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COVID-19 and public credit guarantees: a policy assessment

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COVID-19 and public credit guarantees: a policy assessment☆

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Resumen

La crisis económica derivada del shock del COVID-19 planteó el desafío para los formuladores de políticas de diseñar una respuesta rápida y efectiva para aliviar los efectos negativos sobre la actividad de las pequeñas y medianas empresas. Utilizando datos granulares de préstamos y garantías, estudio el impacto de un esquema de créditos con garantía estatal implementado en Uruguay. Los resultados de las estimaciones sugieren que la política llegó efectivamente a las industrias objetivo, ofreciendo evidencia a favor del sector financiero privado operando como conducto de liquidez respaldada por el gobierno para las microempresas y medianas empresas. También encuentro evidencia empírica que sugiere una leve comportamiento oportunista a través de la sustitución de garantías ilíquidas y sobre la papel de los bancos estatales en la provisión de crédito durante la pandemia.

JEL: G21, G28, E65
Palabras clave: COVID-19, créditos con garantía estatal, bancos estatales

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Abstract

The global business shutdown derived from the COVID shock posed the challenge for policymakers of designing a quick an effective response to cushion the negative impact of the pandemic on the activity of small firms. Using granular data on loans and guarantees, I study the impact of a Public Credit Guarantee Scheme implemented in Uruguay. The results of the estimations suggest that the policy effectively reached the targeted industries, offering evidence in favor of the private financial sector operating as a conduit of government-backed liquidity for microsmall- and medium-sized firms. I also find empirical evidence suggesting a mild opportunistic behavior through substitution of illiquid guarantees and about the role of state-owned banks in credit provision during the pandemic.

JEL: G21, G28, E65
Keywords: COVID-19, public credit guarantee, state-owned banks

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1 Introduction

Access to credit is widely recognized as problematic for micro-, small- and medium-sized enterprises (MSMEs). To address this challenge, public authorities around the globe intervene in SME credit markets through public credit guarantee (PCG) schemes. A PCG offers risk mitigation to lenders by taking a share of the lenders' losses on SME loans in case of default. It may also facilitate the discovery of borrowers' riskiness by lenders that would prefer not to lend without such a guarantee scheme. Then, PCG can contribute to expand access to finance for MSMEs. Yet, if poorly designed, they may introduce inefficiencies in credit allocation, target the incorrect firms and even foster opportunistic behavior by lenders and borrowers.

PCG schemes have been extensively used as one measure on the policy toolkit to respond to the economic impact of the COVID-19 pandemic and the associated lockdowns. In several cases, existing schemes were extended to provide a prompt response to the emerging risk, with the aim of ameliorating the credit crunch and reduce lenders' exposure to systemic risk. The COVID-19 pandemic, its effects and PCG schemes are ongoing. Yet, after more than a year of being used with the objective of fighting against the negative effects of the pandemic, it is important to evaluate PCG schemes. Which has been the impact of PGC schemes so far? Are they reaching the right firms, i.e. the more affected, still viable ones? Do they have a significant impact on supporting credit to MSMEs? Or, are they being misused to solve idiosyncratic legacy problems of lenders?

In this paper I contribute empirical evidence on the use and impact of a PCG scheme implemented since April 2020 to support credit to MSMEs in a less developed economy. The scheme extended a previous instrument introduced in September 2009 and was carefully designed in an attempt to provide effective support to MSMEs during the emergency (indeed, the scheme was named "SiGa Emergency"). SiGa Emergency guaranteed 27%

of credit to MSMEs at its peak in August 2020. Moreover, in the fourteen months period between April 2020 and June 2021 SiGa Emergency guaranteed loans by the equivalent of one and a half times all the credit guaranteed by the previous scheme in the ten years between it started in 2009 and 2019.

The results found inform policymakers about the usefulness of the PCG scheme, while also identifying perfectible aspects on its design. Specifically, I find that the PCG scheme helps ameliorate the credit crunch by allowing guaranteed credit to MSMEs to grow more than non-guaranteed one, particularly during the COVID-19 pandemic. Moreover, during this period MSMEs in the most affected economic sectors are more likely to being allocated a PCG, and credit to these firms increased even more than the average growth of guaranteed credit. Interestingly, MSMEs with higher non-performing loan ratio, higher write-off ratio or debt-restructured ratio are less likely to receive a PCG, which is consistent with the incentives provided in the design of the mechanism. On a more negative side, there is empirical evidence suggesting mild opportunistic behavior through substitution of illiquid guarantees with the PCG scheme. Other results suggest that previous bank relationships of firms matter to increase the likelihood of receiving a PCG, and that credit growth in the stated-owned commercial bank, with and without PCG, was larger during the COVID-19 pandemic.

I exploit granular data from three databases compiled by the Banco Central del Uruguay in its role as banking regulator and supervisor. The sample covers the period from January 2015 to January 2021 and has a monthly frequency. One database, the Credit Registry, contains detailed information about all the performing and non-performing loans granted by the financial system. A particular feature of this database is that it contains very detailed information about all the guarantees offered by borrowers, including the type of guarantee such as the liquidity of the assets offered as collateral. Another database contains specific information associated to the loans contracts that are backed by the PCG scheme, including information about the loan destination, the frequency of amortization, the amount, rate and currency of the loan, the period of grace, and the percentage of coverage. Finally, I also have balance sheet and income statement data of all the financial institutions. As a result, my dataset includes loans granted from 11 banking institutions to an average of approximately 35.000 different firms per year between 2015 and 2021.

I start by estimating a linear probability model to provide evidence on who gets a PCG backed loan. According to my results, firms operating in sectors that were affected or moderately affected by the pandemic are more likely to receive a PCG. Interestingly, while the coefficient of moderately affected MSMEs is positive and statistically significant through the whole sample, the coefficient of the most affected firms is only significant during the COVID-19 period. These results hold after controlling for firm-loan and bank characteristics, and are robust to considering other probability models, e.g. probit.

As one would expect from the design of the PCG scheme, I find empirical evidence that firms with a poor debt performance (high non-performing loan debt ratio, positive write-off ratio, positive debt-restructured ratio) are less likely to receive a PCG. Finally, I find that the probability of receiving a PCG is larger for a firm operating with the bank that owns the largest share of its debt and is increasing in the number of bank relationships of firms. Hence, previous engagement of firms with banks matter to improve the probability of being supported by a PCG.

Later, I assess what is the impact of a PCG on credit growth using the identification strategy suggested by Khwaja and Mian (2008). The results indicate that the PCG scheme has a positive impact on credit growth. Specifically, my estimates indicate that there is an average monthly credit growth of about 6 percentage points higher in credit backed with a PCG during the COVID pandemic period, i.e. from March 2020 onward.

I also explore whether there are differences in credit growth among banks by focusing on the characteristic of private versus state-owned banks. In so doing, I confirm previous results: monthly credit growth is higher when the borrower receives a PCG, whether the bank is private or state-owned. Results also suggest that the monthly credit growth for the state-owned banks is higher than for private-owned banks, regardless of the borrower holding a PCG.

Finally, I find empirical evidence suggesting that at the same time of obtaining a PCG, firms reduce the amount of other, specially illiquid, guarantees with the lender. Although this may represent an opportunistic behavior by banks, looking closer to the data I find that the cases in which a MSME displays a decline in the stock of non-liquid guarantees kept with a bank while simultaneously receiving a PCG for a loan with that bank is only around 5% of the total of operations and involves just a few firms.

The rest of the paper is organized as follows. The next section presents a review of the related literature. Section 3 revises the main characteristics and design of the PCG scheme. Section 4 describes the data, its sources and provides descriptive statistics. Section 5 presents the empirical strategy. Section 6 shows the main results. Section 7 concludes with final remarks. Tables containing detailed empirical results are in the Appendix.

2 Literature Review

From a theoretical point of view, the introduction of a credit guarantee scheme might have ambiguous effects. If firms are not capable of complying with collateral requirements, a credit guarantee scheme may allow access to credit for these type of firms. For instance, Meyer and Nagarajan (1996) argue that credit guarantees can lead to a learning process, where banks discover that borrowers benefiting from the guarantee are not as risky and unprofitable as initially expected and become willing to provide loans to them in the future, even without a PCG. Following this perspective, Abraham and Schmukler (2017) claim that public credit guarantees can be used to subsidize the initial costs of learning about new groups of borrowers. On the opposite side, a credit guarantee scheme might also lead to a riskier behavior by both the borrower and the bank (see, for instance, Lelarge et al. (2010), Galetovic and Sanhueza (2006)). Specifically, guarantees might lead to adverse selection, attracting riskier firms and worsening the overall pool of borrowers Core and De Marco (2021). In addition, banks could have lower incentives for assigning resources to screening and monitoring activities, which would eventually lead to future loan defaults de Blasio et al. (2018).

According to Cowan et al. (2015), PCG reduce banks' exposure to systematic risk while also reducing banks' capital requirements in a moment in which these are binding. As a result, this softening of the capital constraint has a positive impact on the aggregate supply of credit. When compared to direct subsidies, the appeal of PCG is based on the fact that the screening and monitoring can be performed by private institutions that have more expertise in performing these tasks than the provider of the guarantees. The authors compare the performance of loans with and without guarantees, finding that for each additional unit of guarantees to a banking institution, its credit to MSMEs increases by 0.65. Similarly, I provide empirical evidence on the positive impact of a PCG scheme over credit growth to MSMEs during the COVID-19 pandemic. Additional arguments in favor of PCG are based on the idea that, by delegating screening and monitoring to private banks, issuing public guarantees mitigates the risk of politically connected lending (Khwaja and Mian (2005)).

