Policy response to COVID-19 shock: measuring policy impacts on lending interest rates with granular data*

Respuesta de política ante el shock de COVID-19: medición del impacto sobre las tasas de interés activas con datos granulares

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Abstract

As a response to the COVID-19 shock, the Uruguayan government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements. Policies of the same nature were also implemented by several governments throughout the world. This paper contributes to the financial additionality literature and the literature on the bank lending view of the monetary policy by analyzing the impact of this type of policies on loans' interest rate spread over the interbank rate. Using a very detailed database on loan contracts, we estimate a dynamic panel model to analyze the effects of policy responses to the COVID-19 shock over loan interest rates. We find that the PCG policy had a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy.

Key words: *banks, COVID-19, PCG, reserve requirements, interest rate caps.*

JEL Classification: *G21, E65.*

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Resumen

Como respuesta al shock de COVID-19, el gobierno uruguayo extendió una garantía de crédito público existente e introdujo deducciones en los requisitos de reserva en moneda nacional. Este artículo contribuye a la literatura sobre adicionalidad financiera y la literatura sobre el canal crediticio de la política monetaria. A partir de datos detallados de contratos de préstamos, estimamos un modelo de panel dinámico para analizar los efectos de las respuestas de política al shock de COVID-19 sobre las tasas de interés de los préstamos. Encontramos que la política de garantías públicas de crédito tuvo un efecto relativamente mayor sobre las tasas de interés de los préstamos en comparación con la política de deducción de requisitos de reserva.

Palabras clave: *bancos, COVID-19, PCG, requisitos de reserva, topes de tasas de interés.*

Clasificación JEL: *G21, E65.*

1. Introduction

Following the COVID-19 shock, several governments around the globe implemented a set of policies in order to cope with the contraction in the supply of credit. Uruguay was no exception; among other policy measures, between March and April 2020 the Uruguayan Government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements.

Regarding the first policy measure, public credit guarantees were one of the most popular policy actions implemented throughout the world in support of micro-, small and medium-sized firms (MSMEs from now on) during the pandemic and the associated lockdowns. Loans backed with a public guarantee offer risk mitigation to lenders by taking a share of the lenders' losses in case of default. According to the financial additionality hypothesis (Uesugi et al. (2010), de Blasio et al. (2018)), public credit guarantees (PCG from now on) allow targeted firms to experience an increase in their credit supply and/or an improvement in their borrowing terms. For example, previous studies from Ciani et al. (2020), Calcagnini et al. (2012), and d'Ignazio and Menon (2013) find that guaranteed firms were benefited from a reduction in interest rates charged in their term loans. In addition, as was the case in other economies, the PCG policy included interest rates ceilings in order to prevent banks' predatory practices and also to facilitate cheap credit to firms suffering the impact of the pandemic. As has been analysed by the literature, although interest rate caps

can make credit more accessible and protect borrowers from exorbitant rates, they may also include side-effects in the form of credit rationing or higher non-interest fees and commissions (Ferrari et al. (2018), Freixas and Rochet (2008)). Regarding the former, the policy implemented in Uruguay also applied a significant reduction in the fees that banks could charge for this type of loans.

In addition, Uruguay's policy toolkit also included deductions in banks' reserve requirements associated to their local currency operations. Specifically, the deductions were conditional on the increase in the supply of loans in this currency. As the literature has shown, this type of monetary policy instrument may have an impact on economic activity through changes on banks' lending behavior (Bernanke and Blinder (1988), Kashyap and Stein (2000), Dassatti Camors et al. (2019)). For example, if the funds that are not subject to reserve requirements are also not covered by deposit insurance, banks will face an adverse selection problem that will disable their ability to fully substitute one unit of insured funds with one unit of non-reservable funds, hence, their lending behavior can be affected. Although other countries also applied reductions in their reserve requirements during the pandemic,[1] the usage of these type of instruments has a long history in the region (Cordella et al. (2014), Tovar Mora et al. (2012), Federico et al. (2014)).

