending activity. One important channel is that REACTIVA sought to diminish the excessive rise of banks' risk aversion since firms' hibernation increased firms' likelihood of not honoring their obligations, Montoro (2020).

Bank credit issued in the REACTIVA program represented in December 2020 around 15 percent of total credit and 23 percent of the credit to firms. In a country like Peru, with a large percentage of entrepreneurs in the tertiary and/or informal sectors (the sectors most affected by the pandemic), REACTIVA was important because it allowed: (i) to give cheap credit to the most affected sectors and hence to avoid a stronger reduction of employment; and (ii) to preserve financial stability.

In this work, we aim to study the impact of REACTIVA program on both the real economy and financial stability. To measure the former, we use the employment level and to measure the latter we use the non-performing loan ratio. To measure the presence and intensity of REACTIVA we might use a dummy or a ratio of REACTIVA loans to total loans, respectively.

To do so we develop two empirical strategies: One that assesses the impact of REACTIVA on bank risk-taking and the other evaluates the impact on real activity (both intensive and extensive margins). Our results suggest that REACTIVA improves financial stability and economic growth. Interestingly, we find that on average there is a trade-off between risk-taking and economic activity: On the one hand REACTIVA avoids a stronger contraction of the real economy, due to a positive impact on employment, and increases bank willingness to take risk, captured by an increase of the risk of the non-REACTIVA credit portfolio. However, during crisis time, for example, the Covid-19 shock, we might argue that REACTIVA might help to diminish any excessive rise of bank risk aversion. In addition, in a diff-in-diff analysis we find on average a positive effect of REACTIVA of between 2.0% and 3.5% over the employment for medium, small and micro-enterprises, the positive effect is greater for groups that received the treatment at the beginning of the pandemic and previous easing of immobility measures.

In addition, we find that the impact of REACTIVA on employment holds even if we define better our control group, and hence consider in our sample only those firms that meet the requirements for receiving REACTIVA. This is, results are robust even if we control by firms' good fundamentals, which might originate an identification issue due to endogeneity problem. It is worth mentioning that even when we improve our control group, this is not being affected by the disruption of the payment chain, as it was supposed to be the case without the presence of REACTIVA, then we partially measure the beneficial impact of REACTIVA. This also explains why we find that the non-performing loan ratio of non-REACTIVA loans increases rather than decreases with the implementation of REACTIVA.

The remainder of this paper is partitioned as follows. Section 3 presents the literature review. In section 4 we explain the REACTIVA program in more detail and its main differences with other similar programs that appear due to the pandemic. Section 5 shows the data used in this paper. Section 6 studies the impact of REACTIVA on financial and macroeconomic stability. Section 7 we develop a strategy to control for endogeneity through the credit demand and study the presence of spillover effects. Finally, section 8 concludes.

3 Literature Review

This work is related to the empirical and theoretical literature on unconventional policy measures originated from the pandemic. We discuss some work for REACTIVA Peru and then similar work performed for other policies and related theoretical papers.

Using a Growth-at-Risk methodology, Chicana & Nivin (2022) propose a reliable specification to evaluate the impact of REACTIVA on macroeconomic and financial stability. They find a quantitatively positive important impact on macroeconomic and financial stability. Also, the health crisis of Covid-19 pandemic had real impacts on the economy. The effect on labor income was documented for the Peruvian case in Sanchez (2022) using fixed effects panel data with instrumental variables. Furthermore, Durán (2021) analyzes their implications for social inequalities and gender gaps. Both works use the National Household Survey data of Peru.

During the pandemic, governments worldwide deployed unconventional monetary policies to limit the economic damage and support the recovery. A strand of the literature analyses the real effect of such policies. Acharya et al. (2019) analyzed the Outright Monetary Transactions (OMT) program launched in 2012. They found that firms receiving loans used these funds not to undertake real economic activity, such as employment and investment, but to build cash reserves. However, Luck & Zimmermann (2020) found a significant increase in local consumption and overall employment as effects of the Federal Reserve's quantitative easing policies (QE).

A second branch of the literature links unconventional policies and the increment of banks' risk-taking. Jiménez et al. (2013) explore the relationship between competition and risk-taking behavior using regressions with granular data from the credit register of the Bank of Spain. Matthys et al. (2020), using a heteroskedastic approach identification in a VAR model, find that there was no risk-taking behavior in the loan market during the unconventional monetary policy period between 2008 and 2015. Furthermore, Anzuini & Rossi (2022) find causal effects of these policies on economic expectations in a direction consistent with central bankers' will.

Recently, Huneeus et al. (2022) analyze a large-scale Covid-19 public credit guarantee program in Chile, using granular credit data matched with tax data. They find that most credit is given to relatively safe firms and macroeconomic risk stays small. Moreover, the aggregate risk increases substantially when credit limits are relaxed.

4 The REACTIVA Peru Program

REACTIVA Peru was a public guarantee program for up to S/ 60 billion (initially S/ 30 billion) where the amount of the loans is related to working capital needs. Likewise, the guarantee of the Government was granted, according to a percentage (between 80 and 98 percent), which decreases with the amount of the loan. Thus, the guaranteed percentage is higher for smaller loans, which are also associated with smaller firms. Also, the program included a graced period of one year, which was later extended for another year.

Table 1: *Loans per company (in soles).*

Guarantee percentage	Reactiva 1 [1/]	Reactiva 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 credits before June 1, 2020. [2/] Guaranteed loans after June 1, 2020.

The program was aimed at companies that were solid before the COVID-19 shock, including good taxpayers and debtors with good preconditions. In this way, the companies that could access to REACTIVA were required to have a qualification of Normal or With Potential Problems in February 2020.[1] This ensured that the companies with good fundamentals might default, due to the important liquidity shock that occurred because of Covid-19 shock.

This type of unconventional credit program was common in the rest of the countries. Also, as Altavilla et al. (2020) state, financial institutions during the COVID-19 shock

[1] According to the Superintendency of Banking, Insurance and Private Pension Fund Administrators (SBS) the qualifications are: normal, with potential problems, deficient, doubtful and loss. February 2020 is some days before the confinement measures.

could divert resources away from the intended policy objective of shielding the economy. In this way, Central Banks and governments needed to give a buffer for them to absorb losses and to continue to support lending to non-financial firms.

Regarding the programs from advanced economies (the United States or European countries), these have similarities with REACTIVA because also include, for example, a grace period and government guarantees (even of 100 percent). In contrast to Peru, these economies have a relatively low level of informality, solid institutions, and a developed infrastructure that allowed them to better target the beneficiaries. These characteristics are very different from the Latin American economies.

The environment in which developing economies implemented this type of policy was very different. It was because the great levels of informality in these economies make them more vulnerable to shocks like COVID-19, than developed economies. In this sense, Humala (2020) comment on the programs that the authorities in Brazil, Chile and Colombia implemented during the COVID-19 shock.