Following a similar motivation, Gropp et al. (2014) analyze the impact of PCG on the risk-taking of banks in the context of a natural experiment in Germany. Specifically, they analyze the response of banks to a removal of a governmental guarantee program, comparing the behavior of banks subject to the program versus that of those not included in the scope of the program. They find that the removal of government guarantees resulted in a significant reduction in banks' exposure to credit risk relative to a control group of German banks that Ire never subject to the guarantee. They mention two effects of public guarantees on bank risk-taking that work in opposite directions. On the one hand, government guarantees may reduce market discipline because creditors anticipate their bank's bail-out and therefore have fewer incentives to monitor the bank's risk-taking or to demand risk premia for higher observed risk-taking. As a consequence, the risk-taking of the protected banks' increases. On the other hand, government guarantees also affect banks' risk-taking through their effect on banks' margins and charter values. Hence, government guarantees may alternatively be viewed as an implicit subsidy that reduces banks' risk-taking through their future value. Their results appear to be in line with the first effect.

D'Ignazio and Menon (2020) state that despite the popularity of guarantee schemes, there are no conclusive theoretical findings on the net effect of these type of schemes on firms' finance. They try to fill this gap by estimating the casual effect of a credit guarantee scheme implemented in Italy during 2008. Their main results are the following: credit guarantee schemes are associated with an increase in firms' bank debt, an increase in the share of long-term debt, an increase in the firms' probability of default and an increase in firms' investments. In a similar study but exploiting the temporarily extension of the PCG program in Japan between 1998 and 2001, Uesugi et al. (2010) study the effect of the program not only on credit availability but also on firms' performance after participating in the program. On one hand, they find that the PCG program make credit available to otherwise credit constrained firms, but, access to the program resulted in firms being less profitable in the following years. Moreover, their results confirm that the program had an effect on the behavior of banks as undercapitalized banks substituted non-guaranteed loans with loans with collateral. These results are in line with the *loan-*

portfolio substitution hypothesis described in Uesugi et al. (2010), which could overcome the positive effect of the *loan availability hypothesis*. My results show a relatively low substitution effect, leading to an overall positive effect of public credit guarantees.

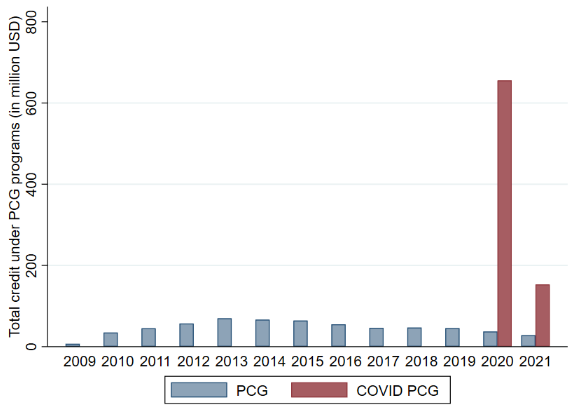
In addition to the risk-taking effects that credit guarantee schemes may introduce, another possible outcome from such schemes is that the loans might not go to the targeted firms. For example, when studying the effectiveness of a publicly funded guarantee scheme for SMEs implemented in Italy, Zecchini and Ventura (2009) find that the PCG scheme did not necessarily targeted the most financially disadvantaged firms, since there was no screening to assess whether a loan proposed by a bank to the fund would have been granted even in the absence of a guarantee. I find the opposite result. More precisely, I find empirical evidence that the PCG scheme implemented in Uruguay during the COVID-19 pandemic reached the most affected MSMEs and allowed bank credit to them to growth at higher rates than for other MSMEs.

Another branch of the literature, currently in early stages, studies the availability of PCG programs during the COVID-19 pandemic. In that respect, the study of its effects on firms profitability and delinquency rates seems to be, at this stage, preliminary and incomplete as the overall effect is expected to be reached some time ahead. In that sense, my focus, as well as that of Core and De Marco (2021), is on the effect of the PCG program during the pandemic. Whilst I study credit availability and resources allocation, Core and De Marco (2021) study how the private sector allocated funds after the expansion of the PCG program in Italy during the COVID-19 pandemic focusing on the characteristics of borrowers and lenders.

3 Policy framework

As one element in the policy toolkit to respond to the economic impact of the COVID-19 pandemic on MSMEs in Uruguay, the authorities extended an existing PCG scheme. Although the scheme started in September 2009, until 2019 it reached just a relatively small scale and was not widely used by financial institutions. Specifically, while the total credit granted with a PCG was approximately USD 45 million in 2019, and the accumulated guaranteed credit between 2009 and 2019 reaches USD 538 million, the total amount of guaranteed credit granted during the COVID-19 pandemic (April 2020 to June 2021) was USD 780 million: approximately one and a half times the accumulated guaranteed credit in the previous ten years. The total amount of guarantees granted was USD 550 million during the COVID-19 pandemic period, representing and average coverage of 70% (see Figure 1).

Figure 1: *Total credit to MSMEs through the PCG scheme (in million USD)*



The extension of the PCG scheme involved changes in its design with the aim of including new features, softening some of the restrictions of the original mechanism, helping to reach the more needed MSMEs, and providing the correct incentives to avoid misuse and opportunistic behavior. The requisites for applying to the guarantee line starting in April 2020, which is called *"SiGa Emergency"* were the following:

- To be a formalized company, with payment capacity and up to date with tax obligations.
- The company's annual sales must be below UI 75.000.000 (approximately 8 million US dollars).[1]
- If the company already had an active loan in February 2020, it must be less than 59 days past due in the payment of its loans as of February 29, 2020.
- The company must be rated "2B" or better in the Credit Registry of the Central Bank of Uruguay as of February 2020. If the firm had a lower rating, it was still eligible as long as one of the following conditions is met: (i) its debt was lower than U$S 100 or its equivalent in Uruguayan pesos as of February 2020, (ii) the firm had improved its rating and at the time of receiving the guarantee it is 2B or better.

In addition, the loan destination was amplified. Besides loans for new capital –the previous setup of the mechanism allowed to grant SiGa loans for working capital o investing capital–, the new regulation allowed to grant SiGa loans for past debt restructures or to extend payment maturities. Also, the coverage of the guarantees was increased; if the company is asking for a new loan, the guarantee could cover up to 80% of the borrowed capital (the previous regulation defined a coverage of 60%), while if the company is restructuring a previous debt, the guarantee could cover up to 50% of the credit balance.

The maximum loan amount that can be granted was UI 1.200.000 (approximately USD 150.000), and the loan could be granted either in national currency (Uruguayan pesos or UI) or in American dollars. Also, the maturity of the amortizing loan could vary from a minimum of 3 months to a maximum of 3 years, including a grace period of up to 6 months. In addition, the fees charged decreased and varied depending on the currency

[1] UI stands for Unidad Indexada. It is a unit of value that is readjusted according to inflation measured by the Consumer Price Index.

of the loan[2]: an annual rate of 0,6% of the guaranteed amount for loans in national currency, and a 0,8% annual rate on the guaranteed amount for loans in US dollars. As for the loan rates, a new characteristic of the mechanism design was the introduction of a price cap depending on the currency of the loan:

- Uruguayan Pesos: ITLUP[3], 4y node + 450 b.p. (17.22%, April 2020)
- UI: CUI[4], 4y node + 250 b.p. (5.65%, April 2020)
- US Dollars: CUD[5], 4y node + 250 b.p. (5.24%, April 2020)

Finally, the decision-making on borrower eligibility and credit risk was fully devoted to the lender.

The program started with what was called "SiGa Emergency", which was the main type of fund developed in order to cope with the economic impact of the pandemic in micro, small and medium-sized firms. Later, other funds were launched: "SiGa Corporate", targeting large enterprises and "SiGa Tourism", which focused on firms operating in the Touristic Industry.

4 Data

4.1 Datasets

I exploit three databases from the Central Bank of Uruguay in its role as banking regulator and supervisor, all of which cover the period from January 2015 to January 2021 and are available on a monthly basis.

[2]The previous design of the mechanism included fees cosiderable higher than the ones applied from 2020 on.

[3]The ITLUP Curve is a Spot Curve of Yields of Uruguayan Securities with sovereign risk issued in current national currency (Uruguayan pesos).

[4]Yield Spot Curve of Uruguayan Sovereign Securities issued in national currency indexed to inflation.

[5]Yield Spot Curve of Uruguayan Sovereign Securities issued in United States dollars.

The first dataset is the Credit Registry of the Central Bank of Uruguay (*"Central de Riesgos Crediticios"*), which is an exhaustive record of all loans granted in the system with detailed information at the loan level.[6] It contains information about the identity of the borrower, the country of residence, the economic sector to which the firm belongs, all the financial institutions with which it has a loan and/or a collateral, the amount of the loan, the currency of the loan, its maturity, and a credit rating assigned to the borrower. The second dataset includes balance sheet and income statement information of all the financial institutions operating in the Uruguayan financial system during the period considered. Finally, I also have a dataset of the portfolio of SiGa[7] loans, which contains detailed monthly information of these loans' contracts, including the percentage of coverage, the destination of the guaranteed loan, the amount, currency and maturity of the loan, as Ill as the grace period and the frequency of amortization.

My initial dataset includes 2.044 million observations and consists of all the accounting codes associated with performing and non-performing loans granted by all financial institutions that must report to the Central Bank of Uruguay's Credit Registry, as well as the accounting codes associated with collaterals and personal guarantees. Next, I focus only on banking institutions and on credit granted to firms, reducing the sample to 37 million observations. The non-banking institutions were excluded from the sample because their operative focuses mainly on consumer lending. After reshaping all the variables associated with type of debt and collapsing the dataset at the bank-firm-currency level, I exclude accounting codes associated with contingencies and credit cards and observations with loan amounts lower than 1.000 Uruguayan pesos (USD 23 approximately), arriving to a final sample of 3 million observations. As a result, my dataset includes loans granted from 11 banking institutions to an average of approximately 35.000 different firms per

[6]From June 2013, the Credit Registry has a reporting threshold of zero, so I am able to observe all lending.