Both measures intended to enhance firms' liquidity, one in a more general manner, and the other one targeting a specific segment of the corporate sector. In addition, the interest rate cap on loans backed by public guarantees reflects the intention of the policymaker of keeping the costs of PCG loans low. As a result, if the cap set were not binding, banks could have incentives to charge higher rates which could have rationed firms targeted by the policy. Regarding the other policy, according to the well known Monti-Klein model (Freixas and Rochet (2008)) of bank competition, reserve requirements' deductions could also translate into lower loan interest rates by reducing banks' cost of funding.

Our focus in this paper is to analyse the impact of these policies on loan's interest rates. Specifically, a relevant question is whether under a credit crunch situation it is better to release reserve requirements conditional on the growth in the supply of credit or to grant PCG loans with interest rate caps. In Uruguay, lending interest rates fell during 2020 and the first half of 2021; this fall may be explained, among other things, by a combination of domestic factors associated with an expansionary monetary policy (with an instrument change implemented in September 2020), the release of reserve requirements, and the PCG policy.

[1] During the pandemic, reserve requirements were also reduced in the United States, China, Indonesia, The Philippines and Brazil.

Applying panel data regression methods with a detailed database for 11 commercial banks from April 2020 to April 2021, this paper contributes to the financial additionality literature and the literature on the bank lending view of the monetary policy by analysing the impact of this type of policies on loans' interest rate.

The rest of the paper is structured as follows. Section 2 introduces the main features of the policy response to the COVID-19 shock. Section 3 describes our dataset and the main figures. Section 4 describes the empirical strategy and Section 5 shows the results of the estimations. Finally, Section 6 concludes.

2. Policy Framework

One of the main policies implemented by the Uruguayan government during the pandemic was the expansion of an existing PCG mechanism in April 2020. Specifically, some of the restrictions of the original mechanism were softened with the aim of reaching the more affected firms and also providing good incentives to lenders in order to avoid inefficient allocations and opportunistic behaviors.

In particular, the possible destinations of guaranteed loans now included the restructure of past loans and the extension of their maturities, in addition to the already existing possible uses as working or investment capital. The coverage of the guarantee increased to a level of up to 80% of the loan (before it was 60%) and could cover up to 50% of the credit balance of a firm restructuring previous loans. The maximum loan amount that could be covered was UI 1.200.000 (approximately US dollar 150.000),[2] and the loan could be granted either in national currency (Uruguayan pesos or UI) or in US dollar. 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 to banks decreased considerably and varied according to the currency of the loan (annual fee of 0.6% for a guarantee in domestic currency, and 0.8% in US dollar). Finally, the interest rate of guaranteed loans were now subject to caps.[3]

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2 UI stands for "Unidad Indexada"; it is a unit of value that adjusts according to inflation measured by the Consumer Price Index.

3 For loans in Uruguayan Pesos the cap was ITLUP 4y node + 450 basic points: 17.22% as of April, 2020. The *ITLUP Curve* is a spot yield curve of Uruguayan Securities with sovereign risk issued in current national currency (Uruguayan pesos). For loans in UI the cap was CUI 4y node + 250 basic points: 5.65% as of April, 2020. The *CUI Curve* is the spot curve of Uruguayan sovereign securities issued in national currency indexed to inflation. For loans in US Dollar, the cap was CUD 4y node + 250 basic points: 5.24% as of April, 2020. The *CUD Curve* is the spot yield curve of Uruguayan sovereign securities issued in US Dollar.

While the decision-making on borrower eligibility and credit risk was fully devoted to the lender, there were still a series of pre-established requirements. Firstly, the eligible firm needed to be formally established, with payment capacity and up to date with tax obligations. Secondly, the firms' annual sales must be below UI 75.000.000 (approximately 8 million US dollar). Thirdly, if the firm had already 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. Fourthly, the firm must have a relatively good rating (i.e. "2B" or better[4]) in the credit registry as of February 2020. If it had a lower rating, it would still be eligible as long as one of the following conditions were met: (i) its debt was lower than 100 US dollar 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 was at least 2B.

