Measuring the Impact of An Unconventional Credit Policy: REACTIVA Peru*

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Abstract

This paper studies empirically the impact of an unconventional credit policy as REACTIVA Peru that was implemented due to the Covid-19 pandemic. We find that REACTIVA has a positive impact on the credit cycle at the bank level. It might provide evidence of positive general equilibrium effects on credit (see, Pozo and Rojas, 2020). Results are qualitatively robust if we split our loans by currency type, credit type, and economic sector.

Keywords: Unconventional credit policy, REACTIVA Peru, credit cycle.
JEL Classification: E44, E5, G21.

1 Introduction

One of the goals of economic policies implemented during the pandemic crisis was to help firms with liquidity problems, and credit facilities were among the most common measures. In the aggregate these credit policies had direct and indirect effects on the economy. In this paper we relate direct effects to trend level of credits and indirect effects to cycle of credit. Although a credit policy may influence developments on the trend level, we focus on whether credit policy would had indirect or spillover effects, which we argue are captured by credit deviations from its trend. This choice is also influenced by the theoretical work in Pozo and Rojas (2020), which consistently considers credit deviation from its steady state.

In our empirical study we use the effects of the credit policy implemented in Peru. As other countries Peru was strongly affected by the Covid-19 pandemic, (BIS, 2020).

*The views expressed in this paper do not necessarily represent those of the Central Reserve Bank of Peru.

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However, Peru was one of the countries with very severe confinement measure. In that context, policy makers were motivated to carry out different fiscal, monetary and financial policy measures to diminish the impact of the confinement in the economy. One of the key measures, that seeks to reduces the impact of the Covid-19 on credit market, in the continuity of the payment chain and its impact on the economic activity, is REACTIVA Peru, which was created on April 6, 2020, (Montoro , 2020).

In a context of low interest rates and in a jointly effort of the Ministry of Economy and Finance (MEF by its Spanish acronym), the responsible of carrying out fiscal policies, the Central Reserve Bank of Peru (BCRP by its Spanish acronym) and the Development Finance Corporation (COFIDE by its Spanish acronym), which is the development bank of Peru, designed this program (REACTIVA Peru). This program consists in providing liquidity to banks so they can convert these resources in government-guaranteed loans to firms. The liquidity injection was implemented through REPO operations with auctions on the lending interest rate.

The amount of the REACTIVA program was S/ 30 thousands of millions and then it increases to S/ 60 thousands of millions. At December 2020, it represents 22.4% of total credit to firms. It is worth to mention that other countries in the region as Brasil, Chile and Colombia implemented similar policies, oriented to restore credit activity, (Humala, 2020).

To our knowledge, there is no formal study about the impact of REACTIVA Peru on the credit market. This could be due to the difficulty of isolating the impact of REACTIVA from the Covid-19 shock and other fiscal and monetary policies. However, in this work using bank level information that publicly available at several dimensions and a particular identification strategy, we aim to capture the general equilibrium effects of REACTIVA on the credit market.

We perform an empirical analysis to identify the impact of REACTIVA. Even though REACTIVA Peru is temporal, it is easy to believe of its long-term impact through avoiding the disruption of the payment chains. Here we do not aim to measure this impact, but other positive spillover impacts or positive general equilibrium effects on credit. In particular, we focus on the impact of REACTIVA Peru on credit deviations from its long-term trend (cycle). This is to control for any substitution effect of REACTIVA (or the "direct" impact on credit) and to better capture the general equilibrium effects on credit demand and supply.

We find empirical evidence of a positive impact of REACTIVA on credit cycle. This might support the positive spillover effects of REACTIVA on both credit supply and demand, in addition to the substitution effect or long-term effect. These results are robust if we disaggregate the loans by currency, credit type and economic sector.

The remainder of this paper is partitioned as follows. Section 2 presents the literature review. Section 3 shows the data, the empirical model and the empirical results. Finally, section 4 concludes.

2 Literature Review

We summarize the theoretical and empirical literature related to the recent unconventional credit policies motivated by the Covid-19 pandemic,[1] compare methodologies and highlight the main contributions of our paper.

Recent empirical papers have focused on the impact of government guarantees on the credit market and banking structure. Jiménez et al. (2022) using credit register data study the impact of government-guaranteed credit in borrower-lender relationships in Spain. They find that firms are more likely to obtain a public guaranteed loan from banks to which they have larger pre-COVID credit exposures. In addition, they find that a substitution effect with nonguaranteed (private) credit. Also, Cascarino et al. (2022) using loan-level data study the public loan guarantee program in Italy. In particular, they focus on the impact of different coverage ratios, depending on the size of the loan. They find that the higher the coverage ratio the higher the impact on credit, which decreases over time.

Using firm-level data during the Covid-19 pandemic, Koulischer et al. (2021) find that government guarantees improve firms' debt capacity and fiscal support to firms creates a substitution effect, which reduces firms' incentives to demand bank loans. And similar to Jiménez et al. (2022), Altavilla et al. (2021) show that state-guaranteed loan programs implemented during COVID, while stimulating credit, they also lead to a substitution of non-guaranteed for guaranteed credit, especially for smaller and riskier firms strongly affected by the pandemic.

There are also two recent empirical papers for the USA that highlight the impact of the unconventional program as a backstop. Marsh and Sharma (2022) find that the U.S. Paycheck Protection Program (PPP), a credit guaranteed program, stimulates credit growth and provides a backstop that prevents contractions of non-guaranteed loans. Minoiu et al. (2022) find that the Main Street Lending Program[2] in the USA during the Covid-19 pandemic, increase banks' willingness to lend more outside the program. Since the use of the program was about 2.7% of its available capacity, it influence banks' lending behavior, by serving as a backstop, assuring banks would have access to credit. In addition, participating banks were more likely to originate new loans to both small and

[1] Cantú et al. (2021) present a novel database that contains information of policy measures to Covid-19 pandemic in 39 both advanced and emerging market economies. It includes both conventional an unconventional measures.