[7]From now on, I will use indistinctively the terms PCG and SiGa to refer to these particular type of loans.

year between 2015 and 2021 (a total of 60.347 firms appear at least once during the whole period considered). [8]

A relevant feature of my dataset is that it includes detailed information about the characteristics of the collateral and personal guarantees that the borrower has offered the banking institution. This is an advantage in comparison to other Credit Registries since I can identify those loans granted under the partial public guarantee scheme implemented during the COVID-19 crises; in addition, I can also classify firms' personal guarantees according to the liquidity of the assets offered as guarantee. Moreover, given that I also have the detailed information about PCG, I complement the information from the Credit Registry with variables such as the destination of the PCG loan (working capital, investment capital, restructured loans), the days past due of the loan, the type of SiGa Fund (MSMEs, Tourism, SiGa Corporate), the interest rate charged, the grace period, and the frequency of amortization.

Finally, I also have data on the economic impact of the pandemic over the Uruguayan economy, through which I can identify the economic sectors that were affected or moderately affected by the pandemic.

4.2 Descriptive Statistics

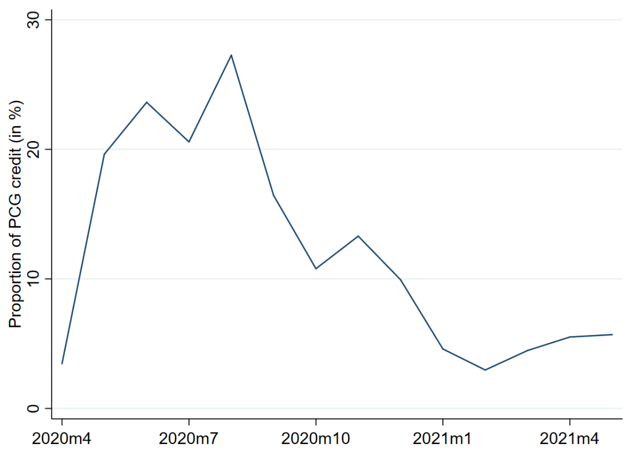
4.3 The PCG Scheme

The first cases of COVID-19 in Uruguay were detected the 13th March 2020. As a reaction, the economy shuted down and many businesses were closed temporarily. The authorities implemented a battery of policies in order to support households and firms through the pandemic. In particular, in order to cope with the effects of the COVID-19 pandemic and support credit to MSMEs, the existing PCG scheme was extended in

[8] It is important to mention that in November 2015 Scotiabank acquired Discount Bank; given that my sample starts in January 2015, I decided to treat this acquisition as if it had occurred at the beginning of the period.

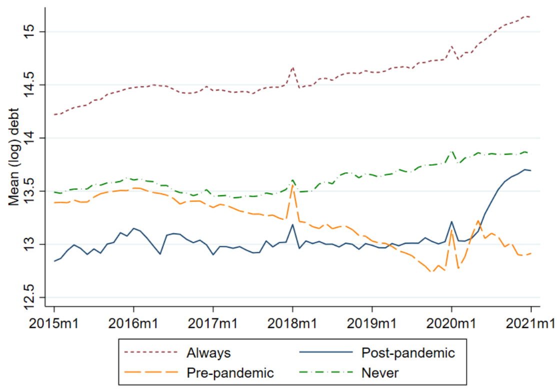
April 2020. Since that month, the credit granted using the PCG program reached a total of USD 780 million, which on average represented almost 13% of total monthly credit granted to MSMEs. Figure 2 shows the proportion of credit to MSMEs granted through the new PCG program. At its peak in August 2020, 27% of credit to MSMEs was backed with a PCG.

Figure 2: *Proportion of credit to MSMEs through the PCG scheme (in %)*



Albeit in a smaller scale, given that the PCG program was available before the pandemic, I can classify firms in four groups: those that never received a loan with a PCG, those that received a loan with a PCG before the pandemic, those that received a PCG backed loan during the pandemic and those that received a loan under the PCG program before and during the pandemic. Figure 3 shows the average (log) debt for each of these four groups of firms during the period between January 2015 and January 2021. Average credit increased the most among firms that received a PCG backed credit in the pandemic period, i.e. after March 2020. For that group of firms, average debt increased 66% between February 2020, the month immediately before the start of the pandemic in Uruguay, and January 2021. Average debt increased 40% among firms that already got a PCG credit before the pandemic and continue having one during the pandemic. Finally, average debt for those that never received a PCG backed loan and those that received one only before the pandemic increased 10% and 14% respectively during that period.

Figure 3: *Average debt by firm type (in log)*



In addition, a relevant question is whether these SiGa borrowers ask for these type of loans to their main bank or if they Int for an alternative banking institution (with which they have a relationship or with an entirely new one). As can be seen in Table 1, approximately 91% of those firms with SiGa Funds taken during the pandemic period decided to take these type of loans from the main bank with which they hold a debt relationship.

Table 1: *PCG Granted by the main bank (2020)*

Bank granting PCG Loan	**%**
Non-main bank	9,4%
Main bank	90,6%

4.4 The banking system

Uruguay's banking system offers an excellent setup for the analysis in this paper because among the 11 banking institutions there is a state-owned bank that accounts for approximately 30% of the bank loan market.[9] The other banks are private-owned, international

[9]We exclude from the analysis the other state-owned bank because its only line of business are mortgage loans.

banks mainly organized as branches. Despite its differential ownership, all banks are subject to exactly the same banking regulation and supervision. Moreover, the state-owned bank declares to behave as any other commercial bank, pursuing the objective of maximizing profits.

Nevertheless, there are some observable differences with respect to private-owned banks. For instance, the board members of the state-owned bank are appointed by the government. In general, the proportion of members representing the government and opposition parties approximates the proportion of votes obtained by each party in the last national election. Another difference is that the state-owned bank has a broad physical net of branch offices throughout the country, reaching areas with a relatively low density of population and possibly out of a cost-efficient range.

The banking system displays a sound situation in terms of solvency and liquidity. Figure 4 shows the solvency ratio. The average capital adequacy ratio (CAR) is 13% during the period under analysis. All banks have a ratio above 10%. In particular, the state-owned bank has a capital adequacy ratio well above the regulatory minimum of 10%, which includes the systemic risk requirement: the bank's average CAR in 2020 was 21%.

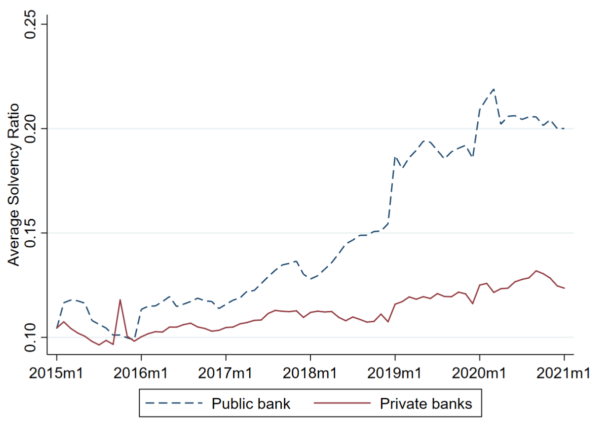


Figure 4: *Average Capital Adequacy Ratio*

In addition, the quality of the total portfolio of loans –measured by the non-performing loans (NPL) ratio– may also be considered adequate: the average NPL ratio has been between 3-4% in the period under analysis (see Figure 5). The increase in the portion of NPL between 2017 and 2018, although departing from low levels, is mainly explained by the performance of loans associated to the primary sector, which suffered an idiosyncratic shock during that period. Although the ratio of NPL is slightly higher for the state-owned bank, both private and state-owned banks share a similar trend and the ratio is below 5% from 2019 onward.

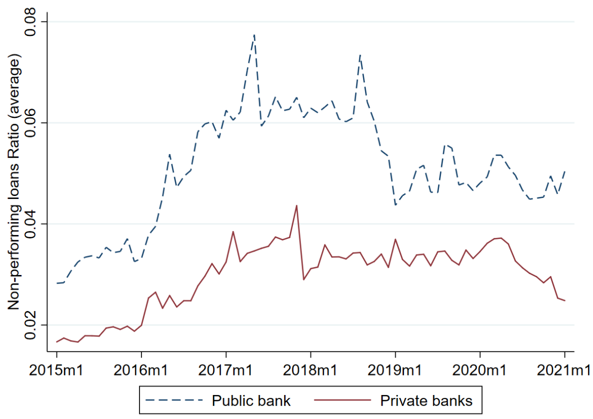


Figure 5: *Average Non-Performing Loans Ratio*

5 Empirical Strategy

5.1 Which firms get a PCG loan?

To assess which characteristics of the firms are relevant to get PCG backed lending, I estimate the following linear probability model:

$$PCG_{f,b,t} = \delta_b + \gamma_t + \beta_1 A_f + \beta_2 X_{f,b,t} + \beta_3 H_{b,t} + \epsilon_{f,b,t}, \quad (1)$$

where the dependent variable, $PCG_{f,b,t}$, is a dummy variable that equals 1 if firm f at time t gets a PCG backed loan by bank b, and 0 if the loan is not backed by a PCG.

Among firms' characteristics I include a time-invariant variable, A_f, that classifies firms according to the impact of COVID in their economic sector into "Affected", "Moderately Affected", "Not affected", and "No Information". This variable was elaborated by the Economic Statistics Division of the Banco Central del Uruguay using key economic indicators and data that is routinely used in the compilation of National Accounts.