Brazil executed two programs similar to REACTIVA: (i) PEAC (*Programa Emergencial de Acesso a Crédito*); and (ii) PRONAMPE (*Programa Nacional de Apoio às Microempresas e Empresas de Pequeno Porte*). Both were not linked with private financial institutions, but to the state bank, with guarantees between 80 to 100 percent. Chile implemented two programs FCIC (*Facilidad de Crédito Condicional al Incremento de Colocaciones*) and FOGAPE-COVID (*Fondo de Garantía para Pequeños Empresarios*). As highlighted by Acosta-Henao et al. (2022), the former was a new credit line from the central banks to commercial banks conditional on an increase in their lending to either firms or households. The latter, more like REACTIVA, was a program implemented over a preexisting program since that dating from 1980 with guarantees between 60 and 85 percent. Also, contrary to the preexisting program, during COVID-19 shock the interest rate was capped at a ceiling of the monetary policy rate plus 300 basis points. Finally, Colombia, similarly to Chile, used a preexisting program, FNG (*Fondo Nacional de Garantías*), to provide credit to medium and small companies with guarantees between 80 and 90 percent.

Although these programs in Brazil, Chile and Colombia were similar to REACTIVA, the Peruvian case is more interesting because: (i) It was the first experience in Peruvian history that a program of this magnitude was implemented; (ii) the interest rate was determined by the market, over an auction system that allowed all private financial institutions to compete, and was not implemented from the state bank; (iii) the guarantee's size over the program that was executed was higher than Colombia's or Chile's (countries most similar to Peru); and (iv) in terms of percentage of GDP, the Peruvian case were higher than the others Latin American countries.

5 Data

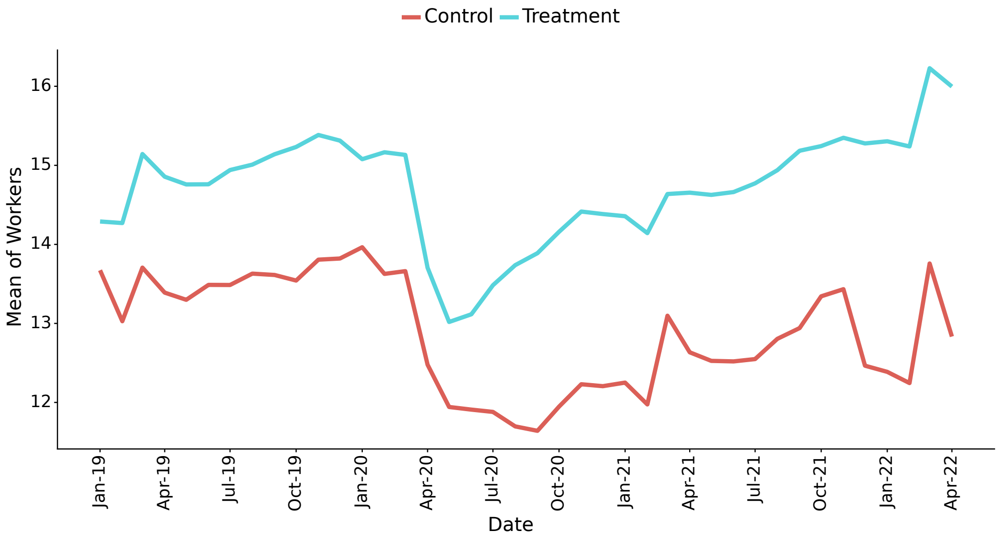
We use the credit information, which is obtained from the credit register (RCC) and is reported to the Peruvian Bank Regulator (SBS) and constitutes one of the main data sets used in this work. This report records loan-level information of all individuals and firms in a monthly frequency. In particular, we work with the monthly information of all loans issued to non-financial firms in the Peruvian financial system. In particular, in Peru we have five main firm segments classified by the size of the firm: corporate, large, medium, small and micro companies.

We also work with the employment data set of the National Superintendency of Customs and Tax Administration (SUNAT).[2] This report records the monthly evolution in the number of employees of approximately 400,000 companies. In addition, we use information from PADRON RUC[3] to obtain information about the economic sector and location of the firm. In Peru, there are 25 regions (including the Constitutional Province of Callao), we exclude loans issued by branches located outside Peru; and we can split the loans across 15 economic sectors.

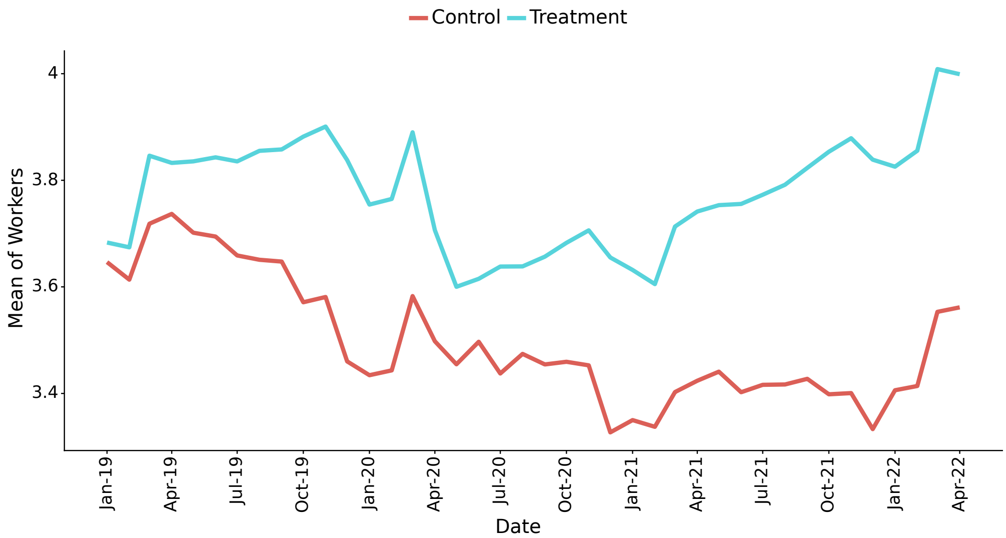
Figure 1 reports the mean of workers in medium and small businesses from January 2019 to April 2022. We divide the sample into two groups: (i) Treatment, businesses that accessed to REACTIVA Program; and, (ii) Control, businesses that could access to REACTIVA, but did not. For medium businesses, we see parallel trends in both groups (treatment and control) from January 2019 to February 2020, just before the start of the Covid-19 shock in Peru. However, for small businesses, the figure reports a negative trend for control group. In addition, after May 2020, month in which REACTIVA program started, we observe in both medium and small businesses, a relatively higher trend for the treatment group. This difference is quantitatively more important for small businesses.

[2]The information of the number of employment does not include pensioners and service providers.