[2] An emergency lending facility for small and mid-sized firms without access to the corporate bond market.

large firms and less likely to tighten lending standards. The program also increases banks' levels of risk tolerance.

In the Eurozone, Da Silva et al. (2022) study the impact of the Targeted long-term refinancing operations (TLTRO) in the five largest countries of the Eurosystem from January 2021 to December 2021, using the unexpected increase of the amount that banks were allowed to borrow from the program. The policy increases credit through the "targeted" and profit "profit" channels, being the latter the more relevant.[3] Finally, For a sample of 37 countries, Wei and Han (2021) estimate the impact of Covid-19 pandemic on the transmission of the monetary policy on government bonds, stocks, exchange rate and credit default swap. They find that unconventional credit policies are slightly more effective (than conventional ones).

Several theoretical papers study the impact of the credit policy in DSGE models with financial frictions. (see, e.g., Gertler and Kiyotaki, 2011; Gertler and Karadi, 2011; Gertler and Kiyotaki, 2015; Gertler, Kiyotaki and Queralto, 2012). The financial friction is modeled as a moral hazard problem between banks and depositors.[4] Then, the credit policy aims to reduce the moral hazard problem since authors claim that it is harder for the bank to divert bank assets that are funded with central bank liquidity, or they just assume that central bank can directly lend to firms.

In a more recent study, Pozo and Rojas (2020) study the design of an unconventional credit policy in a DGSE model with credit demand and credit supply frictions. The difference with previous credit policies is that these loans are government-guaranteed and their cost is the risk-free interest rate. Similar to REACTIVA, the unconventional credit policy was about providing liquidity to banks so they can commit to issuing government-guaranteed loans (by the same amount) at very low interest rates. They find that the unconventional credit policy has a positive impact on banks' and firms' incentives to supply and demand credit, respectively. On one side, the policy increases aggregate credit supply by reducing the credit supply frictions. Furthermore, on the other side, it raises aggregate credit demand by lowering credit demand frictions.[5]

3 Data and Model Description

In this section we describe the REACTIVA program, the data we use, the identification technique, the model description and the regression results.

[3]The profit channel is because bank could earn 50 bps per euro borrowed by the TLTRO program and placing the proceeds at the deposit facility.

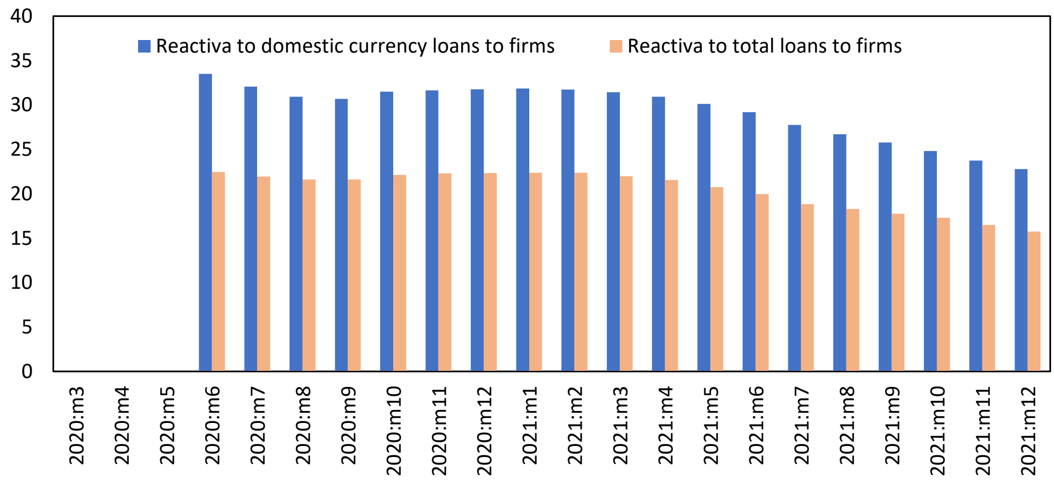
[4]Specifically, bankers can divert a portion of bank assets, and thus depositors may want bankers to put some of their money into funding bank assets, so that the bank charter value exceeds the value of diverting bank assets. As a result, there is an endogenous leverage constraint.

[5]Pozo and Rojas (2021) assess the impact of the unconventional credit policy in a zero lower bound environment in a two-period model.

The REACTIVA program (named REACTIVA Perú) was launched on the 6 of April 2020 by both the fiscal and monetary authorities to facilitate solvent firms with liquidity, in a context of very low interest rates, that restricted conventional monetary policy. In short, through this credit program the Central Bank provides liquidity to commercial banks through REPO operations backed by high quality loans. Banks that received the REPO, through an auction, previously committed to making loans to firms in domestic currency at the most favorable lending interest rate (charged to firms).[6] The available amount of REACTIVA Perú was first 30 millions PEN soles and then it was increased to 60 millions PEN soles on May 10, 2020, which represented the 22.4% of total loans to firms in December 2020. REACTIVA loans are guaranteed by the government. The coverage ratio (which varies from 80% to 98%) was in function of the size of the loan. The higher the size, the lower the coverage ratio.[7]

Figure 1 hows the evolution of participation of REACTIVA loans on total loans to firms. It shows a relatively important participation and reaches its maximum participation by December 2020.

Figure 1: *Share of REACTIVA loans (% of total loans to firms)*



Note: This figure shows the shares of REACTIVA loans over the total loans to firms in domestic currency or total loans in both domestic and foreign currency. Source: SBS. Own calculations.

3.1 Data

We use credit information at the bank-level, which is publicly available at the Financial System Regulator of Peru's website (*Superintendencia de Banca, Seguros y Administradoras de Fondos de Pensiones*, SBS, website)[8]. It includes credit information in several dimensions as: total, domestic and foreign currency; credit type (four and seven

[6]The Central Bank liquidity injection to commercial banks was also in domestic currency.

[7]For a detailed explanation of the REACTIVA program (called REACTIVA Peru), see Montoro (2020).