Other characteristics of the firms are defined at the firm-bank level, $X_{f,b,t}$. They are captured by a set of variables describing (i) the portfolio of loans of the firm: *Firm USD Debt Ratio*, *Firm Short-term Debt Ratio*, and *Switch Collaterals*; (ii) the performance of firms' credit portfolio: *Firm NPL Ratio*, *Firm Write-Off Ratio*, and *Firm Debt Restructuring Ratio*; and (iii) other characteristics: the *Number of bank relationships*. The definitions of these variables are in Table A.1 in the Appendix.

Regarding banks' characteristics, $H_{b,t}$, I include the following: *Solvency Ratio*, defined as the ratio of capital to risk weighted assets; *Credit/Asset Ratio*, given by the ratio between total loans to total assets; *Non-Performing Loan Ratio*, the ratio of non-performing loans over the total loan portfolio of the bank; and *RoE*, a profitability measure given by the ratio of Return-on-Equity. The definitions of these variables are in Table A.2 in the Appendix.

All estimations are performed for the pre-COVID period (March 2019 to February 2020) and for the COVID period (March 2020 to January 2021).[10] All regressions are estimated using ordinary least squares. Fixed-effects are included at the firm, α_f, bank, δ_b, and time, γ_t, level depending on the specification. Standard errors are clustered at the bank-economic sector level in order to account for potential correlation in the residuals.

[10] The first confirmed cases of COVID where identified on the 13th March 2020.

5.2 Financial additionality: which is the impact of a PCG on credit growth?

Next, I explore whether the provision of PCG loans has an impact on credit growth using the following specification:

$$\triangle \ln C_{f,b,t} = \alpha_f + \delta_b + \gamma_t + \beta_1 PCG_{f,b,t} + \beta_2 X_{f,b,t} + \beta_3 H_{b,t} + \epsilon_{f,b,t}. \tag{2}$$

The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months $t-1$ and t. The key explanatory variable is $PCG_{f,b,t}$, which indicates whether the firm received a loan backed by a PCG from bank b at time t. Other covariates include firm characteristics ($X_{f,b,t}$) and bank characteristics ($H_{b,t}$). Firm, bank and time fixed effects are also included. In the most saturated estimations we also include the interaction of the firm and time fixed effects to control for different dynamics among firms.

Following Khwaja and Mian (2008), I restrict the sample to those firms with more than one bank relationships. Hence, identification of the effect of a PCG loan on credit growth comes from within firm variation. To be more specific, in order to be able to identify the effect of the PCG program on credit growth I need to have firms with a regular loan in one bank and a PCG backed loan in another bank.

5.3 Loan portfolio substitution: which is the impact of a PCG on other guarantees?

It is likely that loans backed by a PCG entail lower credit risk than similar loans with other type of collateral. If this is the case, they are cheaper for banks in terms of capital consumption, which may create incentives for banks to substitute non-liquid guarantees with a PCG (see, for instance, Uesugi et al., 2010). To test for this kind of guarantee substitution, I estimate the following model:

$$\ln NonPCG_{f,b,t+1} = \alpha_f + \delta_b + \gamma_t + \beta_1 PCG_{f,b,t} + \beta_2 X_{f,b,t} + \beta_3 H_{b,t} + \epsilon_{f,b,t}. \tag{3}$$

The dependent variable is the logarithm of the total amount of guarantees that are different from the PCG scheme for the pair of bank b and firm f in $t+1$. Again, the independent variable of interest is $PCG_{f,b,t}$ and, as before, $X_{f,b,t}$ and $H_{b,t}$ stand for firm-loan and bank characteristics respectively. I also saturate the specification with fixed effects.

5.4 Are there differences between private- and state-owned banks?

When coping with shutdowns like the one experienced after the COVID-19 shock, a relevant question is which is the most effective channel to direct funds in order to help the most affected MSMEs. I try to answer this question by analyzing if the impact of the PCG policy on lending is different whether the banking institution is a private commercial bank or a state-owned bank (Equation 4).

$$\triangle \ln C_{f,b,t} = \alpha_f + \delta_b + \gamma_t + \beta_1 State_{b,t} + \beta_2 X_{f,b,t} + \beta_3 H_{b,t} + \epsilon_{f,b,t}. \tag{4}$$

The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months $t-1$ and t. $State_{b,t}$ is a dummy variable taking the value one when the bank granting the loan is the state-owned one, and zero otherwise. Other controls include firm characteristics ($X_{f,b,t}$), bank characteristics ($H_{b,t}$), and fixed effects.

6 Results

6.1 *Determinants of getting a PCG*

The main estimation results for Equation 1 are in Table 2.[11] Coefficients in Table 2 should be interpreted with respect to firms in non-affected sectors, which is the omitted category. Columns (2) and (4) show that firms operating in affected and moderately affected sectors are more likely to receive a PCG loan during the pandemic. The coefficients are statistically significant, positive and higher than the corresponding coefficients for the pre-COVID period (columns (1) and (3)). These results hold after controlling for firm and bank characteristics (see columns (3) and (4)).

Table 2: *Affected and moderately affected firms get more PCG during the pandemic*

	(1) Pre-COVID	(2) COVID	(3) Pre-COVID	(4) COVID
Affected_f	0.028**	0.077**	0.019	0.050*
	(0.013)	(0.032)	(0.012)	(0.026)
$\text{Moderately Affected}_f$	0.036***	0.087***	0.029***	0.066***
	(0.011)	(0.028)	(0.010)	(0.022)
No information_f	0.017*	0.064**	0.007	0.037
	(0.010)	(0.031)	(0.009)	(0.026)
Firm FE	N	N	N	N
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
Bank Controls	N	N	Y	Y
Observations	424,689	369,935	424,689	369,935
R-squared	0.024	0.106	0.032	0.122

The dependent variable is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors are clustered at bank-economic sector level and reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

In addition, some firm characteristics have a statistically significant and positive relationship with the probability of being granted a PCG loan. Specifically, firms with a

[11] Tables C.1 and C.2 in the Appendix show detailed results and a robustness check using a probit specification instead of a linear probability model, respectively.

larger number of bank relationships are more likely to receive a PCG loan during the pandemic. Moreover, firms with a weaker debt performance (i.e. higher non-performing loan ratio and write-off ratio) are less likely to receive a PCG loan (see column (4) in Table C.1 in the Appendix). This result is desirable from a credit risk perspective, and it is also consistent with the design of the PCG mechanism (see Section 3). On top of that, firms with larger USD debt ratio and Short-term debt ratio are less likely to get a PCG loan.

6.2 *Financial Additionality: Impact on credit growth*

The main results of estimating equation 2 are in Table 3. Table C.3 in the Appendix shows detailed results. As before, all estimations are performed for the pre-COVID period (March 2019 to February 2020) and for the COVID period (March 2020 to January 2021). Standard errors are clustered at the bank-economic sector level. Given that the number of firms with more than one banking relationship is approximately one third of the total number of firms with bank loans, there might be concerns about the external validity of the results. Table C.4 in the Appendix shows that the results remain robust when Equation 2 is estimated for the whole sample of firms.

Results show that the PCG program has a statistically significant, positive impact on credit growth during the pandemic. Specifically, the results suggest that there is a monthly credit growth approximately 6 percentage points higher among PCG loans than among the rest of loans (Columns (2)-(3), (5)-(6) and (8)-(9)). However, we do not find significant differences in credit growth among firms operating in economic sectors that were (moderately) affected by the pandemic.

Table 3: *PCG have a positive impact on credit growth*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) COVID
$PCG_{f,b,t}$	0.008**	0.075***	0.067***	0.009**	0.075***	0.062***	0.007*	0.074***	0.066***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
$PCG_{f,b,t} \times Affected_f$				-0.018**	0.001	0.014			
				(0.009)	(0.008)	(0.010)			
$PCG_{f,b,t} \times \text{Moderat. Affected}_f$				0.001	-0.007	-0.001			
				(0.007)	(0.008)	(0.008)			
$PCG_{f,b,t} \times \text{No Information}_f$				0.016	0.002	0.014			
				(0.010)	(0.014)	(0.012)			
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y
Firm Controls	N	N	N	N	N	N	Y	Y	Y
Bank Controls	N	N	N	N	N	N	Y	Y	Y
Observations	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891
R-squared	0.062	0.052	0.430	0.062	0.052	0.430	0.065	0.053	0.430

The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months $t-1$ and t. $PCG_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

6.3 *Loan portfolio substitution: Impact of a PCA on other guarantees*

Table 4 shows the main results and Table C.5 in the Appendix shows more detailed results. There is evidence of some degree of guarantee substitution both before and during the pandemic. Nevertheless, the size of the coefficients is smaller in the COVID period, implying that guarantees' substitution does not increase during the pandemic.