On the other hand, regarding the reserve requirements deductions, although this type of policy was already implemented in the past, it had a novel feature since the deductions were conditional on the increase in the stock of credit granted in local currency (Uruguayan pesos and UI) between February and June 2020. In addition, the increase in the supply of credit admitted for applying the deductions had a limit defined by a weighted sum of liabilities according to their maturities.[5]

The magnitude of both policies was significant. As a result of the PCG policy, the total loans granted as of April 2021 reached a level of USD 724 million. Before the pandemic the total stock of credit with a PCG was approximately USD 45 million, and the accumulated guaranteed credit between 2009 and 2019 reached USD 538 million. As can be seen, the total amount of guaranteed credit up to April 2021 was almost one and a half times the accumulated guaranteed credit in the previous ten years. In addition, these credits represented, on average, 3,4% of the amount of the new loans granted by the banking system per month (10% if we consider loans to MSMEs), and only 37% of these loans were granted in local currency. On the other hand, in the second half of 2020, total reserve requirements deductions reached USD 167 million per month, arising to USD 204 million during 2021. These values represent, on average, 60% of the total monthly supply of credit in local currency.

4 See Appendix A.1

5 Specifically, the weights were the following: 7% of liabilities with a maturity of less than 30 days, 5% of liabilities with a maturity between 30 and 90 days, 5% of liabilities with a maturity between 91 and 180 days, 3% of liabilities with a maturity between 181 and 367 days.

3. Data And Descriptive Statistics

3.1 Data

We exploit three databases from the Central Bank of Uruguay in its role as banking regulator and supervisor. All datasets cover the period from April 2020 to April 2021 and are available on a monthly basis.

The first database contains monthly detailed information on new loan contracts granted to firms, including variables such as the type of loan-product, the currency in which it was granted, the maturity, the interest rate and the amount of the loan, the economic sector to which the firm belongs, the size of the firm and the banking institution that granted the loan. This data is complemented with a second database with monthly information on the loan contracts guaranteed with PCG Funds, including the same variables as the previous dataset, as well as new variables associated with these type of loan contracts, such as: the period of grace, the frequency of amortization, the credit rating of the firm as of February 2020 and the current credit rating, the percentage covered by the PCG guarantee, the type of PCG Fund,[6] and the destination of the loan (working capital, investment capital, restructured debt).

We also have monthly balance sheet and income statement information from all the banking institutions operating in the Uruguayan financial system during the period considered, which we also complement with detailed information on reserve requirements deductions applied to the banks that satisfied the conditions imposed by the policy design.

After combining all datasets, we start with 910,965 observations, from which we exclude loan contracts associated to credit card debt and to operations from the Public Sector or from foreign borrowers. We then have 656,606 observations which we collapse by creating an id given by the combination of the following variables: banking institution, currency of the loan, type of loan, the industry of destination of the loan, the firm size and the maturity of the loan. The justification for this level of analysis is twofold: first, we do not have information at the firm level; second, working at the industry level would lead to results that are too aggregated. To cope with this challenge, we decided to have a unit of analysis that identifies different type of loan contracts, where the type of contract is not only given by the accounting code but also by the

[6] Initially, when the policy was created in 2009, the funds were targeted for the MSME segment of the corporate sector. During the pandemic, new specific funds were created. The first and most important fund was denominated “PCG Emergency”, since it targeted all micro, small and medium-sized firms that were being affected by the COVID-19 shock. Later on, in November 2020, a new fund (“PCG Corporate”) was created in order to target big firms (not included in the first fund during the pandemic). Finally, a “PCG Tourism” fund was created with the objective of maintaining the operative of firms in the tourism industry during the summer season.