[8]Available at https://www.sbs.gob.pe/estadisticas-y-publicaciones/estadisticas-/sistema-financiero_

categories) and economic sectors. We name REACTIVA loans to those loans issued by banks under the program of REACTIVA Perú.

We use monthly data and the time period analyzed spans from 2004:m1 to 2021:m12. We start from 2003 to consider only the inflation-targeting period in Peru. We begin our investigation by focusing solely on banks[9], which account for 85.3 % of total credit in the financial system in December 2019, and accounts for 94.8% of the total REACTIVA loans in December 2020.

REACTIVA loans start in May 2020; however, information is available in the SBS from September 2020. So, we repeat the information of September from May to August 2020. And we have that 9 banks out of 16 banks received REACTIVA. We measure the intensity of the REACTIVA program (our intervention variable) as the ratio of REACTIVA loans to total loans. This measure captures the participation of REACTIVA in the credit market.

We include control variables for individual bank characteristics, such as return on assets (ROA), bank size or loan market share (SIZE), the risk weighted asset to capital ratio (RWA) and the non-performing loans ratio (NPL). The ROA controls for the profitability of financial institutions. The RWA controls for individual bank characteristics regarding bank capacity to handle a financial crisis and also individual preferences on risk-taking.[10] The NPL controls for the risk level of the loans portfolio.

We also include additional indicators to control for other conventional and unconventional policies. In particular, we use the domestic monetary policy rate (r^d) and the effective reserve requirement ratio (RR), which is available in domestic and foreign currency and that were relaxed after the start of the Covid-19 pandemic. These two variables are publicly available from the Central Bank website.

Tabla 1 presents the descriptive statistics for the variables. The average ratio of REACTIVA loans to total loans at bank-month level, conditional on those banks that received REACTIVA, is 12%. The table also reports the statistics for the control variables. All control variables show a relatively high standard deviation except for the RWA ratio. It shows also the average of the effective reserve requirement ratios in domestic and foreign currency, being this latter on average higher but relatively less volatile.

[9] We exclude state-owned banks.

[10] See Agur et al. (2012, 2019) and Dell'Ariccia et al. (2014) for a detailed explanation of the effect of bank leverage on bank risk-taking (i.e., the *leverage channel*). Intuitively, the higher the leverage the lower the participation of owners' wealth in funding bank investment activities, the smaller the losses of the owners if banks default (due to limited liability), and hence the stronger the preference to take higher risk.

Table 1: *Descriptive statistics for bank-month observations*

Variables	Obs	Mean	S.D.	Minimum	Maximum
Total					
REACTIVA_{it}	180	0.12	0.06	0.01	0.23
RWA_{it} (%)	2826	7.01	1.28	1.17	10.24
NPL_{it} (%)	2826	3.25	2.09	0.01	12.58
ROA_{it} (%)	2806	1.71	1.80	-7.73	8.06
SIZE_{it}	2826	0.08	0.10	0.00	0.38
r_t^d (%)	216	3.36	1.42	0.25	6.50
Domestic Currency					
REACTIVA_{it}	180	0.15	0.08	0.02	0.33
RR_{it} (%)	2167	9.44	5.88	4.01	64.20
Foreign Currency					
RR_{it} (%)	1855	38.11	9.96	6.05	270.33

Source: SBS, BCRP. Own elaboration. We exclude extreme values. For the descriptive statistics of REACTIVA_{bt}, we consider only observations higher than zero.

3.2 Identification Strategy

We are interested in capturing the impact of REACTIVA Peru on credit, apart from any substitution effect (or "direct" effect) and other long-term effects. In other words, we are interested in capturing some additional spillover effects that might affect demand and/or supply of credit as suggested by Pozo and Rojas (2020) and Pozo and Rojas (2021). We think that the former effects are captured by the trend of credit and the later effect by the cycle of credit.