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



Medium-sized Businesses



Small-sized Businesses

Figure 1: *Mean of Workers*

As we said, we work with the employment and credit data sets of the SUNAT and the Credit Register (RCC), respectively. In this line, our universe is the companies with credit records that report the number of workers on SUNAT. This data is available from January 2010 until now. Table 2 presents the descriptive statistics of the data. We can see that the number of companies grew between 2009 and 2021. Even in May 2020, when the confinement measures were stronger, the number of companies was greater than in December 2019 by 0.5%, months before the start of the Covid-19 pandemic. However, the number of workers dropped from December 2019 to Mayo 2020 by 13.5%.

In addition, since May 2020, when REACTIVA started, we can see the percentage of companies and workers that receive REACTIVA funds rise. For example, up to December 2021, the growth rates were 2.97% and 17.43%, respectively. Table 2 also reports the number of companies that receive REACTIVA (column 3) and the number of workers associated with those companies (column 4). In particular, the number of companies that receive REACTIVA represents 12 percent of the total, but the number of workers represents a third part of the total.

Table 2: *Descriptive Statistics*

Period	Companies (1)	Workers (2)	Reactiva Comp. (3)	Reactiva Workers (4)
Dec.2019	989,631	5,594,437	-	-
May.2020	994,363	4,837,615	117,876 $(11,9\%)$	1,698,972 $(35,1\%)$
Dec.2020	1,005,436	5,396,457	119,280 $(11,9\%)$	1,975,356 $(36,6\%)$
Dec.2021	1,023,943	5,680,688	121,123 $(11,8\%)$	2,060,467 $(36,3\%)$

Source: SUNAT, RCC. Own elaboration.

To measure the level of bank risk-taking we use the non-performing loan ratio and to measure the real activity, we use the employment growth. Also, to measure the intensity of the REACTIVA program, we use a ratio de REACTIVA loans to total loans.

Table 3 reports the descriptive statistics from April 2020 to January 2021 of the four variations of the non-performing loan ratio:[4] NPL_{rbt} is going to be the typical non-performing loans ratio. NPL^{a}_{rbt} represents a ratio where the definition of the non-performing loans is more strict or more acid.[5] NPL^{wr}_{rbt} stands for a non-performing loans ratio of the loan portfolio without REACTIVA loans. This is, we exclude REACTIVA loans from both the numerator and denominator. $\text{NPL}^{wr,a}_{rbt}$ is as NPL^{wr}_{rbt} but with the stricter definition of non-performing loans. The table also reports the REACTIVA loans to total loans ratio, REACTIVA_{rbt} at the financial institution-region-month level. The average REACTIVA ratio is 36%, with a standard deviation of 24%. The average NPL ratio is 8.4%, while its acid version is 11.5%. The average NPL ratio of the loan portfolio without REACTIVA is 12.4%, while its acid version is 16.8%.

[4]Non-performing loans include: expired credits and judicial collection.

[5]Acid definition of NPLs: expired credits, in judicial collection, refinanced and restructured loans.

Table 3: *Descriptive statistics for financial institution-region-time observations: April 2020 - January 2021*

Variables	Obs	Mean	S.D.	Minimum	Maximum
REACTIVA_{rbt}	2909	36,30	24,39	0,07	99,94
NPL_{rbt}	2477	8,36	11,18	0,00	89,65
NPL^{a}_{rbt}	2543	11,46	13,47	0,00	89,76
NPL^{wr}_{rbt}	2458	12,40	14,44	0,00	89,71
$\text{NPL}^{wr,a}_{rbt}$	2518	16,77	16,94	0,00	89,71

Source: RCC. Own elaboration. S.D.: Standard deviation. We omit extreme values. Thus we consider: $0<\text{NPL}_{rbt-1} < 0.9$, $0<\text{NPL}^{a}_{rbt-1} < 0.9$, $0<\text{NPL}^{wr}_{rbt-1} < 0.9$, $0<\text{NPL}^{wr,a}_{rbt-1} < 0.9$, $0<\text{REACTIVA}_{rbt} <100$. We omit credit information that we are able to assign to a specific region due to lack of information.

Table 4 reports the descriptive statistics of employment growth EG_{rbt} and the number of firms n_{rbt} at the financial institution-region-month level from March 2020 to August 2020, which is going to be the period used to assess the real impact of REACTIVA. The average employment monthly growth rate, EG_{rbt}, is 2.16%, and its standard deviation is 28.4%. The mean of n_{rbt} is 69.31, and its standard deviation is 474.3. Finally, the mean of REACTIVA ratio is 12.6%, and its standard deviation is 22%.

Table 4: *Descriptive statistics for financial institution-region-time observations: March 2020 - August 2020*

Variables	Obs	Mean	S.D.	Minimum	Maximum
REACTIVA_{rbt}	7207	12,58	22,07	0,00	100,00
EG_{rbt}	7207	2,16	28,36	-198,59	198,59
n_{rbt}	7412	69,31	474,39	1,00	11 801,00

Source: RCC. Own elaboration. S.D.: Standard deviation. We exclude observations with $\text{REACTIVA}_{rbt} = 1$.

Finally, figure 2 presents the average REACTIVA ratio per region. Despite the fact that Peru is a centralized country, there are regions that have REACTIVA loans that are relatively more important than in the capital of Peru, Lima. This is probably driven by the concentration of big firms in Lima, which represents a small number of firms. This distribution of REACTIVA across regions captures the idea of REACTIVA being able to reach firms across regions. And from a strategic point of view, having this heterogeneity across regions helps us to better identify the impact of REACTIVA.

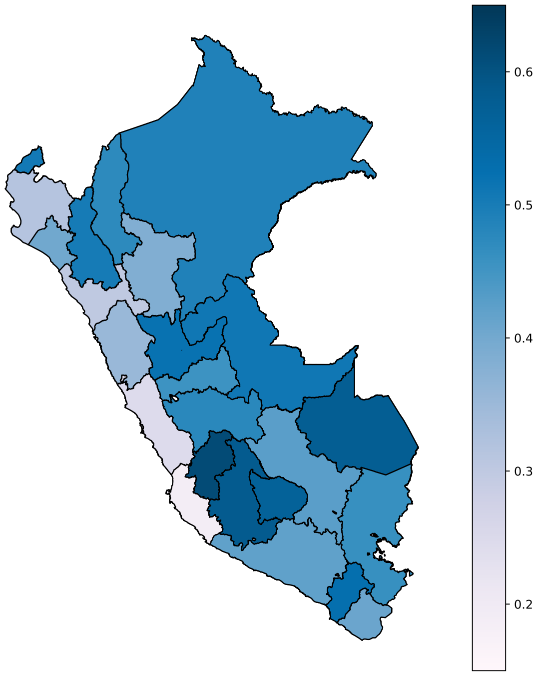


Figure 2: *REACTIVA ratio per region*

6 The impact of REACTIVA on the Financial and Macroeconomic Stability

In this section, we empirically explore the impact of REACTIVA on financial and macroeconomic stability. Unless otherwise stated, we run the regressions for all financial institutions (banks, financial firms, CRACs, and CMACs).[6] And unless otherwise stated, we consider all firms (that received and have not received REACTIVA)

We start evaluating the impact first on the risk-taking of financial institutions, and then the impact of REACTIVA on employment. Notice that in all cases we only consider loans to firms, so we exclude from our analysis personal loans and mortgage loans.