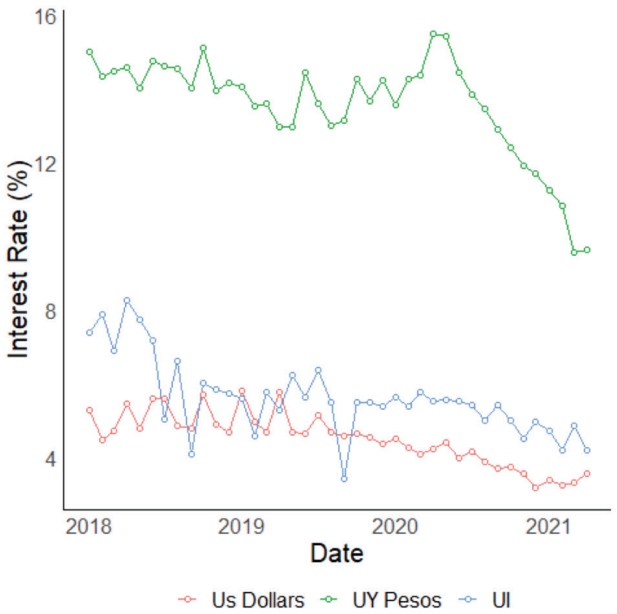
maturity and the currency of the loan operation. In order to reach a unit that uniquely identifies each of these operations, we collapse the loan amount at the id level. After this, we finish with a total of 23,844 observations that include specific loan contract data for the period between April 2020 and April 2021.[7]

3.2 Descriptive Statistics

We compute monthly interest rates at the bank level and for the aggregate of the banking system as a weighted average where the weights are given by the capital of each loan operation. This methodology was also applied for obtaining the monthly average rates of the PCG operations by bank.

FIGURE 1

BANKS' LOAN INTEREST RATE (JAN/2018 - APR/2021)



As can be observed in Fig 1, interest rates experienced a clear decrease from March 2020 onward. As we have already mentioned, this fall may be explained by a combination of factors associated to the change in monetary policy, the release of reserve requirements and the PCG policy of credit guarantees. The objective of this document is to understand how much of the effect on loan interest rates may be explained by the last two factors.

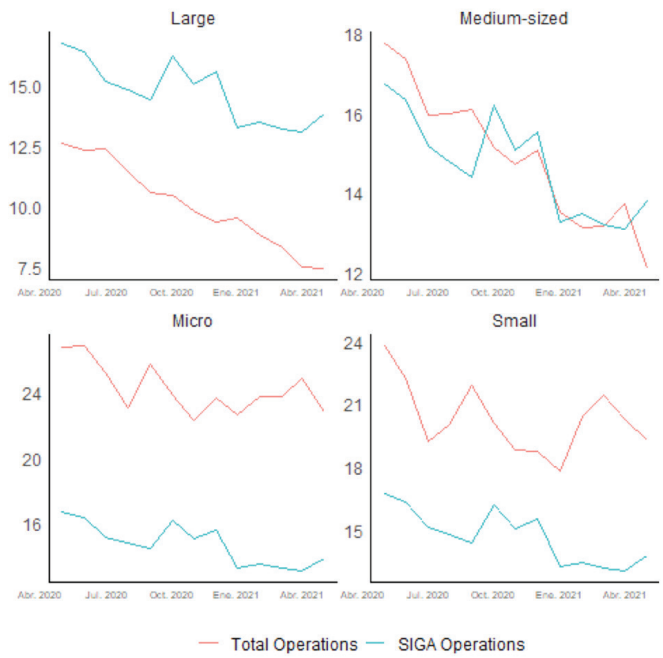
[7] We have an unbalanced panel, with 13 months and more than 400 individuals appearing in all periods.

Like most countries, Uruguay maintained an expansionary monetary policy stance during 2020. In September 2020, it changed its monetary policy instrument from money aggregates to interest rate, setting the interest rate at 4.5%, a level that was maintained until August 2021 with an inflation above 8%.