Figure 2: *Identification technique*

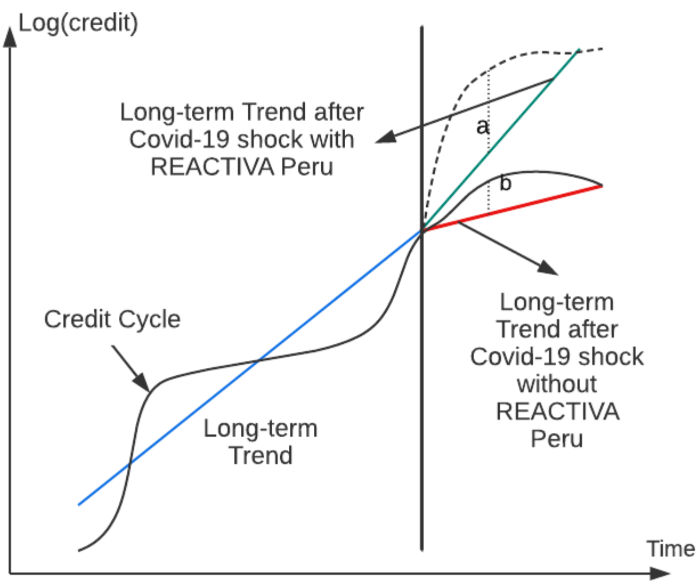


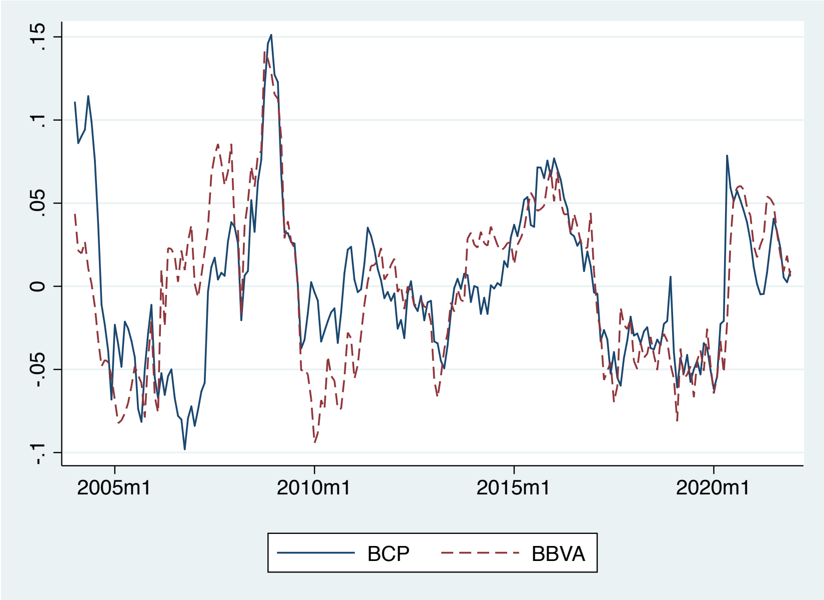
Figure 2 shows the credit cycle and long-term of two identical banks, except that one receives REACTIVA and the other does not. The vertical solid black line, points the Covid-19 shock and the start of the REACTIVA program. The red solid line (after the Covid-19 shock) represents the long-term trend of the loans of the bank that does not receive any REACTIVA, while the blue solid line represents the long-term trend of the bank that receives REACTIVA. As expected, we illustrate a more positive long-term trend for those banks that receive REACTIVA. The key point is then to compare the cycle (or the deviations from the trend) of the credit after the Covid-19 shock. For example, if "a", the positive deviation for the bank that receives REACTIVA, is higher than "b", the deviation of the bank that does not receive REACTIVA, then we might argue that REACTIVA indeed might had induced a positive spillover short-term impact on credit on top of any substitution and/or long-term effect.

Although credit policy may have influenced developments on the trend level, we focus on whether credit policy would had indirect or spillover effects, which we argue are captured by credit deviations from its trend. This choice is also influenced by the theoretical work in Pozo and Rojas (2020), which consistently considers credit deviation from its steady state.

To proxy for the credit cycle we use the log deviation of credit from its trend, where the credit trend has been estimated using a HP filter, with a smoothing parameter of 1600*(numb of periods in a quarter)[4], following Ravn and Uhlig (2002); Drehmann et.al (2012). Although the HP filter has several drawbacks (Hamilton, 2018), the there is sill not a consensus in the literature on the advise of the literature to stop using this empirical filter relative to others (Jonsson, 2020; Wolf et.al, 2020; Phillips and Shi, 2021).

Figure 3 reports the credit cycle for two of the four largest banks in Peru, BCP and BBVA. We notice that the cycle motivated by REACTIVA was not superior to other positive deviations since 2004. For example, the cycle in 2007-2008 was stronger.

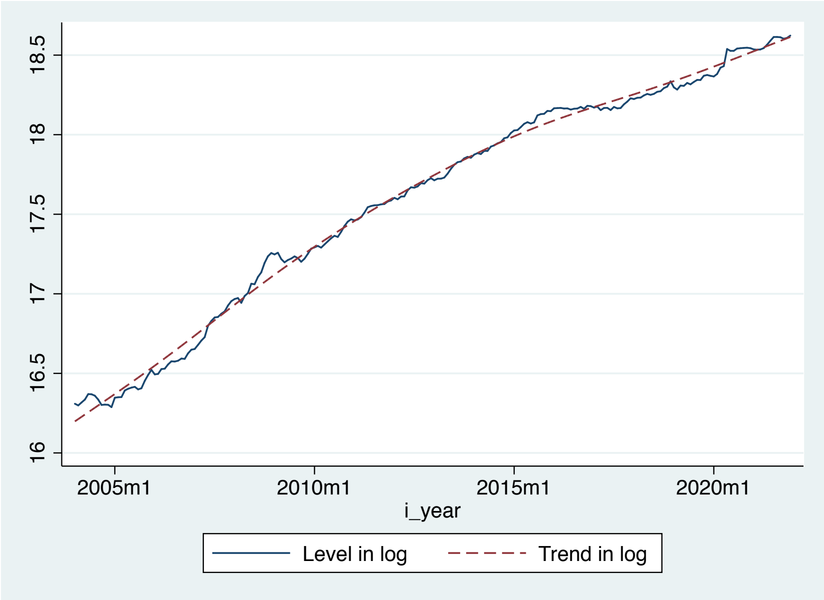
Figure 3: *Credit Cycles: BCP and BBVA*



Source: SBS. Own calculations. Credit Cycles = Log deviation from the long-term trend. Credit is in in thousands of S/.

Figure 4 reports the long-term trend and levels in logs of the credit for the BCP bank. We notice a long-term trend with a slightly smaller slope since around 2015. This is capturing the structural change of aggregate credit since 2015 but also the long-term impact negative effects of the Covid-19 shock.

Figure 4: *Level and Trend: BCP*



Source: SBS. Own calculations. Credit is in in thousands of S/.

Table 2 reports the descriptive statistics of the credit cycle (Y), log deviation from the long-term trend, for total, domestic and foreign currency. As expected, the average is virtually zero. We also find that the volatility of the domestic credit cycle is relatively higher and hence it reports higher extreme values.

Table 2: *Descriptive statistics for bank-month observations: credit cycle*

Variables	Obs	Mean	S.D.	Minimum	Maximum
Total					
Y_{it}	3041	0.00	0.24	-6.97	0.92
Domestic Currency					
Y_{it}	3032	0.00	0.26	-6.97	0.92
Foreign Currency					
Y_{it}	2696	0.00	0.23	-5.37	0.64

Source: SBS. Own elaboration.

By considering the full available historical data of credit, we aim to control by the common cycle across time and capture the marginal impact of the REACTIVA program.

Also, according to our interpretation that banks that have not received REACTIVA, could be considered as the treatment group, and allow us to control for the impact of the Covid-19 shock.

As we explain later, adding other dimensions might help us to better identify the impact of REACTIVA in the credit cycle.