[6]Indeed, the definition of financial institutions is broader. However, we focus on institutions that issue loans and are able to capture deposits from the public. Of course, due to data availability, we ignore *Cooperativas*. CRAC and CAMC stand for *Cajas Rurales de Ahorro y Crédito* and *Cajas Municipales de Ahorro y Crédito*. Banks issue around 85% of total loans in the financial system.

6.1 Impact on Risk-Taking:

We propose the following empirical model:

$$NPL_{rbt} = \beta_0 + \lambda_b + \omega_{rt} + \beta_1 NPL_{rbt-1} + \beta_2 REACTIVA_{rbt} + \varepsilon_{rbt}, \qquad (1)$$

where r, t and b subscripts refer to a region, a sample month and a financial institution, respectively. NPL_{rbt} is the non-performing loans to total loans ratio at the region-bank-time level. Indeed, instead of using NPL_{rbt}, we can also use the other three definitions of NPL ratio. REACTIVA_{rbt} is going to help us to capture the impact across different dimensions.

We also include additional controls. For example, with ω_{rt} we control by regional demand shocks and regional economic cycles. Importantly, this helps us to control for different confinement measures across regions during the pandemic period. Also, we include λ_b to control by unobservable bank characteristics that do not vary across time.

Even though, REACTIVA starts in May 2020, it is needed some time to observe the quality of new loans issued and the risk profile of the loan portfolio. For that reason, the time period analyzed spans from April 2020 to January 2021.[7]

Table 5 shows the impact of REACTIVA on the non-performing loans ratio. While columns (1) and (2) consider the entire portfolio, columns (3) and (4) exclude REACTIVA loans. The results suggest that REACTIVA had a negative impact on the risk of the entire bank loan portfolio; meanwhile, if REACTIVA loans are excluded, column (3), the impact becomes positive. This might suggest that REACTIVA increases incentives to take risks on its traditional loan portfolio. This holds even when using a stricter measure of non-performing loans, column (4).

To understand this effect, it must be taken into account, as mentioned in section 4, that the program's beneficiaries are relatively solid companies with good credit scores. In this sense, if there had been a substitution between traditional credit with REACTIVA loans, the financial entities would not necessarily have been able to transfer an important part of the risk of their portfolio to the government. Therefore, as the results suggest, having a part of their portfolio safe (with REACTIVA loans, which are government-guaranteed) increases banks' incentives to take more risk in the rest of their portfolio (columns 3 and 4). In other words, it seems that banks might have issued riskier non-REACTIVA loans to accommodate their overall level of risk to a level like what they used to operate.

It is worth mentioning two important points: 1) During the pandemic period the riskier non-REACTIVA loan portfolio due to REACTIVA might have occurred due to

[7] Results are robust for a time period that spans from April 2020 to April 2022, and if we do not exclude extreme REACTIVA ratios of zero and one.

a diminishing effect on the excessive increases of bank's risk aversion; 2) Unfortunately, the model so far is not able to fully capture the positive impact on financial stability due to avoid further disruption of the payment chain. This is because the control group is not being affected by definition by the payment chain disruption, as was supposed to be the case without the presence of REACTIVA. Thus, this might explain why we find that REACTIVA has a net positive impact on the non-performing loan ratio of non-REACTIVA loan portfolio instead of a negative impact. This claims for harder work and it is part of our research agenda.

Table 5: *Regression Results*

	(1) NPL	(2) NPL^{a}	(3) NPL^{wr}	(4) $NPL^{wr,a}$
$REACTIVA_{rbt}$	-0.0389***	-0.0476***	0.0266***	0.0220***
NPL_{rbt-1}	0.841***			
NPL^{a}_{rbt-1}		0.870***		
NPL^{wr}_{rbt-1}			0.926***	
$NPL^{wr,a}_{rbt-1}$				0.953***
Observations	2,477	2,543	2,458	2,518
R-squared	0.903	0.928	0.928	0.941
Bank FE	YES	YES	YES	YES
Region-Time FE	YES	YES	YES	YES

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We omit extreme values. Thus we consider: $0<NPL_{rbt-1} < 0.9$, $0<NPL^{a}_{rbt-1} < 0.9$, $0<NPL^{wr}_{rbt-1} < 0.9$, $0<NPL^{wr,a}_{rbt-1} < 0.9$, $0<REACTIVA_{rbt} <100$. We omit credit information that we are able to assign to a specific region due to lack of information. Period: 2020:M4-2021:M1.

Next, we include the economic sector dimension in our analysis. In Peru, we can split credit across 15 economic sectors.[8] It might help us to control for heterogeneous shocks that faced the economic sectors, for example, the Covid-19 shock, which was not homogeneous across industries. There were some like tourism that were much more affected. Table 6 reports the regression when using this more granular information, which allows having sector-time fixed effects. According to table 6 results are qualitatively and quantitatively robust.[9]

[8]These are: Agriculture, livestock, hunting and forestry; Fisheries; Mining; Manufacturing industry; Electricity, gas and water; Construction; Commerce, Hotels and restaurants; Transport, storage and communications; Real estate and rental activity; Business activity; Education; Social Services and Health; other community service activities; and other branches of activity.

[9]Results are robust for a time period that spans from April 2020 to April 2022, and if we do not exclude extreme REACTIVA ratios of zero and one.

Table 6: *Regression Results*

	(1) NPL	(2) NPL^{a}	(3) NPL^{wr}	(4) $NPL^{wr,a}$
$REACTIVA_{rbst}$	-0.0560***	-0.0669***	0.0131***	0.00915**
NPL_{rbst-1}	0.807***			
NPL^{a}_{rbst-1}		0.827***		
NPL^{wr}_{rbst-1}			0.919***	
$NPL^{wr,a}_{rbst-1}$				0.937***
Observations	12,705	13,445	12,401	13,058
R-squared	0.855	0.876	0.885	0.910
Bank FE	YES	YES	YES	YES
Region-Time FE	YES	YES	YES	YES
Sector-Time FE	YES	YES	YES	YES

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We omit extreme values. Thus we consider: $0<NPL_{rbst-1} < 0.9$, $0<NPL^{a}_{rbst-1} < 0.9$, $0<NPL^{wr}_{rbst-1} < 0.9$, $0<NPL^{wr,a}_{rbst-1} < 0.9$, $0<REACTIVA_{rbst} <100$. We omit credit information that we are able to assign to a specific region due to lack of information. Period: 2020:M4-2021:M1.