In 2020, the evolution of credit to the non-financial sector showed different performances in domestic and foreign currencies. In the former case, it increased in real terms by 3.4%, while in foreign currency it fell by 1.8%.

FIGURE 2

AVERAGE INTEREST RATES VERSUS PCG RATES IN LOCAL CURRENCY



When comparing loan interest rates charged by the banking system according to firms' size with the rate charged in PCG loans (Fig 2), we observe that the latter is lower than the average loan rate for micro and small firms. In contrast, the PCG interest rate is higher than the average rate charged to large firms. The same pattern is observed in loan contracts denominated in foreign currency. Although large firms are not included in the most important portion of the supply of loans backed with public guarantees, the comparison is relevant. Large firms have more credit history than MSMEs and are more likely to offer collateral/personal guarantees to the bank. In that sense, large firms

obtain lower interest rates due to a higher repayment probability and a smaller expected loss given default. Although the PCG policy improves MSMEs credit profile by providing a high-quality guarantee, these firms still are charged higher interest rates when compared to those paid by large firms.

When focusing on loan operations in local currency (Table 1), the average lending interest rate in the whole period is 19.2%, while the PCG interest rate is 14.7% and the mean of the spread between lending interest rate and interbank call rate is 14.3%. In addition, the rate cap associated to PCG operations is binding in 28% of these loan contracts and PCG operations represent, on average, only 4% of the total amount of new loans granted each month –considering loan operations from MSME firms, these ratio rises to 8.5%–. In addition, during the second half of 2020, total reserve requirements deductions reached USD 167 million per month, arising to USD 204 million during 2021. These values represent, on average, 60% of the total amount of credit (Table 1).

TABLE 1
DESCRIPTIVE STATISTICS - LOCAL CURRENCY

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
Loan.Rate	9836	19.20	8.58	0.00	55.51
Siga.Rate	7779	14.69	1.98	5.50	17.22
Max.SigaRate	7779	16.09	1.18	14.41	17.22
Deposit.Rate	9722	5.27	1.95	2.90	10.52
Rate.Spread	9836	14.29	8.57	-6.75	50.52
Inflat.Expect.	9836	7.71	0.63	6.95	9.00
Binding	9836	0.28	0.45	0.00	1.00
SIGARatio	9836	0.04	0.05	0.00	0.18
ResReqRatio	9836	0.60	0.61	0.00	4.71
Act.Share	9836	0.14	0.09	0.00	0.35
Log(loan.amount)	9836	12.19	2.76	-4.61	20.79
Solvency Ratio	9836	1.62	0.34	1.14	3.09

When focusing on loan operations denominated in foreign currency, the cap rate associated to PCG operations is binding in 14% of these loan contracts (Table 2), the average lending interest rate in the whole period is 5.5%, while the PCG interest rate is 4.3%.

TABLE 2
DESCRIPTIVE STATISTICS - FOREIGN CURRENCY

Variable	N	Mean	SD	Min	Max
Loan.Rate	12199	5.45	1.95	0.00	12.35
Siga.Rate	10800	4.34	0.66	2.92	5.28
Max.SigaRate	10800	5.00	0.35	4.23	5.31
Deposit.Rate	12103	0.18	0.20	0.03	1.58
Rate.Spread	12199	4.48	1.94	-2.31	11.46
Binding	12199	0.14	0.35	0.00	1.00
SIGARatio	12199	0.03	0.03	0.00	0.14
Act.Share	12199	0.16	0.09	0.00	0.32
%USD.Deposits	12199	0.79	0.05	0.35	0.99
Country Risk	12199	177.63	48.80	125.00	44.19
Log(loan.amount)	12199	13.47	2.72	-0.86	20.64

4. Empirical Strategy

To analyse the impact of the policy response to the COVID-19 shock over banking loans' interest rates, we will use static and dynamic panel data models.