3.3 Model Description

In short, the model seek to describe the relationship between individual credit cycle and REACTIVA loans' participation, controlling for bank characteristics. In particular, the empirical model is as follows:

$$Y_{it} = \alpha + \nu_t + \lambda_i + \beta_1 Y_{it-1} + \beta_2 REACTIVA_{it} + \beta_3 \Delta r_t^d + CTRL_{it} + \epsilon_{it}, \tag{1}$$

where the i subscript refers to a bank, the t subscript refers to a sample month. Y_{it} is credit cycle (percentage deviation from the long-term trend), computed with the Hodrick-Prescott (HP) filter, of bank i at month t, r_t^d is the domestic policy interest rate $\mathrm{REACTIVA}_{it}$ is the ratio of REACTIVA loans of bank i at month t to total loans of bank i at month t. This measure the participation of REACTIVA in the credit market. In addition, λ_i controls for unobservable bank characteristics invariant over time. Thus me focus on the intertemporal relation between credit cycle and the intensity of the REACTIVA program. ν_t controls for time fixed effects, so we identify the effect of intensity REACTIVA program on credit cycle by comparing banks in the same month. It also controls for foreign exchange (FX) fluctuations, economic activity trends, and the additional induced aggregate changes induced by tge COVID pandemics. Among the control variables, CTRL_{it}, we use variables associated with bank characteristics variant over time: risk-weighted assets to capital ratio (RWA), return on assets (ROA), non-performing loans ratio (NPL) and market participation or loan market share (SIZE). Finally, ϵ_{it} is a random error that has a normal distribution.

In the model a positive statistically significant value of β_2 supports a positive impact of REACTIVA program on the credit cycle. And a negative statistically significant value of β_3 supports the expected impact of the conventional monetary policy.

In the next subsection, we present the results for this baseline model. And in the following subsection we explore how other dimensions in the data might help us to better identify the impact of the REACTIVA.

3.4 Empirical Results

According to table 3 in our baseline specification with only banks and without controlling for bank characteristics, we find a statistically and economically significant positive impact of REACTIVA on credit. In particular, in the specification with bank fixed effects, on average a participation of 20% of REACTIVA loans in the credit market increases credit (deviation from long-term trend) in 2.7% without the AR1 term (column 2) and in 1.2% with the AR1 term (column 5). Recall this impact captures the effect of REACTIVA on top of the "direct" effect (or "substitution" effect), which is the impact on the long-term trend.

Interestingly, with both bank and time fixed effects the impact of REACTIVA is quantitatively higher. This suggests that if we do not control for the conventional credit policy, we might overestimate the impact of REACTIVA.

Table 3: *Baseline regression: Banks*

	(1)	(2)	(3)	(4)	(5)	(6)
Y_{it-1}				0.587***	0.587***	0.578***
REACTIVA_{it}	0.0877***	0.138***	0.488***	0.0131	0.0601***	0.299***
$\Delta\ r_t^d$	-0.0525***	-0.0516***		-0.0154***	-0.0144***	
Observations	3,024	3,024	3,024	3,024	3,024	3,024
R-squared	0.005	0.016	0.138	0.782	0.792	0.820
F test (ρ-value)	5.98e-08	0	0	0	0	0
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors.

Table 4 reports the results when considering the control variables. Results qualitatively hold. In addition, we find that bank leverage, non-performing loans ratio, and return on assets have a positive association with the credit cycle. And credit market share is positively related to the credit cycle. In addition, we find that the credit cycle is very persistent.

Table 4: *Baseline regression: Banks and more controls*

	(1)	(2)	(3)	(4)	(5)	(6)
Y_{it-1}				0.937***	0.940***	0.936***
$REACTIVA_{it}$	0.118***	0.167***	0.688***	0.0251*	0.0282*	0.111***
$\Delta\ r_t^d$	-0.0609***	-0.0603***		0.00491*	0.00548**	
RWA_{it-1}	-0.000696***	-0.000800***	0.000134	-1.38e-05	2.45e-05	4.45e-05
NPL_{it-1}	-0.00433***	-0.00667**	-0.00534**	-0.00133***	-0.00238***	-0.00223**
ROA_{it-1}	-0.0110***	-0.00974***	-0.0142***	-0.000736**	-0.00113**	-0.00164***
$SIZE_{it-1}$	-0.0594***	2.001***	2.082***	-0.00701	-0.0510	-0.0432
Observations	2,851	2,851	2,851	2,851	2,851	2,851
R-squared	0.089	0.165	0.327	0.922	0.923	0.936
F test (ρ-value)	0	0	0	0	0	0
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors.

In Appendix A we perform a robustness exercise for regressions presented in tables 3 and 4. It consists in using the lags of both REACTIVA and change of the domestic policy rate. Tables 9 and 10, respectively, report that the results qualitatively holds. Quantitatively, in the specification without controls, the AR1 terms are qualitatively higher (columns 4-6), and the impact of both unconventional and conventional measures are smaller. In the specification with controls, the impact of REACTIVA diminishes when including the AR1 term (columns 5-6), but increases otherwise (with a cost of a smaller impact of the conventional policy, columns 2-3).

Regarding the possible impact of repeating the same REACTIVA loans' information of September 2020 for the three previous months, we might suggest that this, if anything, might underestimate the impact of REACTIVA.

3.5 Additional Evidence

So far we are based our analysis with bank-time level data. In this subsection, we include other dimensions, so we can exploit the public available data and better identify the impact of REACTIVA.

Domestic and Foreign Currency Loans

Peru is a dollarized economy. Banks issue loans in domestic and foreign currency.

Loan dollarization has declined from 2012 to 2019 from 43.5% to 27.0%.[11] And after the Covid-19 pandemic and the implementation of REACTIVA, it continue decreasing to reach 24.3% in 2021. However, it remains at an economically important level. Next, we add to a model a new dimension: currency.[12] In other words, we split our loans between domestic and foreign currency. The empirical model becomes:

$$Y_{ict} = \alpha + \nu_t + \lambda_i + \theta_c + \beta_1 Y_{ict-1} + \beta_2 REACTIVA_{ict} + \beta_3 \Delta r_t^d + \epsilon_{ict}, \tag{2}$$

where $c \in \{$ domestic currency, foreign currency $\}$ refers to the currency type, and θ_c is the currency fixed effects. This time Y_{it} is the credit cycle, computed at the bank-currency-month level.