6.2 Impact on Employment:

In this subsection, we assess the impact of REACTIVA on employment in two dimensions, the number of employees, which we consider accounts for both the intensive and extensive margins,[10] and the number of firms, which captures the extensive margin only. Finally, we develop a more dynamic difference-in-Difference analysis based on Callaway & Sant'Anna (2021) that might help us to deal with some identification issues.

6.2.1 Intensive and Extensive Margin

The following specification aims to capture both the impact of REACTIVA across the intensive and extensive margin:

$$EG_{rbt} = \beta_0 + \lambda_b + \omega_{rt} + \beta_1 REACTIVA_{rbt} + \varepsilon_{rbt}, \qquad (2)$$

where r subscript refers to a region, t subscript refers to a sample month, b subscript refers to a financial institution, EG_{rbt} is the monthly growth rate of workers at the region-bank-time level.[11] The time period analyzed spans from March 2020 to August 2020. Due to the several shocks around REACTIVA, we focus on a short time window so we can

[10] Since the number of employees includes employees from old and new firms, with this indicator we capture both intensive and extensive margins.

[11] To compute this latter we add up of all workers at the region-bank-time level. To do so we define a "main bank" or "principal bank" for each bank and so add up at the region-bank-time level to avoid duplicity when some firms borrow from more than one bank. Principal bank: main provider of loans to a firm.

better control for the impact of the pandemic shock and the confinement measures.

Table 7 reports the results, when considering all firms and when splitting the loans by firm segment, and specifications with and without the AR(1) term. We find that when considering all firms, micro-sized firms, small-sized firms, medium-sized firms and big-sized firms, REACTIVA program has a statistically significant positive impact on the growth rate of workers. Notice that the impact is quantitatively stronger the smaller the size of the firm. For example, for micro-sized firms, on average a 1% increase of REACTIVA participation in total loans, increases the employment growth rate by 0.4%. Results are robust with or without AR(1) term, or if we use the lagged REACTIVA ratio instead of the current ratio.

Notice that results for the corporate segment are not statistically significant and even do not have the expected sign. One might argue that this is because region-time effects control for demand-driven shocks, and because to some extent, we might argue that in the corporate loan market, credit demand shocks are quantitatively more important than other shocks. Consequently, the positive shock of REACTIVA in the corporate segment has a stronger impact through the demand channel, and hence controlling by region-time effects, we miss the REACTIVA effect. Interestingly, when controlling only by region and bank-time effects (supply shocks), results hold.

In general, we might claim the impact of REACTIVA on employment was strongest the smaller the size of the firms.

As a robustness exercise, we include in our analysis the economic sector dimension, so we can control by sector-time fixed effects, which might help us to control to some degree from the Covid shock. According to table 12 in Appendix A results qualitatively hold but quantitatively, we observe a smaller impact of REACTIVA on the worker's growth rate.

Table 7: *Regression results*

	All	micro	small	medium	big	corporate
Without AR(1) term						
REACTIVA$_{rbt}$	0.232***	0.397***	0.323***	0.108**	0.108*	-0.0337
Observations	7,207	1,147	2,351	2,228	874	581
R-squared	0.098	0.200	0.192	0.168	0.273	0.217
F test (ρ-value)	1.88e-06	3.56e-05	7.91e-07	0.0378	0.0669	0.608
With AR(1) term						
EG$_{rbt-1}$	-0.0646***	-0.0573*	-0.142***	-0.0448*	-0.0696	-0.0722
REACTIVA$_{rbt}$	0.240***	0.411***	0.359***	0.120**	0.120*	-0.0222
Observations	7,137	1,110	2,336	2,217	871	576
R-squared	0.104	0.205	0.204	0.171	0.280	0.239
F test (ρ-value)	2.76e-06	0.000339	7.25e-06	0.0397	0.0781	0.218

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We omit extreme values. This is we only consider: REACTIVA$_{rbt}$ < 1 and -200 $<$ EG$_{rbt-1}$ < 200. In all regression, we include bank and region-time fixed effects.

6.2.2 Extensive Margin

Here, we focus on the impact of REACTIVA on the extensive margin of employment. This is, we study the impact of REACTIVA on the number of firms. Thus, the following specification aims to capture the impact of REACTIVA across the extensive margin:

$$log(n_{rbt}) = \beta_0 + \lambda_b + \omega_{rt} + \beta_1 REACTIVA_{rbt} + \varepsilon_{rbt}, \tag{3}$$

where n_{rbt} is the number of firms at the region-bank-time level.[12] So, the endogenous variable is the natural logarithm of the number of firms. As usual, we control by region-time effects, ω_{rt}, and by bank effects, λ_b. Similar to the previous subsection the time period analyzed spans from March 2020 to August 2020.

As the previous section, table 13 reports the regression for the full sample, and considers each of the five credit segments. According to table 13 the coefficient associated with REACTIVA is positive and statistically significant, except for the corporate loans. So, it seems that REACTIVA has a positive impact on employment through the extensive margin. In particular, on average a 1% increase in the participation of REACTIVA in total credit increases the number of firms by 0.3%. And in the case of micro-sized firms, that account for the largest proportion of employment, the 1% increase in the participation of REACTIVA in total credit increases the number of firms by 0.5% (with bank and region-time fixed effects).[13]

[12] Similar to the previous section, we define a "principal bank" to compute the number of firms at the region-bank-time level.

[13] In general, results are robust in measuring the impact of the lag of REACTIVA. However, this time the coefficient that captures the impact of REACTIVA on the number of firms is only statistically

Next, we include in our analysis the economic sector dimension, so we can control by sector-time fixed effects, which might help us to control to some degree from the Covid-19 shock. As the previous section, quantitatively, results are if anything quantitatively weaker (see table 13 in Appendix A).