Table 4: *Guarantees' substitution does not increase during the pandemic*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) COVID
$\text{PCG}_{f,b,t}$	-0.279***	-0.188***	-0.206***	-0.379**	-0.233***	-0.273***	-0.399**	-0.234***	-0.275***
	(0.098)	(0.041)	(0.062)	(0.162)	(0.051)	(0.079)	(0.157)	(0.051)	(0.078)
$\text{PCG}_{f,b,t}\times\text{Affected}_f$				0.270	0.040	0.070	0.291	0.057	0.089
				(0.265)	(0.094)	(0.146)	(0.264)	(0.095)	(0.148)
$\text{PCG}_{f,b,t}\times\text{Moderat. Affected}_f$				0.315	0.059	0.084	0.340	0.065	0.087
				(0.205)	(0.082)	(0.126)	(0.203)	(0.082)	(0.126)
$\text{PCG}_{f,b,t}\times\text{No Information}_{f,b,t}$				-0.129	0.174**	0.247*	-0.117	0.189**	0.259*
				(0.264)	(0.077)	(0.132)	(0.261)	(0.077)	(0.130)
Firm FE	N	N	N	N	N	N	N	N	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y
Firm Controls	N	N	N	N	N	N	Y	Y	Y
Bank Controls	N	N	N	N	N	N	Y	Y	Y
Observations	119,545	92,177	77,683	119,545	92,177	77,683	119,545	92,177	77,683
R-squared	0.725	0.726	0.710	0.725	0.726	0.710	0.726	0.727	0.711

The dependent variable is the logarithm of the total amount of guarantees that are different from the PCG scheme for the pair of bank b and firm f in $t+1$. $\text{PCG}_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

6.4 *Public vs Private Banks*

Finally, I analyze if there is a differential effect on lending depending on whether the banking institution is a private commercial bank or a state-owned bank

I start the analysis by looking at the lending behavior of the state-owned bank and comparing it with that of private-owned banks. In particular, I first assess whether it is more likely to get PCG backed loans from the state-owned bank than from private-owned ones during the COVID period.

Table 5 reports the coefficients for the bank fixed effects associated to columns (3) and (4) of Table 2, i.e. for the estimation of the most saturated versions of Equation 1. All the statistically significant coefficients are negative, suggesting that the state-owned bank, which is the omitted category, is more likely to grant loan backed with a PCG than private-owned counterparts.

Turning to the analysis of the impact of the state-owned bank on credit growth, to estimate Equation 4 I further restrict the sample by focusing on firms with more than one banking relationship, where one of the relationships is held with the state-owned bank.

Table 5: *The state-owned bank is more likely to give PCG credit*

	(3) Pre-COVID	(4) COVID
Private bank 1	0.066***	-0.343**
	(0.024)	(0.149)
Private bank 2	0.007	-0.546***
	(0.013)	(0.112)
Private bank 3	0.009	-0.483***
	(0.019)	(0.087)
Private bank 4	0.097***	-0.378***
	(0.028)	(0.139)
Private bank 5	0.006	-0.575***
	(0.016)	(0.119)
Private bank 6	-0.011	-0.468***
	(0.020)	(0.127)
Private bank 7	-0.046***	-0.450***
	(0.013)	(0.063)
Private bank 8	-0.042***	-0.134
	(0.014)	(0.117)
Private bank 9	-0.085***	-0.080
	(0.019)	(0.206)
Firm FE	N	N
Bank FE	Y	Y
Time FE	Y	Y
Firm Controls	Y	Y
Bank Controls	Y	Y
Observations	424,689	369,935
R-squared	0.032	0.122

I then check the external validity of the results by estimating Equation **??** for thesample considered in Section 5.

The main results are in Table 6. Tables C.8 and C.9 in the Appendix show detailed results and external validity checks respectively. All estimations are performed for the pre-COVID period (March 2019 to February 2020) and for the COVID period (March 2020 to January 2021); standard errors are clustered at bank-industry level. The omitted variable is the interaction term between non-PCG loans and private-owned bank, and serves as a benchmark for the estimates of the other interactions.

The estimates show several interesting results. First, among private-owned banks PCG credit exhibits a statistically significant higher growth rate than non-PCG loans during the pandemic. More precisely, credit growth was about 8 percentage points higher for loans backed by a PCG than for those that do not get a public guarantee (column

Table 6: *The state-owned bank lends more, even without PCG*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID
Non_PCG$_{f,b,t}$×State$_{b,t}$	0.019***	0.030***	0.030***	0.046***	0.008	0.002
	(0.002)	(0.003)	(0.003)	(0.015)	(0.014)	(0.013)
PCG$_{f,b,t}$×Private$_{b,t}$	-0.005	0.080***	0.072***	-0.005	0.081***	0.073***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
PCG$_{f,b,t}$×State$_{b,t}$	0.051***	0.093***	0.084***	0.077***	0.072***	0.057***
	(0.007)	(0.003)	(0.005)	(0.017)	(0.013)	(0.014)
Firm FE	Y	Y	Y	Y	Y	Y
Bank FE	N	N	N	N	N	N
Time FE	Y	Y	Y	Y	Y	Y
Firm×Time FE	N	N	Y	N	N	Y
Firm Controls	N	N	N	Y	Y	Y
Bank Controls	N	N	N	Y	Y	Y
Observations	90,271	80,721	79,264	90,271	80,721	79,264
R-squared	0.053	0.052	0.417	0.053	0.053	0.418

The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months $t-1$ and t. PCG$_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. State$_{b,t}$ is a dummy that indicates if the bank granting the loan is the state-owned bank. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-broad sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

(2)). Second, when considering credit granted by the state-owned bank, we observe a positive and statistically significant effect during the pandemic for both PCG and non-PCG loans. Specifically, credit growth of non-PCG loans granted by the state-owned bank was approximately 3 percentage points higher compared to non-PCG loans granted by private-owned banks. These results suggest that the PCG and the state-owned bank's lending decisions complement each other. The statistical significance of these results holds after including firm and bank characteristics.

7 Final remarks

The global business shutdown derived from the COVID-19 shock posed the challenge for policymakers of designing a quick an effective response to alleviate the negative impact of the pandemic on the activity of small firms. Using a granular loan and guarantee data, I study the impact of a Public Credit Guarantee Scheme implemented in Uruguay.

According to my results, firms operating in industries that were affected by the pandemic are more likely to receive a PCG loan. These results hold after controlling for firm-loan and bank characteristics.

The results show that the expansion of the PCG program had a positive impact on credit growth. Although I find evidence that suggests that banks may have substituted non-liquid guarantees with SiGa funds, this result is mild with respect to the positive impact on the supply of loans.

When comparing the effect of the PCG policy among private and public banks, I find that although both types of banking institutions granted a higher amount of credit to PCG borrowers, this effect is even higher in the case of state-owned banks (additional effect 3 percentage points higher when compared to private banks). This results show that both policy tools are complements rather than substitutes. On top of the positive effects on credit growth to the most affected firms implied by the PCG scheme, the state-owned bank extends more credit.

Finally, my empirical approach might suffer from some sources of endogeneity that need to be acknowledged. First, there is a problem of selection bias between firms affected by the COVID-19 shock and the non-affected. I try to address this using the qualitative variable "Affected" that is built based on the impact of the pandemic over the value added of each economic sector and exploiting the heterogeneity within firms for the sample of firms with more than one banking relationship. In addition, I have an omitted variable bias because the Uruguayan Credit Registry does not include interest rates. One could try to address this using a complementary dataset from the Central Bank of Uruguay that includes information on new loan contracts for month, which includes the price of loans. Nonetheless, the level of aggregation of this dataset is higher than that of the Credit Registry, which makes it impossible to combine both datasets.

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Appendix

A Definition of the variables

Table A.1: ***Firm-bank characteristics***

Variable	Description
Number of Bank Relationships	Firm's number of banking relations
Firm NPL Ratio	Firm's ratio of non-performing loans over the total amount of loans
Firm Write-Off Ratio	Firm's ratio of written-off debt over the total amount of loans
Firm Debt Rest. Ratio	Firm's ratio of restructured debt over the total amount of loans
Firm USD Debt Ratio	Firm's ratio of USD denominated debt over the total amount of loans
Firm ST Debt Ratio	Firm's ratio of short-term debt over the total amount of loans
Switch Collaterals	Dummy that indicates whether a non-liquid guarantee has been substituted with a liquid (PCG) guarantee

Source: Authors' computation based on data from the Credit Registry of the Central Bank of Uruguay (*"Central de Riesgos Crediticios"*).

Table A.2: ***Bank characteristics***

Variable	Description
Solvency Ratio	Capital over risk-weighted assets
Credit/Assets Ratio	Total credit (net of provisions) over total assets
NPL Ratio	Non-performing loans over total loans
RoE	Annualized return on equity

Source: Supervisory data from the Central Bank of Uruguay.

B Summary Statistics

Table B.1: *Summary statistics*

Variable	count	mean	sd	min	p25	p50	p75	max
# Bank Rela.$_{b,f,t}$	830.289	1,62	1,01	1	1	1	2	8
Firm NPL Ratio$_{b,f,t}$	830.289	0,01	0,1	0	0	0	0	1
Firm Write Off Ratio$_{b,f,t}$	830.289	0,01	0,07	0	0	0	0	1
Firm Debt Reest. Ratio$_{b,f,t}$	830.289	0,04	0,18	0	0	0	0	1
Firm USD Debt Ratio$_{b,f,t}$	830.289	0,63	0,47	0	0	1	1	1
Firm ST. Debt Ratio$_{b,f,t}$	830.289	0,21	0,31	0	0	0	0,4	1
Switch Collaterals$_{b,f,t}$	830.289	0	0,03	0	0	0	0	1
Bank Solvency Ratio$_{b,t}$	830.079	0,15	0,04	0,1	0,12	0,13	0,19	0,27
Bank Credit/Assets Ratio$_{b,t}$	830.079	0,37	0,11	0,07	0,24	0,4	0,45	0,58
Bank NPL Ratio$_{b,t}$	830.079	0,04	0,02	0	0,02	0,03	0,05	0,14
Bank RoE$_{b,t}$	830.079	0,02	0,01	-0,05	0,01	0,02	0,03	0,08