Since REACTIVA loans are domestic currency, we might argue that by splitting our data between foreign currency and domestic currency loans, we better identify the impact REACTIVA.

By considering the currency dimension, we control by other policies that might have equally affected both domestic and foreign currency loans. Indeed, upon the existence of only common policy shocks (for both domestic and foreign currency loans market), the coefficient β_2 should be smaller.

In addition, with the currency dimension we might better control for the Covid-19 shock. Only in the case that the Covid-19 shock affects equally both domestic and foreign currency credit markets, we might perfectly control for the Covid-19 shock. However, we know that economic sectors have different levels of dollarization (BCRP, 2019) and that Covid-19 pandemic affects economic sectors differently.

According to table 5 the coefficients that capture the impact of REACTIVA, if anything, are larger. This validates the relative importance of REACTIVA among other policies in promoting credit during the Covid-19 pandemic.

Interestingly, in this specification, we can use bank-time FE to control for bank supply shocks.

However, so far we cannot still control for any different impact due to changes in reserve requirements in domestic and foreign currency. A couple of days after the start of the confinement (March 16th, 2020) the BCRP relaxes the reserve requirements in both domestic and foreign currency. It reduces the reserve rate from 5% to 4% in domestic currency. In foreign currency, the BCRP reduces the reserve rate for obligations, with a maturity of fewer than two years, from 50% to 9%; and suspends for the rest of the year the additional reserve rate associated with the foreign currency loans.[13]

[11] This is mainly due to the de-dollarization program implemented in 2003 by the Central Bank.

[12] Unfortunately, there is not publicly available the NPL, ROA and RWA by currency type.

[13] In 2013 the BCRP implemented a de-dollarization program in the financial system. It consists of additional reserve requirements in foreign currency based on limits to foreign currency mortgages and

If anything, we should expect that controlling by reserve requirements reduces the significance of the impact of the conventional monetary policy. According to table 11 in Appendix A, the results are robust with reserve requirements rates as additional controls. Interestingly, the results are similar. This could be because of the (counter-cyclical) use of this tool in the later decades. Also, we do not observe a statistically significant impact or reserve requirements on the credit cycle.

Table 5: *Regression: currency type as new dimension*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y_{it-1}					0.725***	0.725***	0.721***	0.915***
$REACTIVA_{it}$	0.117***	0.153***	0.307***	0.182***	0.0214	0.0501***	0.128***	0.0158
Δ r_t^d	-0.0570***	-0.0565***			-0.0108**	-0.0102*		
Observations	5,696	5,696	5,696	5,344	5,696	5,696	5,696	5,344
R-squared	0.004	0.008	0.074	0.547	0.752	0.756	0.769	0.904
F test (ρ-value)	0	0	3.72e-08	6.20e-05	0	0	0	0
Bank FE	No	Yes	Yes	No	No	Yes	Yes	No
Time FE	No	No	Yes	No	No	No	Yes	No
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	Yes	No	Yes	Yes	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors

Four Types of Credit and Currency Types

Here, we add to the baseline specification the currency type dimension and the credit type dimension. We disaggregate loans among the different four credit types (commercial loans, loans to microenterprises, personal loans and mortgages).

The empirical model becomes:

$$Y_{icmt} = \alpha + \nu_t + \lambda_i + \theta_{cm} + \beta_1 Y_{icmt-1} + \beta_2 REACTIVA_{icmt} + \beta_3 \Delta r_t^d + \epsilon_{ict}, \qquad (3)$$

where $m \in \{$ commercial, micro, mortgage, personal loans $\}$ refers to the type of credit. θ_{cm} is the currency-credit type fixed effect. This time Y_{it} is the credit cycle, computed at the bank-currency-credit type-month level.

By the end of July 2010, credit types increase from four to seven. It leads to some reclassification from mortgage loans to loans to firms and loans to microenterprises to loans to commercial loans. Since July 2010, commercial loans include loans to small-sized, medium-sized, large-sized and corporate firms; and loans to microenterprises include loans to micro-sized firms.

In this specification, we can further control by the impact of the Covid-19 pandemic

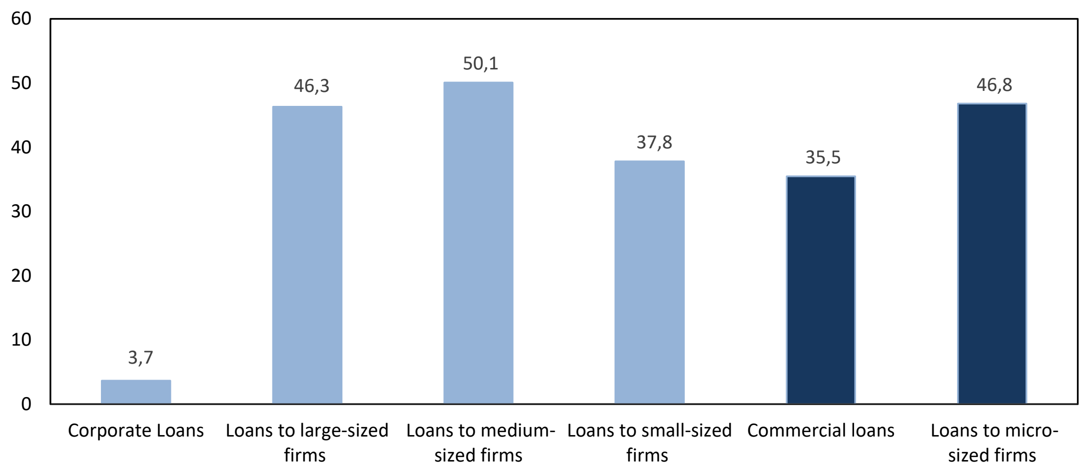
automobile loans.