Table 8: *Regression results*

	(1) All	(2) Micro	(3) Small	(4) Median	(5) Big	(6) Corp
Bank and Region-Time FE						
$\ln(n_{rbt-1})$	0.979***	0.862***	0.959***	0.978***	0.991***	0.976***
$REACTIVA_{rbt}$	0.00294***	0.00458***	0.00388***	0.00100***	0.00125***	-0.000825
Region and Bank-Time FE						
$\ln(n_{rbt-1})$	0.980***	0.878***	0.964***	0.979***	0.987***	0.976***
$REACTIVA_{rbt}$	0.00280***	0.00388**	0.00315**	0.000669**	0.00122**	-0.000286
Bank-Time and Region-Time FE						
$\ln(n_{rbt-1})$	0.980***	0.896***	0.965***	0.980***	0.994***	0.980***
$REACTIVA_{rbt}$	0.00282***	0.00405**	0.00311**	0.000652***	0.000914	-0.00116
Observations	5,899	755	2,136	1,823	595	309

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We exclude extreme values. Thus, we consider only: $n_{rbt-1}>1$

6.2.3 Difference-in-Differences Analysis

Here, we focus on the analysis of the REACTIVA program and its impact over the employment for medium-sized, small-sized and micro-sized enterprises. Based on Callaway & Sant'Anna (2021), we propose the following equation in order to measure the effect of participating in the program:

$$log(E_{it}) = \omega_t + \lambda_g + \sum_{e=-K}^{-2} \delta_e^{anticip}.D_{it}^e + \sum_{e=0}^{L} \beta_e.D_{it}^e + \varepsilon_{it}, \tag{4}$$

where $log(E_{it})$ is the natural logarithm of the number of employees of the business i at time t, ω_t is a time fixed effect, λ_g is a group fixed effect[14], $\delta_e^{anticip}$ is the coefficient associated with the periods of anticipation to the treatment, ε_{it} is an error term, $D_{it}^e = 1\{t-G_i = e\}$ is an indicator for unit i being e periods away from initial treatment at time t, and G_i defines the group that the enterprise belongs to. The parameters of interest are β_e (if $e \geq 0$), which measures the effect of participating in the treatment at different lengths of exposure to the treatment.

The Callaway & Sant'Anna (2021) approach is interesting to evaluate programs like REACTIVA because lets us to deal with some problems, for example:

significant for the full sample, micro-sized loans and small-sized loans.

[14]Firms are grouped according to the month that received REACTIVA.

1. **There is variation in treatment timing** because the credit that was given for the businesses (the treatment) was distributed during the 8 last months of 2020.

2. **There is anticipation behavior** because to some extent we can say that the enterprises "choose" the treatment status.

3. **The relevance of the control group** because allows the comparison between the treated group vs. the "never-treated" or the "not-yet-treated" group[15].

Tables 9 and 10 summarize the treatment effect estimates comparing the treated group vs the never-treated and the not-yet-treated groups. Table 9 assumes that there is no anticipation behavior. The treatment effect estimates support a positive effect of REACTIVA over employment. Panel (a) compare the treated group vs the never-treated and shows that there is a clear statistically significant positive effect for almost every group. It is important to note that there are three groups that were the most benefited, those who received the treatment in May, July and December 2020 (4,1%, 3,9% and 3,6%, respectively). On average REACTIVA increases employment by 4,1%, 3,9% and 3,6%, respectively. This difference in the positive effect may be related to the timeliness of treatment during those dates, because these dates coincide with the first months of the pandemic (May) and the relaxation of immobility measures (July and December). The next row shows (event study) the effects across different lengths of exposure, according to that, if an enterprise is exposed for more months there is an increase in the effect. Finally, the last row (calendar time effects) shows the effect across each period, in this sense there is an increase in effect as time passes.

Panel (b) in table 9 shows a comparison with respect to the not-yet-treated group, the results over the group, length of exposure and calendar time do not change. Finally, the last column of table 9 summarizes the overall parameters, for both, with respect to the never-treated and not-yet-treated group, there is an effect of 3.3% over the level of employment. The rest of the results mentioned above hold. Table 10 shows the same effect estimates, but assuming 1 month of anticipation. This last assumption is plausible because the businesses that received the credit from REACTIVA Peru took at least 1 month in order to take the credit. The effects over group, length and time are reduced, but the rest of the results hold.

Finally, Figure 3 shows the time average treatment effect for both, with non-anticipation and with anticipation approaches. As we can see, the effect of REACTIVA program raises with more periods of exposure.

[15] The "never-treated" group is defined as the enterprises that never received the treatment, but they met the requirements. While the "not-yet-treated" group is defined as the businesses that have not yet received the treatment in a dynamic context.

Table 9: *Reactiva Peru Program Treatment Effect Estimates with Non-Anticipation*

(a) Using Never-Treated Comparison Group

	Partially Aggregated								Single Parameters
Simple Weighted Average									0.034*
									(0.003)
Group-Specific Effects	g=May-20	g=Jun-20	g=Jul-20	g=Aug-20	g=Sep-20	g=Oct-20	g=Nov-20	g=Dec-20	
	0.041*	0.034*	0.039*	0.024*	0.014*	0.016*	0.008	0.036*	0.033*
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)	(0.013)	(0.003)
Event Study	e=8m	e=14m	e=20m	e=24m					
	0.031*	0.041*	0.048*	0.057*					0.033*
	(0.003)	(0.003)	(0.004)	(0.004)					(0.003)
Calendar Time Effects	t=May-20	t=Jun-20	t=Jul-20	t=Aug-20	t=Sep-20	t=Oct-20	t=Nov-20	t=Dec-20	
	-0.010*	-0.001	0.009*	0.014*	0.016*	0.024*	0.028*	0.030*	0.032*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

(b) Using Not-Yet-Treated Comparison Group

	Partially Aggregated								Single Parameters
Simple Weighted Average									0.034*
									(0.002)
Group-Specific Effects	g=May-20	g=Jun-20	g=Jul-20	g=Aug-20	g=Sep-20	g=Oct-20	g=Nov-20	g=Dec-20	
	0.041*	0.033*	0.039*	0.024*	0.014*	0.016*	0.008	0.036*	0.033*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.008)	(0.013)	(0.003)
Event Study	e=8m	e=14m	e=20m	e=23m					
	0.035*	0.041*	0.053*	0.057*					0.035*
	(0.003)	(0.004)	(0.004)	(0.005)					(0.003)
Calendar Time Effects	t=May-20	t=Jun-20	t=Jul-20	t=Aug-20	t=Sep-20	t=Oct-20	t=Nov-20	t=Dec-20	
	-0.005*	-0.002	0.009*	0.012*	0.013*	0.021*	0.028*	0.030*	0.032*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)

* Confidence band does not cover 0. We use the Doubly Robust approach over each regression.