For the static models, the specification is the following:

$$(1) \quad \begin{aligned} lspread_{b,i,t} = {} & \beta_1 lexpinfl_t + \beta_2 X_{b,i,t} + \beta_3 ResReqRatio_{b,t} + \beta_4 PCGRatio_{b,t} + \\ & \beta_5 Binding_{b,i,t} + \beta_6 PCGRatio_{b,t} * Binding_{b,i,t} + \beta_7 Z_{b,t} + \varepsilon_{b,i,t} \end{aligned}$$

where $lspread_{b,i,t}$ is the logarithm of the spread between the local currency loan interest rate and the monthly average rate of interbank call operations of bank b and loan contract i between months t and $t-1$; $X_{b,i,t}$ are loan-contract variables, $lexpinfl_t$ is the logarithm of annual inflation expectations in month t; $ResReqRatio_{b,t}$ is the ratio between monthly reserve requirements deductions and the total amount of new loans granted for bank b in month t; $PCGRatio_{b,t}$ is the ratio between the amount of loans backed with PCG guarantees and the total amount of new loans granted for bank b in month t; $Binding_{b,i,t}$ is a dummy that takes the value of 1 when the PCG interest rate cap is binding for the loan contract i, granted by bank b at month t, 0 otherwise; and $Z_{b,t}$ are bank controls. Following Nikitin and Smith (2009) and Cottarelli and Kourelis (1994), we control for inflation expectations because, given that bank spreads are the difference between two nominal rates, if inflation shocks are not passed through to both rates equally fast, then spreads should reflect this. In addition, we also control for loan-contract and firm variables such as the logarithm of the loan amount and firms' size, while we also include bank controls such as the solvency ratio of bank b at month t.

Given the potential problems of endogeneity in equation (1), we will also use dynamic panel data models, starting from a pooled regression model (P. OLS) and a fixed effects model (FE) and later using the Generalized Method of Moments (GMM). Specifically, we will use the System GMM estimator developed by Arellano-Bover/Blundell-Bond for dynamic panel data (Arellano and Bover (1995), Blundell and Bond (1998)), which augmented the Arellano-Bond (Arellano and Bond (1991)) estimation by making the assumption that first differences of instrument variables are uncorrelated with the fixed effects. This estimator combines the first difference in equations with the equation in levels in which the variables are instrumented by their lags. This approach enables us to work with a dynamic panel with few time periods and with a sufficient number of individuals (small T, large N panel). Blundell and Bond (1998) add that Arellano- Bond estimation performs poorly when instrumenting variables are highly persistent. Some other characteristics of this estimator that make it suitable for this analysis are that the model may include: a dependent variable that depends on its own past realizations (inertial behavior), independent variables that are not strictly exogenous, fixed effects, heteroscedasticity and autocorrelation within individuals but not across them.

As is well known, the proliferation of instruments can cause an overidentification problem when the number of individuals is small in terms of the number of periods and instruments used, which can affect the efficiency of the system GMM estimator. We address this issue applying the two typically used approaches for reducing the number of instruments: curtailing and collapsing (Roodman (2009b), Kiviet (2020)). In addition, we run the specification tests proposed to deal with overidentification problems (Roodman (2009a)): the Sargan and Hansen tests. Finally, we apply the Arellano-Bond serial correlation test to ensure absence of higher-order serial correlation of the differenced error terms, this is crucial for the validity of the lagged values of the dependent variable as instruments and for the instruments of predetermined and endogenous covariates.

In all specifications, we clustered standard errors at the bank-industry level in order to account for potential correlation in the residuals.[8]

The general specification for the dynamic models is the following:

$$(2)\quad \begin{aligned} lspread_{b,i,t} &= \alpha lspread_{b,i,t-1} + \beta_1 lexpinfl_t + \beta_2 X_{b,i,t} + \beta_3 ResReqRatio_{b,t} + \\ &\beta_4 PCGRatio_{b,t} + \beta_5 Binding_{b,i,t} + \beta_6 PCGRatio_{b,t} * Binding_{b,i,t} + \beta_7 Z_{b,t} + \varepsilon_{b,i,t} \end{aligned}$$