C Detailed tables, robustness and external validity checks

Table C.1: *Detailed results: Which firms get a PCG?*

	(1) Pre-COVID	(2) COVID	(3) Pre-COVID	(4) COVID	(5) Pre-COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) Pre-COVID	(10) COVID
Affected_f	0.028**	0.077**	0.019	0.050*	0.028	0.069*	0.019	0.050*		
	(0.013)	(0.032)	(0.012)	(0.026)	(0.017)	(0.035)	(0.012)	(0.026)		
$\text{Moderately Affected}_f$	0.036***	0.087***	0.029***	0.066***	0.033***	0.076***	0.029***	0.066***		
	(0.011)	(0.028)	(0.010)	(0.022)	(0.011)	(0.028)	(0.010)	(0.022)		
No information_f	0.017*	0.064**	0.007	0.037	0.016*	0.057*	0.007	0.037		
	(0.010)	(0.031)	(0.009)	(0.026)	(0.009)	(0.029)	(0.009)	(0.026)		
$\text{\# Bank Rela.}_{f,b,t}$			0.004*	0.014**			0.004*	0.014**	-0.002	0.010*
			(0.002)	(0.007)			(0.002)	(0.007)	(0.002)	(0.005)
$\text{Firm NPL Ratio}_{f,b,t}$			0.017	-0.135***			0.017	-0.133***	-0.007	-0.051***
			(0.014)	(0.028)			(0.014)	(0.027)	(0.008)	(0.015)
$\text{Firm Write Off Ratio}_{f,b,t}$			0.010	-0.202***			0.010	-0.201***	0.002	-0.147***
			(0.018)	(0.030)			(0.018)	(0.030)	(0.012)	(0.029)
$\text{Firm Debt Reest. Ratio}_{f,b,t}$			0.073**	-0.071			0.073**	-0.070	0.111	-0.043
			(0.034)	(0.044)			(0.034)	(0.044)	(0.082)	(0.027)
$\text{Firm USD Debt Ratio}_{f,b,t}$			-0.032***	-0.073***			-0.032***	-0.073***	-0.005	-0.046**
			(0.006)	(0.016)			(0.006)	(0.016)	(0.010)	(0.020)
$\text{Firm ST. Debt Ratio}_{f,b,t}$			-0.000	-0.000*			-0.000	-0.000*	0.000	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)
$\text{Switch Collaterals}_{f,b,t}$			0.925***	0.670***			0.925***	0.669***	0.305***	0.354***
			(0.011)	(0.036)			(0.011)	(0.036)	(0.059)	(0.040)
$\text{Bank Solvency Ratio}_{b,t}$					0.391	2.877***	0.505***	-1.077	0.391**	-0.959*
					(0.396)	(1.052)	(0.186)	(0.649)	(0.174)	(0.533)
$\text{Bank Credit/Assets Ratio}_{b,t}$					0.294*	1.349***	0.023	1.595***	0.023	0.889**
					(0.149)	(0.428)	(0.048)	(0.556)	(0.052)	(0.368)
$\text{Bank NPL Ratio}_{b,t}$					1.149***	2.331**	-0.242	1.047	-0.306	0.140
					(0.338)	(1.096)	(0.224)	(1.459)	(0.207)	(1.186)
$\text{Bank RoE}_{b,t}$					0.036	0.814***	-0.149*	0.055	-0.135*	0.053
					(0.072)	(0.275)	(0.077)	(0.236)	(0.071)	(0.199)
Firm FE	N	N	N	N	N	N	N	N	Y	Y
Bank FE	Y	Y	Y	Y	N	N	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	424,689	369,935	424,689	369,935	424,689	369,935	424,689	369,935	422,297	367,802
R-squared	0.024	0.106	0.032	0.120	0.012	0.084	0.032	0.122	0.723	0.676

This table presents the results of specification 1. The dependent variable is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level and reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.2: *Robustness: Which firms get a PCG using a Probit model*

	(1) COVID	(2) COVID	(3) COVID	(4) COVID
Affected_f	0.263**	0.167*	0.243**	0.167*
	(0.106)	(0.092)	(0.112)	(0.092)
$\text{Moderately Affected}_f$	0.301***	0.233***	0.270***	0.233***
	(0.093)	(0.076)	(0.089)	(0.076)
No information_f	0.219**	0.132	0.196**	0.132
	(0.108)	(0.096)	(0.100)	(0.096)
$\#\ \text{Bank Rela.}_{f,b,t}$		0.058**		0.058**
		(0.026)		(0.026)
$\text{Firm NPL Ratio}_{f,b,t}$		-0.486***		-0.484***
		(0.091)		(0.091)
$\text{Firm Write Off Ratio}_{f,b,t}$		-0.972***		-0.972***
		(0.143)		(0.143)
$\text{Firm Debt Reest. Ratio}_{f,b,t}$		-0.246		-0.245
		(0.195)		(0.195)
$\text{Firm USD Debt Ratio}_{f,b,t}$		-0.260***		-0.260***
		(0.057)		(0.058)
$\text{Firm ST. Debt Ratio}_{f,b,t}$		-0.052*		-0.051*
		(0.027)		(0.027)
$\text{Bank Solvency Ratio}_{b,t}$			8.846***	-6.547***
			(3.411)	(1.018)
$\text{Bank Credit/Assets Ratio}_{b,t}$			5.738***	0.958
			(1.650)	(0.991)
$\text{Bank NPL Ratio}_{b,t}$			14.653***	-0.372
			(4.268)	(2.854)
$\text{Bank RoE}_{b,t}$			4.664***	-0.341
			(1.150)	(0.410)
Firm FE	N	N	N	N
Bank FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	369,302	368,555	369,935	368,555
R-squared	0.107	0.117	0.0893	0.118

This table presents the results of specification 1 using a Probit model. The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months t and t + 1. $\text{PCG}_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.3: *Detailed results: Impact of the PCG scheme on credit growth*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) COVID	(10) Pre-COVID	(11) COVID	(12) COVID	(13) Pre-COVID	(14) COVID	(15) COVID
$PCG_{f,b,t}$	0.008**	0.075***	0.067***	0.009**	0.075***	0.062***	0.007*	0.074***	0.066***	0.008**	0.075***	0.067***	0.007*	0.074***	0.066***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$PCG_{f,b,t}\times Affected_f$				-0.018**	0.001	0.014									
				(0.009)	(0.008)	(0.010)									
$PCG_{f,b,t}\times$Moderately $Affected_f$				0.001	-0.007	-0.001									
				(0.007)	(0.008)	(0.008)									
$PCG_{f,b,t}\times$No $Information_f$				0.016	0.002	0.014									
				(0.010)	(0.014)	(0.012)									
# Bank $Rela._{f,b,t}$							-0.004	-0.016***					-0.004	-0.016***	
							(0.006)	(0.006)					(0.006)	(0.006)	
Firm NPL $Ratio_{f,b,t}$							-0.103***	-0.103***	-0.102***				-0.105***	-0.103***	-0.102***
							(0.031)	(0.016)	(0.018)				(0.031)	(0.016)	(0.018)
Firm Write Off $Ratio_{f,b,t}$							0.022	0.017	0.002				0.021	0.017	0.001
							(0.030)	(0.033)	(0.020)				(0.031)	(0.033)	(0.020)
Firm Debt Reest. $Ratio_{f,b,t}$							0.021***	-0.001	0.002				0.020***	-0.001	0.001
							(0.006)	(0.007)	(0.008)				(0.006)	(0.007)	(0.008)
Firm USD Debt $Ratio_{f,b,t}$							-0.004	-0.017***	-0.019***				-0.005	-0.017***	-0.019***
							(0.007)	(0.006)	(0.006)				(0.007)	(0.006)	(0.006)
Firm ST. Debt $Ratio_{f,b,t}$							-0.000***	0.000**	0.000***				-0.000***	0.000**	0.000***
							(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Switch $Collaterals_{f,b,t}$							0.024	0.033	0.027				0.025	0.032	0.026
							(0.053)	(0.024)	(0.025)				(0.053)	(0.024)	(0.025)
Bank Solvency $Ratio_{b,t}$										-0.335	-0.192	-0.071	-0.334	-0.166	-0.047
										(0.395)	(0.141)	(0.159)	(0.391)	(0.140)	(0.160)
Bank Credit/Assets $Ratio_{b,t}$										2.204**	-0.203	-0.351*	2.217**	-0.203	-0.347*
										(0.845)	(0.220)	(0.200)	(0.844)	(0.219)	(0.200)
Bank NPL $Ratio_{b,t}$										1.940	-0.505	-0.266	1.935	-0.472	-0.237
										(1.320)	(0.458)	(0.494)	(1.320)	(0.460)	(0.495)
Bank $RoE_{b,t}$										-0.000	-0.089*	-0.046	-0.002	-0.088*	-0.043
										(0.216)	(0.051)	(0.050)	(0.216)	(0.050)	(0.050)
Firm FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Observations	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891
R-squared	0.062	0.052	0.430	0.062	0.052	0.430	0.063	0.053	0.430	0.064	0.052	0.430	0.065	0.053	0.430