Table 10: *Reactiva Peru Program Treatment Effect Estimates with 1 month Anticipation*

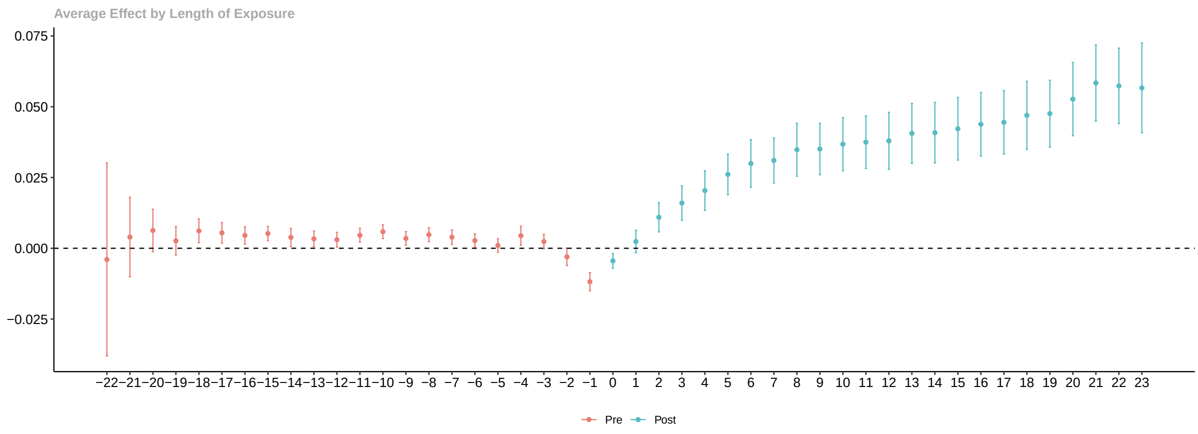
(a) Using Never-Treated Comparison Group

	Partially Aggregated								Single Parameters
Simple Weighted Average									0.021*
									(0.003)
Group-Specific Effects	g=May-20	g=Jun-20	g=Jul-20	g=Aug-20	g=Sep-20	g=Oct-20	g=Nov-20	g=Dec-20	
	0.018*	0.021*	0.042*	0.027*	0.016*	0.019*	0.010	0.035*	0.021*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.008)	(0.013)	(0.003)
Event Study	e=8m	e=14m	e=20m	e=24m					
	0.023*	0.029*	0.038*	0.034*					0.022*
	(0.003)	(0.003)	(0.003)	(0.005)					(0.003)
Calendar Time Effects	t=May-20	t=Jun-20	t=Jul-20	t=Aug-20	t=Sep-20	t=Oct-20	t=Nov-20	t=Dec-20	
	-0.033*	-0.022*	-0.009*	-0.001	0.016	0.011*	0.016*	0.018*	0.019*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

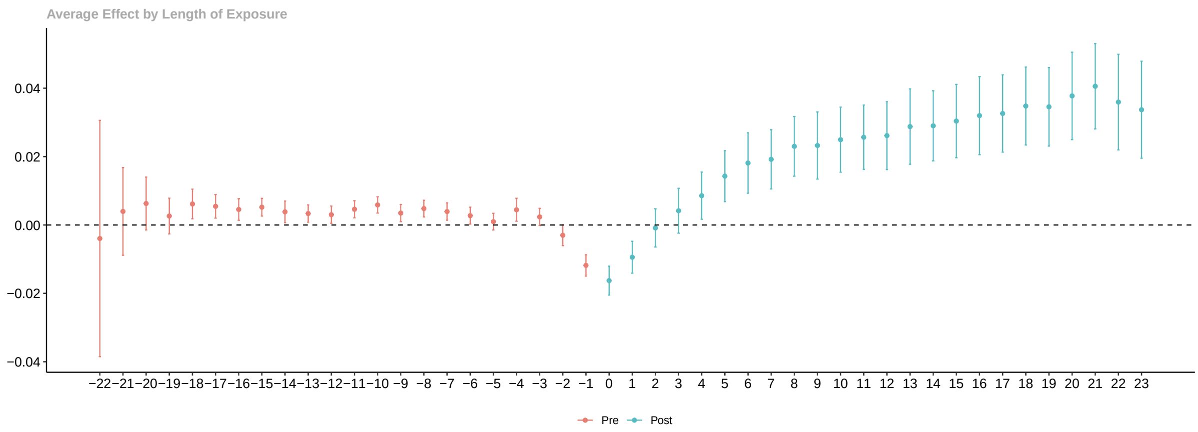
(b) Using Not-Yet-Treated Comparison Group

	Partially Aggregated								Single Parameters
Simple Weighted Average									0.021*
									(0.003)
Group-Specific Effects	g=May-20	g=Jun-20	g=Jul-20	g=Aug-20	g=Sep-20	g=Oct-20	g=Nov-20	g=Dec-20	
	0.018*	0.021*	0.042*	0.027*	0.015*	0.019*	0.010	0.035*	0.021*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.008)	(0.012)	(0.003)
Event Study	e=8m	e=14m	e=20m	e=24m					
	0.023*	0.029*	0.038*	0.034*					0.022*
	(0.003)	(0.003)	(0.003)	(0.005)					(0.003)
Calendar Time Effects	t=May-20	t=Jun-20	t=Jul-20	t=Aug-20	t=Sep-20	t=Oct-20	t=Nov-20	t=Dec-20	
	-0.027*	-0.019*	-0.009*	-0.004	0.002	0.011*	0.016*	0.018*	0.019*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)

* Confidence band does not cover 0. We use the Doubly Robust approach over each regression.



(a) With Non-Anticipation



(b) With 1 month Anticipation

Figure 3: *Reactiva Peru Program Time Average Treatment Effects*

7 Endogenity Issue and Spill Over Effects

In this section, we focus on the impact of REACTIVA on employment through the credit supply side and study any spillover effects.

There could be an important degree of endogeneity in REACTIVA. Indeed, we might argue that those firms who demand and receive REACTIVA are those that forecast for themselves a good performance in the future. It might explain why some firms did not even ask or were not able to ask for REACTIVA.

Hence, we try to capture the REACTIVA effect on employment that was not related to the ex-ante knowledge of the good future firm performance. So, in this section, we do our best effort to isolate any endogenous effect of REACTIVA. To do so we assess the impact of REACTIVA on employment considering only firms that meet the conditions to ask for it.

In particular, we propose a specification that aims to handle the endogeneity issue and try to see if there is any spillover effect across firms. We define the spillover effect as the indirect benefits for firms that have no access to the program. These effects could have occurred because banks that participated in the program come up with a relatively less risky portfolio, due to the government-guaranteed feature of the REACTIVA program and were able to relax some constraints. Thus, banks become more flexible with the rest of the firms as well.

In order to assess this effect, we divide the firms that did not have access to the program into two groups: (i) those that could access to REACTIVA Peru program and they did not; and, (ii) those that could not access to REACTIVA Peru program because do not meet the requirements. And, we propose the following empirical model:

$$EG_{it} = \beta_0 + \lambda_b + \mu_{st} + \eta_{rt} + \beta_1 REACTIVA_{b(i)t} + \beta_2 D_i REACTIVA_{b(i)t} + \varepsilon_{it}, \qquad (5)$$

where EG_{it} refers to the monthly growth rate of the number of workers at the firm-time level. $\mathrm{REACTIVA}_{b(i)t}$ is the percentage of REACTIVA loans over the total portfolio of the main bank of firm i. D_i is our dummy variable and it takes one if the firm participated in REACTIVA program, and zero if the firm did not. We also include bank fixed effects, λ_b, and economic sector-time fixed effects, μ_{st}, and region- time fixed effects η_i.