We decided to exclude from the analysis the foreign currency model because interest rates in this case are mostly influenced by external conditions. In particular, the literature has shown that the pass-through from the reference rate is

[8] The are 78 clusters at the bank-industry level.

weaker for interest rates in foreign currency (Gianelli, 2010), and Lorenzo and Tolosa (2000) have shown that the spread in foreign currency has a stochastic nature. Additionally, under the pandemic context, with expansionary monetary policies around the world, banks were not able to find profitable investment options abroad and kept extremely liquid positions in foreign currency. Also, because of the pandemic, deposits in foreign currency grew faster during 2020, which probably affected the supply of credit in foreign currency. As a results, expansive policies such as deductions on reserve requirements were not necessary to impulse the supply of credit in this currency, and liquidity should not operate as a relevant constraint on credit pricing in foreign currency. On the other hand, despite the importance of foreign-currency loans over the total PCG operations (67%), the interest cap rate imposed on them was binding only for 14% of the cases.

5. Results

We start estimating equation (1), where the dependent variable is the logarithm of the spread between the loan interest rate in local currency of bank *b*, loan-contract *i* at month *t*, and the monthly average rate of interbank call operations. Our regressors of interest are $ResReqRatio_{b,t}$ and the interaction term between the $PCGRatio_{b,t}$ and the dummy variable that indicates whether the PCG rate cap is binding. The expected sign is negative for both coefficients and the intuition is the following. Given that the rates associated with PCG operations were lower than the average interest rate charged by banks (see Section 3), one could expect a downward effect on the interest rate charged by those banks with a relatively more active participation in the PCG scheme and when the PCG rate cap is binding, since those clients that do not have the PCG collateral could demand lower interest rates. Moreover, one could also expect an additional downward effect on the spread of loan rates given by the impact of the reserve requirements' deductions, since banks have more liquidity to offer new loans at a lower cost.

In general, the coefficients have the expected signs and the variables are significant (See Table 3). The results of the Hausman test indicate that the FE model is preferred to the RE to explain the policy response over the interest rate spread in local currency. However, as was expected, when performing complementary tests,[9] we reject the null hypothesis of no autocorrelation, which indicates the need for estimating dynamic panel models.

[9] Following Wursten (2018), we performed the Ionue-Solon test for serial autocorrelation, recommended when the panel is unbalanced and the panel dimension (N) is larger than time series dimension (T).

TABLE 3
ESTIMATES OF THE STATIC MODELS

	(1) OLS	(2) FE	(3) RE
IExplnfl $_{t}$	-0.005	0.061***	0.058***
	(0.009)	(0.005)	(0.005)
Loan Amount $_{b,i,t}$	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Res.Req. Ratio $_{b,t}$	-0.174***	-0.062***	-0.072***
	(0.009)	(0.007)	(0.006)
PCG Ratio $_{b,t}$	-0.804***	0.428***	0.309***
	(0.148)	(0.088)	(0.087)
Binding $_{b,i,t}$	0.183***	0.022***	0.026***
	(0.016)	(0.008)	(0.008)
Binding $_{b,I,t}$ ·PCG $_{b,t}$	-1.099***	-0.776***	-0.781***
	(0.236)	(0.115)	(0.115)
Observations	9,849	9,849	9,849
R-squared	0.141	0.072	
Adjusted R-squared	0.141	-0.0660	
Number of id		1,271	1,271

The results of the estimations of the first set of dynamic models are included in Table 4, where the first column shows the estimates of the Pooled OLS model and column 2 the results from estimating a FE dynamic panel model.