This table presents the results of estimating 2. The dependent variable is the logarithm of the total amount of loans for the pair of bank b and firm f in $t+1$. $PCG_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.4: *External validity: Impact of the PCG scheme on credit growth*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID
$PCG_{f,b,t}$	0.014**	0.103***	0.067***	0.021***	0.102***	0.062***	0.011**	0.102***	0.066***	0.013**	0.103***	0.067***	0.011**	0.102***	0.066***
	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)
$PCG_{f,b,t}\times Affec._f$				-0.026**	0.003	0.014									
				(0.013)	(0.008)	(0.010)									
$PCG_{f,b,t}\times Mod.\ Affec._f$				-0.004	-0.002	-0.001									
				(0.009)	(0.009)	(0.008)									
$PCG_{f,b,t}\times No\ Info._f$				-0.005	0.001	0.014									
				(0.012)	(0.012)	(0.012)									
# Bank Rela.$_{f,b,t}$							-0.012***	-0.021***					-0.011***	-0.021***	
							(0.004)	(0.004)					(0.004)	(0.004)	
Firm NPL Ratio$_{f,b,t}$							-0.086***	-0.069***	-0.102***				-0.087***	-0.069***	-0.102***
							(0.021)	(0.016)	(0.018)				(0.021)	(0.016)	(0.018)
Firm Write Off Ratio$_{f,b,t}$							0.019	0.030	0.002				0.021	0.030	0.001
							(0.061)	(0.048)	(0.020)				(0.061)	(0.048)	(0.020)
Firm Debt Reest. Ratio$_{f,b,t}$							0.028***	0.005	0.002				0.027***	0.004	0.001
							(0.006)	(0.009)	(0.008)				(0.006)	(0.009)	(0.008)
Firm USD Debt Ratio$_{f,b,t}$							-0.008	-0.030***	-0.019***				-0.009	-0.030***	-0.019***
							(0.010)	(0.010)	(0.006)				(0.010)	(0.011)	(0.006)
Firm ST. Debt Ratio$_{f,b,t}$							-0.000	-0.000***	0.000***				-0.000	-0.000***	0.000***
							(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Switch Collaterals$_{f,b,t}$							0.149***	0.026	0.027				0.149***	0.026	0.026
							(0.052)	(0.023)	(0.025)				(0.052)	(0.023)	(0.025)
Bank Solvency Ratio$_{b,t}$										-0.475	-0.339	-0.071	-0.484	-0.322	-0.047
										(0.314)	(0.279)	(0.159)	(0.310)	(0.281)	(0.160)
Bank Credit/Assets Ratio$_{b,t}$										2.935***	-0.109	-0.351*	2.941***	-0.106	-0.347*
										(0.976)	(0.327)	(0.200)	(0.975)	(0.327)	(0.200)
Bank NPL Ratio$_{b,t}$										1.413	-1.164**	-0.266	1.407	-1.158**	-0.237
										(1.435)	(0.445)	(0.494)	(1.435)	(0.449)	(0.495)
Bank RoE$_{b,t}$										-0.256	-0.139	-0.046	-0.256	-0.140	-0.043
										(0.217)	(0.099)	(0.050)	(0.217)	(0.099)	(0.050)
Firm FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Observations	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891
R-squared	0.093	0.089	0.430	0.093	0.089	0.430	0.093	0.090	0.430	0.096	0.089	0.430	0.096	0.090	0.430

This table presents the results of estimating 2 for the whole sample of firms. The dependent variable is the logarithm of the total amount of loans for the pair of bank b and firm f in $t+1$. $PCG_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.5: *Detailed results: Impact of the PCG scheme on other guarantees*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) COVID
$PCG_{f,b,t}$	-0.279***	-0.188***	-0.206***	-0.379**	-0.233***	-0.273***	-0.399**	-0.234***	-0.275***
	(0.098)	(0.041)	(0.062)	(0.162)	(0.051)	(0.079)	(0.157)	(0.051)	(0.078)
$PCG_{f,b,t} \times$ Affec.$_f$				0.270	0.040	0.070	0.291	0.057	0.089
				(0.265)	(0.094)	(0.146)	(0.264)	(0.095)	(0.148)
$PCG_{f,b,t} \times$ Mod.Affec.$_f$				0.315	0.059	0.084	0.340	0.065	0.087
				(0.205)	(0.082)	(0.126)	(0.203)	(0.082)	(0.126)
$PCG_{f,b,t} \times$ No Info.$_f$				-0.129	0.174**	0.247*	-0.117	0.189**	0.259*
				(0.264)	(0.077)	(0.132)	(0.261)	(0.077)	(0.130)
$Lcred_{f,b,t}$	0.434***	0.453***	0.495***	0.434***	0.453***	0.495***	0.434***	0.451***	0.493***
	(0.017)	(0.019)	(0.025)	(0.017)	(0.019)	(0.025)	(0.017)	(0.018)	(0.025)
# Bank Rela.$_{f,b,t}$							-0.027	-0.042**	
							(0.025)	(0.018)	
Firm NPL Ratio$_{f,b,t}$							-0.043	0.221*	0.211
							(0.114)	(0.125)	(0.212)
Firm Write Off Ratio$_{f,b,t}$							-0.898*	-0.571	-0.828
							(0.457)	(0.465)	(0.638)
Firm Debt Reest. Ratio$_{f,b,t}$							0.188**	0.195**	0.191
							(0.078)	(0.096)	(0.138)
Firm USD Debt Ratio$_{f,b,t}$							0.022	0.189**	0.203*
							(0.075)	(0.071)	(0.102)
Firm ST. Debt Ratio$_{f,b,t}$							0.006***	0.004**	0.004*
							(0.001)	(0.002)	(0.003)
Switch Collaterals$_{f,b,t}$							0.040	0.165***	0.286***
							(0.110)	(0.051)	(0.103)
Bank Solvency Ratio$_{b,t}$							0.182	0.118	0.164
							(1.220)	(1.187)	(1.682)
Bank Credit/Assets Ratio$_{b,t}$							1.189*	0.238	0.863
							(0.634)	(0.372)	(0.578)
Bank NPL Ratio$_{b,t}$							3.350	-6.388***	-8.517**
							(3.678)	(1.691)	(3.262)
Bank RoE$_{b,t}$							-0.223	0.616***	0.936***
							(0.264)	(0.173)	(0.334)
Firm FE	Y	Y	N	Y	Y	N	Y	Y	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y
Observations	119,545	92,177	77,683	119,545	92,177	77,683	119,545	92,177	77,683
R-squared	0.725	0.726	0.710	0.725	0.726	0.710	0.726	0.727	0.711

This table presents the results of specification 3. The dependent variable is the logarithm of the total amount of guarantees that are different from the PCG scheme for the pair of bank b and firm f in $t+1$. $PCG_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.6: *Detailed results: Impact of the State Bank on credit growth*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID	(7) Pre-COVID	(8) COVID	(9) COVID	(10) Pre-COVID	(11) COVID	(12) COVID	(13) Pre-COVID	(14) COVID	(15) COVID
$\text{State}_{b,t}$	0.022***	0.036***	0.034***	0.025***	0.033***	0.032***	0.022***	0.035***	0.034***	0.050***	0.038***	0.027***	0.051***	0.042***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.012)	(0.009)	(0.010)	(0.013)	(0.009)	(0.011)
$\text{State}_{b,t}\times$ Affec._f				-0.010***	0.011**	0.009*									
				(0.003)	(0.004)	(0.005)									
$\text{State}_{b,t}\times$ Mod.Affec._f				-0.012***	0.009	0.008									
				(0.003)	(0.006)	(0.008)									
$\text{State}_{b,t}\times$ No Info._f				-0.004	-0.004	-0.004									
				(0.006)	(0.005)	(0.006)									
# Bank $\text{Rela.}_{f,b,t}$							-0.004	-0.016***					-0.004	-0.016***	
							(0.006)	(0.006)					(0.006)	(0.006)	
Firm NPL $\text{Ratio}_{f,b,t}$							-0.103***	-0.107***	-0.105***				-0.103***	-0.109***	-0.107***
							(0.031)	(0.016)	(0.017)				(0.031)	(0.016)	(0.017)
Firm Write Off $\text{Ratio}_{f,b,t}$							0.022	0.008	-0.006				0.024	0.008	-0.005
							(0.030)	(0.033)	(0.022)				(0.030)	(0.033)	(0.021)
Firm Debt Reest. $\text{Ratio}_{f,b,t}$							0.020***	-0.002	0.001				0.021***	-0.003	-0.000
							(0.006)	(0.006)	(0.006)				(0.006)	(0.006)	(0.006)
Firm USD Debt $\text{Ratio}_{f,b,t}$							-0.003	-0.020***	-0.021***				-0.003	-0.023***	-0.023***
							(0.007)	(0.005)	(0.005)				(0.006)	(0.005)	(0.005)
Firm ST. Debt $\text{Ratio}_{f,b,t}$							-0.000***	0.000**	0.000***				-0.000***	0.000**	0.000***
							(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Switch $\text{Collaterals}_{f,b,t}$							0.026	0.068***	0.070***				0.027	0.067**	0.069***
							(0.053)	(0.025)	(0.025)				(0.053)	(0.025)	(0.025)
Bank Solvency $\text{Ratio}_{b,t}$										-0.355	-0.104	-0.059	-0.344	-0.151	-0.117
										(0.315)	(0.109)	(0.123)	(0.310)	(0.105)	(0.128)
Bank Credit/Assets $\text{Ratio}_{b,t}$										0.078***	-0.062**	-0.072**	0.082***	-0.064**	-0.071**
										(0.024)	(0.029)	(0.032)	(0.024)	(0.029)	(0.033)
Bank NPL $\text{Ratio}_{b,t}$										0.382	-0.343**	-0.284*	0.361	-0.378***	-0.309**
										(0.300)	(0.135)	(0.144)	(0.294)	(0.132)	(0.142)
Bank $\text{RoE}_{b,t}$										0.069	-0.005	0.023	0.066	-0.015	0.013
										(0.054)	(0.026)	(0.028)	(0.053)	(0.027)	(0.028)
Firm FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Observations	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891	154,470	133,584	130,891
R-squared	0.062	0.048	0.427	0.062	0.048	0.427	0.063	0.048	0.427	0.062	0.048	0.427	0.063	0.049	0.427