The time period analyzed spans from June 2020 to December 2021. Notice that in this case we focus on a period when the REACTIVA program was already in place and we include all financial institutions (banks, CMACs, CRACs and financial companies).

Table 11 reports the econometrics results when considering all segments of firms (micro, small, medium, big and corporate firms). Panel (a) is our benchmark, it reports the results when including all firms. Panel (b) we use as a counterfactual the companies which did not participate in REACTIVA Peru, but they could do it. In other words, D_i takes one if the firm participates in REACTIVA program, and zero if the firm does not participate, but they could do it since meet the requirements.

Considering only the group that meets the requirements is important because the companies that did not have access to REACTIVA ($D_i = 0$) also had solid fundamentals before the Covid-19 shock. As a result, the effect captured by β_2 could be considered strictly because of the program and not because of the ex-ante firms' good fundamentals.

According to panel (b) REACTIVA program has a positive effect on employment in the firms that receive it (i.e., $\beta_2 > 0$). And the larger the firm's size, the more quantitatively important the impact of REACTIVA. Moreover, results suggest that on average across all-sized firms there is a negative spillover effect on firms that do not participate in the REACTIVA program (i.e., $\beta_1 < 0$). This could be due to a relatively stronger bank preference for relatively safe firms, that receive REACTIVA. However, across firm size, there are negative spillover effects on median-sized firms and positive spillover effects on corporate firms. This could be explained because of the relatively stronger bank preference for less risky corporate firms. In other words, REACTIVA might have also produced a reallocation of credit across segments.

Also, panel (c) shows the results when we use as a counterfactual the companies which did not participate in REACTIVA because they did not meet the application requirements. This is, D_i takes one if the firm participates in the REACTIVA program, and zero if the firm does not participate and they couldn't do it since they don't meet the requirements. The results confirm a positive effect of the program on the employment of the companies that participated in it.

Table 11: *Regression results*

	(1) All	(2) Micro	(3) Small	(4) Median	(5) Big	(6) Corp
a. Sample: All firms						
REACTIVA$_{b(i)t}$	-0.00551	-0.0123	0.00588	-0.0113	-0.0131	0.0392***
D*REACTIVA$_{b(i)t}$	0.00528***	-0.00340*	-0.00859***	0.0136***	0.0311***	0.0452***
Observations	3,220,912	816,811	1,299,765	985,717	84,845	33,736
R-squared	0.007	0.004	0.009	0.011	0.029	0.035
b. Sample: Firms meet requirements to get REACTIVA						
REACTIVA$_{b(i)t}$	-0.00798*	0.0133	-0.00353	-0.0213**	-0.00740	0.0378**
D*REACTIVA$_{b(i)t}$	0.0145***	0.000131	0.00895***	0.0172***	0.0279***	0.0310***
Observations	1,901,032	120,850	843,437	835,450	75,148	26,109
R-squared	0.010	0.009	0.010	0.012	0.032	0.048
c. Sample: Firms that get REACTIVA and firms that do not meet the requirements						
REACTIVA$_{b(i)t}$	-0.00597	-0.0202**	0.0114	-0.0160	-0.0125	0.0272**
D*REACTIVA$_{b(i)t}$	0.00294***	-0.00384*	-0.0137***	0.0115***	0.0379***	0.0646***
Observations	2,890,931	734,383	1,155,637	904,501	71,021	25,332
R-squared	0.007	0.005	0.009	0.011	0.033	0.039

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. We include bank fixed effects, region-time fixed effects, economic sector-time fixed effects. Clustered (at region level) standard errors.

8 Conclusions and Remaining work

In this paper, we aim to study the impact of REACTIVA on the financial and macroeconomic stability. We find a negative impact of it on total bank risk-taking and evidence of a positive impact of REACTIVA on employment. In a diff-in-diff analysis, we find a positive effect of between 2.0% and 3.5% over the employment for medium, small and micro businesses, the positive effect is greater for groups that received the treatment at the beginning of the pandemic and previous easing of immobility measures. Also, the positive impact of REACTIVA on employment is robust, when we run firm-level regressions with counterfactual firms, which did not receive REACTIVA but meet the requirements.

As in other empirical papers that aim to evaluate a policy never implemented before and in the middle of an important crisis, it is never easy to find the counterfactual. In other words, here we measure the impact of REACTIVA in normal times, but not necessarily in crisis times. To have a measure of this latter, we need to propose a more complete specification with a state variable that helps us to capture the state of the economy and the shock faced. With this, we should be able to fully capture the beneficial impact of REACTIVA, when the economy, for example, is facing a pandemic shock.

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Appendices

A Intensive and Extensive Margin: Robustness Check

Table 12: *Regression results*

	All	micro	small	medium	big	corporate
Without AR(1) term						
REACTIVA$_{rbt}$	0.138***	0.106*	0.272***	0.0729***	-0.00409	-0.0509*
Observations	34,098	3,877	13,762	11,918	2,805	1,721
R-squared	0.068	0.088	0.105	0.120	0.197	0.149
F test (ρ-value)	1.81e-08	0.0516	0	0.00122	0.835	0.0534
With AR(1) term						
EG$_{rbt-1}$	-0.115***	-0.210***	-0.109***	-0.0597***	-0.0720**	-0.177***
REACTIVA$_{rbt}$	0.151***	0.116*	0.294***	0.0813***	-0.00429	-0.0358
Observations	33,444	3,619	13,526	11,799	2,780	1,704
R-squared	0.086	0.153	0.118	0.125	0.201	0.191
F test (ρ-value)	0	8.30e-08	0	0.000121	0.0459	1.94e-08

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We omit extreme values. This is we only consider: REACTIVA$_{rbt}$ < 1 and -200 < EG$_{rbt-1}$ < 200. In all regression, we include bank, region-time and sector-time fixed effects.

Table 13: *Regression results*

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Micro	Small	Median	Big	Corp
Bank FE, Region-Time FE and sector-time FE						
$\ln(n_{rbt-1})$	0.947***	0.807***	0.927***	0.969***	0.968***	0.963***
$REACTIVA_{rbt-1}$	0.000767***	0.000393	0.00131***	0.000170	0.000377*	0.000131
Region FE, Bank-Time FE and sector-time FE						
$\ln(n_{rbt-1})$	0.949***	0.806***	0.932***	0.969***	0.965***	0.962***
$REACTIVA_{rbt-1}$	0.000511	-0.000401	0.000526***	-2.21e-06	0.000558***	0.000142
Bank-Time FE, Region-Time FE and sector-time FE						
$\ln(n_{rbt-1})$	0.980***	0.896***	0.965***	0.980***	0.994***	0.980***
$REACTIVA_{rbt}$	0.00282***	0.00405**	0.00311**	0.000652***	0.000914	-0.00116
Observations	21,994	2,280	9,282	8,101	1,474	778

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors. We exclude extreme values. Thus, we consider only: n_{rbt-1}>1