(or the confinement measure) and hence better identify the REACTIVA impact, since by regulation REACTIVA loans were only issued to firms and hence mortgage and personal loans were not affected (at least directly) by REACTIVA.

However, we are aware of possible spillover effects across currency and credit types. These effects can mainly appear through the credit demand channel, since a firm and a household might borrow simultaneously in both domestic and foreign currencies; but also through the credit supply channel since the same bank might lend in both currencies.

We know that REACTIVA loans were issued within the commercial and micro types. In numbers, according to figure 5 in December 2020 the participation of REACTIVA loans within the commercial loans and loans to micro-sized firms in domestic currency were 35.5% and 46.8%, respectively.

Figure 5: *REACTIVA loans participation in the domestic currency credit market (%)*



Source: SBS. Own elaboration.

According to table 6 the impact of REACTIVA loses statistical significance but gains economic significance or is quantitatively more important.

In normal times, loans to microenterprises are relatively more supply-driven, and similarly, commercial loans are relatively more demand-driven. Under that scenario, we might expect that REACTIVA has a relatively more important impact on loans to microenterprises. In other words, since commercial loans are expected to be demand-driven than loans to micro-sized firms, by excluding those in the regression, we are controlling more by demand effects, and we might expect a more important impact of REACTIVA.

However. we are aware that the Covid-19 pandemic and REACTIVA do not necessarily affect in the same way the four types of credit. In particular, we find that if we do not consider commercial loans, results are quantitatively similar. It might suggest that during Covid-19 pandemic the demand shocks were equally important during the pandemic as expected.

Table 6: *Regression: Credit Type - Four categories - Currency Types*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y_{icmt-1}					0.712***	0.712***	0.710***	0.732***
REACTIVA_{it}	0.443**	0.446**	0.460**	0.456**	0.165	0.166	0.173	0.170
$\Delta\ r_t^d$	-0.0538***	-0.0536***			-0.00309	-0.00260		
Observations	17,824	17,824	17,824	17,496	17,824	17,824	17,824	17,496
R-squared	0.014	0.014	0.035	0.200	0.665	0.665	0.670	0.723
F test (ρ-value)	0.000166	0.000179	0.0439	0.0329	0	0	0	0
Bank FE	No	Yes	Yes	No	No	Yes	Yes	No
Time FE	No	No	Yes	No	No	No	Yes	No
Currency-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	Yes	No	Yes	Yes	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors

Seven credit Type and Currency Types

In this case, we consider the seven types of credit and hence our period of analysis starts in July 2020. The specification of the model is very similar to equation (3). However, now $m \in \{$ corporate loans, loans to large-sized firms, loans to medium-sized firms, loans to small-sized firms, loans to micro-sized firms, mortgage, personal loans $\}$.

According to table 7 when desegregating commercial loans by the size of the firm, estimates become more statistically significant. In other words, the heterogeneity of types of firms by size helps us to better identify the impact of REACTIVA. For example, from figure 5 REACTIVA loans within the corporate loans market is relatively smaller, which should be associated with a relatively smaller short-term deviation of these type of loans. In addition, with this heterogeneity we might be better controlling by demand shocks due to Covid-19 pandemic.

Table 7: *Regression: Credit Type - Seven categories*

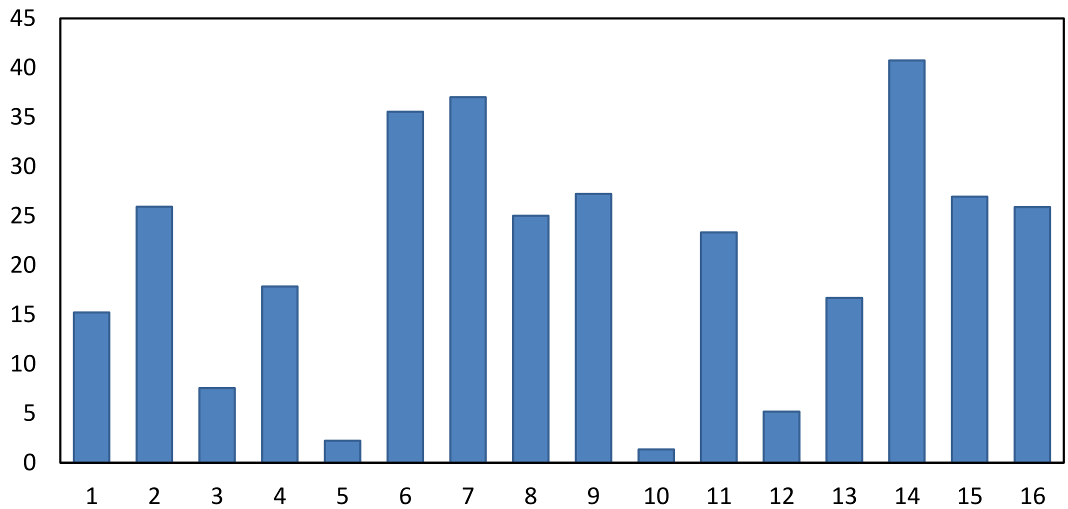
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y_{icmt-1}					0.747***	0.747***	0.743***	0.741***
REACTIVA_{it}	0.403***	0.406***	0.459***	0.410***	0.159**	0.161**	0.178**	0.162**
$\Delta\ r_t^d$	-0.0259*	-0.0259*			-0.000206	-0.000157		
Observations	24,302	24,302	24,302	23,965	24,302	24,302	24,302	23,965
R-squared	0.012	0.012	0.029	0.184	0.684	0.684	0.687	0.724
F test (ρ-value)	0.00157	0.00157	0.00117	0.00168	0	0	0	0
Bank FE	No	Yes	Yes	No	No	Yes	Yes	No
Time FE	No	No	Yes	No	No	No	Yes	No
Currency-Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	Yes	No	Yes	Yes	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors

Economic Sectors

In this part, we use the dimension of the economic sector. The SBS reports loan information grouped in sixteen economic sectors.[14] However, due to data availability we lose individual financial institution and currency type dimensions. So, in this case we consider loans to firms, disaggregated in the sixteen economic sectors, in addition to mortgage and personal loans. Figure 6 reports the heterogeneity level of REACTIVA' participation across economic sectors by the end of 2020. REACTIVA has a relatively important participation in loans to firms within the social and health services sector, construction and trade. Other industries, for example, as electricity, gas and water, and financial intermediation exhibit very low participation of REACTIVA. This is since they were almost not affected by the confinement measures due to the Covid-19 pandemic.