This table presents the results of estimating 2. The dependent variable is the logarithm of the total amount of loans for the pair of bank b and firm f in $t+1$. $\text{State}_{b,t}$ is a dummy variable equal to 1 if the banking institution is the state-owned bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.7: *External validity: Impact of the State Bank on credit growth*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID	Pre-COVID	COVID	COVID
$\text{State}_{b,t}$	0.023***	0.038***	0.034***	0.026***	0.036***	0.032***	0.022***	0.037***	0.034***	0.073***	0.053***	0.027***	0.075***	0.056***	0.033***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.017)	(0.019)	(0.010)	(0.018)	(0.019)	(0.011)
$\text{State}_{b,t} \times$ Affec.$_f$				-0.009**	0.010*	0.009*									
				(0.004)	(0.006)	(0.005)									
$\text{State}_{b,t} \times$ Mod.Affec.$_f$				-0.014***	0.009	0.008									
				(0.004)	(0.007)	(0.008)									
$\text{State}_{b,t} \times$ No Info.$_f$				-0.002	-0.003	-0.004									
				(0.006)	(0.006)	(0.006)									
# Bank Rela.$_{f,b,t}$							-0.011***	-0.020***					-0.011***	-0.020***	
							(0.004)	(0.004)					(0.004)	(0.004)	
Firm NPL Ratio$_{f,b,t}$							-0.085***	-0.074***	-0.105***				-0.086***	-0.075***	-0.107***
							(0.021)	(0.016)	(0.017)				(0.021)	(0.016)	(0.017)
Firm Write Off Ratio$_{f,b,t}$							0.020	0.016	-0.006				0.020	0.016	-0.005
							(0.061)	(0.049)	(0.022)				(0.061)	(0.049)	(0.021)
Firm Debt Reest. Ratio$_{f,b,t}$							0.029***	0.001	0.001				0.029***	0.000	-0.000
							(0.007)	(0.008)	(0.006)				(0.007)	(0.008)	(0.006)
Firm USD Debt Ratio$_{f,b,t}$							-0.007	-0.036***	-0.021***				-0.008	-0.039***	-0.023***
							(0.009)	(0.010)	(0.005)				(0.009)	(0.010)	(0.005)
Firm ST. Debt Ratio$_{f,b,t}$							-0.000	-0.000***	0.000***				-0.000	-0.000***	0.000***
							(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Switch Collaterals$_{f,b,t}$							0.152***	0.063**	0.070***				0.152***	0.063**	0.069***
							(0.051)	(0.024)	(0.025)				(0.051)	(0.024)	(0.025)
Bank Solvency Ratio$_{b,t}$										-0.188	-0.127	-0.059	-0.192	-0.168	-0.117
										(0.332)	(0.201)	(0.123)	(0.327)	(0.190)	(0.128)
Bank Credit/Assets Ratio$_{b,t}$										0.198***	-0.046	-0.072**	0.202***	-0.053	-0.071**
										(0.048)	(0.068)	(0.032)	(0.048)	(0.065)	(0.033)
Bank NPL Ratio$_{b,t}$										0.433	-0.458*	-0.284*	0.408	-0.534*	-0.309**
										(0.409)	(0.264)	(0.144)	(0.402)	(0.267)	(0.142)
Bank RoE$_{b,t}$										0.008	-0.057	0.023	0.005	-0.070	0.013
										(0.068)	(0.079)	(0.028)	(0.067)	(0.081)	(0.028)
Firm FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y	N
Firm×Time FE	N	N	Y	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Observations	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891	404,306	351,734	130,891
R-squared	0.093	0.084	0.427	0.093	0.084	0.427	0.093	0.085	0.427	0.093	0.084	0.427	0.093	0.085	0.427

This table presents the results of estimating 2 for the whole sample of firms. The dependent variable is the logarithm of the total amount of loans for the pair of bank b and firm f in $t+1$. $\text{State}_{b,t}$ is a dummy variable equal to 1 if the banking institution is the state-owned bank b at month t, 0 otherwise. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.8: *Detailed results: Does the state-owned bank lend more?*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID
Non_PCG$_{f,b,t}\times$ State$_{b,t}$	0.019***	0.030***	0.030***	0.046***	0.008	0.002
	(0.002)	(0.003)	(0.003)	(0.015)	(0.014)	(0.013)
PCG$_{f,b,t}\times$ Private$_{b,t}$	-0.005	0.080***	0.072***	-0.005	0.081***	0.073***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
PCG$_{f,b,t}\times$ State$_{b,t}$	0.051***	0.093***	0.084***	0.077***	0.072***	0.057***
	(0.007)	(0.003)	(0.005)	(0.017)	(0.013)	(0.014)
# Bank Rela.$_{f,b,t}$				-0.012	-0.022***	
				(0.008)	(0.008)	
Firm NPL Ratio$_{f,b,t}$				-0.071**	-0.100***	-0.103***
				(0.034)	(0.016)	(0.019)
Firm Write Off Ratio$_{f,b,t}$				0.048	0.016	0.000
				(0.033)	(0.040)	(0.028)
Firm Debt Reest. Ratio$_{f,b,t}$				0.012**	-0.005	-0.006
				(0.005)	(0.006)	(0.007)
Firm USD Debt Ratio$_{f,b,t}$				0.001	-0.015*	-0.016**
				(0.007)	(0.007)	(0.007)
Firm ST. Debt Ratio$_{f,b,t}$				-0.000***	0.000***	0.000**
				(0.000)	(0.000)	(0.000)
Switch Collaterals$_{f,b,t}$				-0.117*	0.012	0.017
				(0.065)	(0.026)	(0.027)
Bank Solvency Ratio$_{b,t}$				-0.223	0.183	0.180
				(0.267)	(0.171)	(0.197)
Bank Credit/Assets Ratio$_{b,t}$				0.083**	-0.157***	-0.158***
				(0.037)	(0.045)	(0.048)
Bank NPL Ratio$_{b,t}$				0.232	-0.850***	-0.715**
				(0.280)	(0.234)	(0.276)
Bank RoE$_{b,t}$				0.032	-0.073*	-0.027
				(0.051)	(0.040)	(0.047)
Firm FE	Y	Y	N	Y	Y	N
Bank FE	N	N	N	N	N	N
Time FE	Y	Y	N	Y	Y	N
Firm$\times$Time FE	N	N	Y	N	N	Y
Observations	90,271	80,721	79,264	90,271	80,721	79,264
R-squared	0.053	0.052	0.417	0.053	0.053	0.418

This table presents the results of specification ??. The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months t and $t+1$. PCG$_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. State$_{b,t}$ is a dummy that indicates if the bank granting the loan is the state-owned bank. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Table C.9: *External validity: Does the state-owned bank lend more?*

	(1) Pre-COVID	(2) COVID	(3) COVID	(4) Pre-COVID	(5) COVID	(6) COVID
Non_PCG$_{f,b,t}\times$ State$_{b,t}$	0.021***	0.022***	0.029***	0.073***	0.018	0.014
	(0.003)	(0.004)	(0.003)	(0.018)	(0.018)	(0.010)
PCG$_{f,b,t}\times$ Private$_{b,t}$	0.002	0.097***	0.067***	-0.000	0.098***	0.069***
	(0.006)	(0.006)	(0.004)	(0.006)	(0.007)	(0.004)
PCG$_{f,b,t}\times$ State$_{b,t}$	0.060***	0.125***	0.083***	0.107***	0.122***	0.067***
	(0.007)	(0.005)	(0.005)	(0.020)	(0.019)	(0.012)
# Bank Rela.$_{f,b,t}$				-0.011***	-0.021***	
				(0.004)	(0.004)	
Firm NPL Ratio$_{f,b,t}$				-0.086***	-0.071***	-0.106***
				(0.021)	(0.016)	(0.018)
Firm Write Off Ratio$_{f,b,t}$				0.021	0.029	-0.002
				(0.061)	(0.049)	(0.020)
Firm Debt Reest. Ratio$_{f,b,t}$				0.025***	0.005	0.002
				(0.006)	(0.009)	(0.008)
Firm USD Debt Ratio$_{f,b,t}$				-0.008	-0.035***	-0.023***
				(0.009)	(0.010)	(0.006)
Firm ST. Debt Ratio$_{f,b,t}$				-0.000	-0.000***	0.000**
				(0.000)	(0.000)	(0.000)
Switch Collaterals$_{f,b,t}$				0.148***	0.025	0.026
				(0.052)	(0.023)	(0.025)
Bank Solvency Ratio$_{b,t}$				-0.203	-0.073	-0.023
				(0.325)	(0.189)	(0.140)
Bank Credit/Assets Ratio$_{b,t}$				0.201***	-0.162**	-0.148***
				(0.048)	(0.065)	(0.034)
Bank NPL Ratio$_{b,t}$				0.419	-0.749***	-0.524***
				(0.401)	(0.278)	(0.166)
Bank RoE$_{b,t}$				0.008	-0.091	-0.015
				(0.067)	(0.075)	(0.034)
Firm FE	Y	Y	N	Y	Y	N
Bank FE	N	N	N	N	N	N
Time FE	Y	Y	N	Y	Y	N
Firm$\times$Time FE	N	N	Y	N	N	Y
Observations	404,306	351,734	130,891	404,306	351,734	130,891
R-squared	0.093	0.089	0.429	0.093	0.090	0.430

This table presents the results of specification **??** for the whole sample of firms. The dependent variable is the change in the logarithm of the total amount of loans of firm f in bank b between months t and $t+1$. PCG$_{f,b,t}$ is a dummy variable equal to 1 if firm f receives a PCG loan from bank b at month t, 0 otherwise. State$_{b,t}$ is a dummy that indicates if the bank granting the loan is the state-owned bank. All regressions are estimated using ordinary least squares. Robust standard errors clustered at bank-economic sector level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.