Figure 6: *REACTIVA loans participation in credit market by economic sectors (%)*



Source: SBS. Own elaboration. (1) agriculture, livestock, hunting and forestry,(2) fishing, (3) mining, (4) manufacturing industry, (5) electricity, gas and water, (6) construction, (7) trade, (8) hotels and restaurants, (9) transportation, storage and communications, (10) financial intermediation, (11) real estate activities, (12) public administration and defense, (13) teaching, (14) social and health services, (15) other community service activities, and (16) private homes with domestic services and extraterritorial organs

Including economic sectors allows us to and differentiate and control for some sectors that have been more (tourism, restaurants, etc.) and less (agriculture, construction, etc.) affected by the confinement measures. With this, the empirical model becomes:

$$Y_{st} = \alpha + \nu_t + \theta_s + \beta_1 Y_{st-1} + \beta_2 REACTIVA_{st} + \beta_3 \Delta r_t^d + \epsilon_{it},$$

[14]These sixteen economic sectors include the following sectors: (1) agriculture, livestock, hunting and forestry,(2) fishing, (3) mining, (4) manufacturing industry, (5) electricity, gas and water, (6) construction, (7) trade, (8) hotels and restaurants, (9) transportation, storage and communications, (10) financial intermediation, (11) real estate activities, (12) public administration and defense, (13) teaching, (14) social and health services, (15) other community service activities, and (16) private homes with domestic services and extraterritorial organs.

where s rerefs to the economic sectors. And Y_{it} is the credit cycle, computed at the group-sector-month level.

According to table 8, results are qualitatively robust. The different combination of fixed effects do not significantly affect the sensitivity of the credit cycle to REACTIVA.

Table 8: *Regression: Economic Sectors*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y_{st-1} ,					0.870***	0.859***	0.870***	0.859***
REACTIVA_{st}	0.204***	0.269***	0.211***	0.294***	0.0446***	0.0591***	0.0464***	0.0652***
$\Delta\ r_t^d$	-0.0229***		-0.0231***		0.000992		0.000935	
Observations	4,085	4,085	4,085	4,085	4,085	4,085	4,085	4,085
R-squared	0.014	0.189	0.015	0.190	0.768	0.790	0.768	0.790
F test (ρ-value)	0	0	0	0	0	0	0	0
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Sector FE	No	No	Yes	Yes	No	No	Yes	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors

4 Conclusions

In this paper we have empirical evidence of a positive impact of REACTIVA on the credit cycle, i.e., on top of the long-term effect of any substitution effect. Indeed, this might provide evidence of positive general equilibrium effects of REACTIVA on credit (see, e.g., Pozo and Rojas, 2020). Results are qualitatively robust, if we split our loans by currency and credit type. When using the four segments (old classification), results lose significance; while with seven segments (new classification), results become more significant. Finally, results are also robust when considering the economic sector dimension.

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Appendices

A Robustness

Table 9: *Baseline regression: Banks*

	(1)	(2)	(3)	(4)	(5)	(6)
Y_{it-1}				0.792***	0.785***	0.772***
$REACTIVA_{it-1}$	0.0588**	0.128***	0.581***	-0.0109	0.0198*	0.193***
$\Delta\ r^d_{t-1}$	-0.0461***	-0.0447***		-0.00408	-0.00380	
Observations	3,007	3,007	3,007	3,007	3,007	3,007
R-squared	0.005	0.035	0.176	0.824	0.830	0.849
F test (ρ-value)	4.17e-06	0	0	0	0	0
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors.

Table 10: *Baseline regression: Banks and more controls*

	(1)	(2)	(3)	(4)	(5)	(6)
Y_{it-1}				0.937***	0.932***	0.930***
$REACTIVA_{it-1}$	0.0321	0.233***	0.717***	0.0123	0.0270**	0.0935***
$\Delta\ r^d_{t-1}$	-0.0452***	-0.0456***		0.00224	0.00237	
RWA_{it-1}	-0.00339	0.0120***	0.00534	0.00101	0.000616	0.000439
NPL_{it-1}	-0.00597***	-0.0225***	-0.0216***	-0.000807**	-0.00303***	-0.00369***
ROA_{it-1}	-0.0120***	-0.0161***	-0.0188***	1.63e-05	-0.000784	-0.00112
$SIZE_{it-1}$	-0.0483***	1.906***	2.057***	-0.00631	-0.0215	-0.0231
Observations	2,781	2,781	2,781	2,781	2,781	2,781
R-squared	0.071	0.201	0.353	0.922	0.923	0.936
F test (ρ-value)	0	0	0	0	0	0
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors.

Table 11: *Regression: currency type as new dimension*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y_{it-1}					0.725***	0.725***	0.721***	0.915***
$REACTIVA_{it}$	0.117***	0.153***	0.307***	0.182***	0.0214	0.0501***	0.128***	0.0158
Δ r_t^d	-0.0570***	-0.0565***			-0.0108**	-0.0102*		
Observations	5,696	5,696	5,696	5,344	5,696	5,696	5,696	5,344
R-squared	0.004	0.008	0.074	0.547	0.752	0.756	0.769	0.904
F test (ρ-value)	0	0	3.72e-08	6.20e-05	0	0	0	0
Bank FE	No	Yes	Yes	No	No	Yes	Yes	No
Time FE	No	No	Yes	No	No	No	Yes	No
Currency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	No	Yes	No	Yes	Yes	Yes

*** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Robust standard errors