TABLE 4
ESTIMATES OF THE STATIC MODELS

	(1)	(2)
	OLS pooled	FE
ISpread $_{b,i,t-l}$	0.841***	0.194***
	(0.026)	(0.045)
IExplnfl $_{t}$	-0.002	0.056**
	(0.010)	(0.010)
Loan Amount $_{b,i,t}$	-0.000**	-0.000***
	(0.000)	(0.000)
Res.Req. Ratio $_{b,t}$	-0.025***	-0.034***
	(0.008)	(0.009)
PCG Ratio $_{b,t}$	-0.287***	0.333
	(0.084)	(0.231)
Binding $_{b.i.t}$	0.070***	0.029**
	(0.018)	(0.012)
Binding $_{b.i.t}$ · PCG $_{b,t}$	-0.093	-0.623***
	(0.243)	(0.175)
Observations	7,553	7,431
CIuster	bank*industry	bank*industry
R-squared	0.790	0.887
r2	0.790	0.887
r2 a	0.790	0.873

Given the potential correlation between the independent variables and past events and the correlation between the error term and the lagged endogenous variable, these estimations deliver biased results. To deal with this, we perform estimations based on the Generalized Method of Moments (Table 5).

TABLE 5
ESTIMATES OF GMM MODELS

	(1) GMM Difference	(2) GMM system
ISpread $_{b,i,t-1}$	0.184***	0.326***
	(0.052)	(0.064)
IExpInfI $_{t}$	0.540***	0.386***
	(0.108)	(0.138)
Loan Amount $_{b,i,t}$	-0.030***	-0.028***
	(0.009)	(0.008)
Res.Req. Ratio $_{b,t}$	-0.003	-0.074***
	(0.015)	(0.023)
PCG Ratio $_{b,t}$	0.450***	0.243**
	(0.154)	(0.102)
Binding $_{b,i,t}$	0.068***	0.074***
	(0.021)	(0.026)
Binding $_{b,i,t}$ · PCG $_{b,t}$	-1.297 ***	-1.121**
	(0.441)	(0.516)
Observations	6,325	7,553
Cluster	bank*industry	bank*industry
Number of id	788	953
Wald Test p-value		0.000
AR(1)	0.00	0.000
AR(2)	0.88	0.798
Hansen Test p-value	0.10	0.124
Number of Instruments	54.00	61.000

Following Bond (2002), in order to evaluate the coefficients found in the Difference and System GMM models, it is possible to compare them to those found in Table 4, where the coefficients associated with the Pooled OLS and the FE model deliver the maximum and minimum values that these parameters could achieve. For the GMM Difference model, the lagged variable parameter was 0.184, while for the GMM System model the value found was 0.326.

Although the Difference GMM estimator assesses the autocorrelation problems that arise from first differentiation, the properties of this estimator are weak when variables are highly persistent over time. Simulations obtained by Blundell and Bond (1998) show that, in the context of persistent series, the finite sample bias for the Difference GMM estimator is at a level close to that of the Fixed Effect estimator. We obtained an estimate of 0.184 by the Difference GMM estimator, which was very close, and even lower, to the estimate obtained by Fixed Effects -0.194-.

In order to check for persistence, we performed Fisher-type unit root tests and conclude that we cannot reject the null hypothesis that all panels contain unit roots under the assumption of inverse normal distribution (Table 6). According to Choi (2001) simulations, considering the trade-off between sample size and test´s power, the inverse normal statistic outperforms other unit root tests developed for panel data analysis.

TABLE 6
RESULTS FROM UNIT-ROOT TEST

Fisher-type unit-root test for Ispread Based on augmented Dickey—Fuller tests		
HO: All panels contain unit roots		Number of panels = 1271
Ha: At least one panel is stationary		Avg. number of periods = 7.75
AR parameter: Panel-specific Panel means: Included Time trend: Not included Drift term: Not included		Asymptotics: T -> Infinity ADF regressions: 1 lag
	Statistic	p-value
Inverse normal	z	3.2760 0.9995
P statistic requires number o panels to be finite. Other statistics are suitable for finite or infinite number of panels.		

In light of the above evidence, and considering also that we have a relatively small T and large N, we decided to choose our System GMM specification. The main results of our estimations are included in Table 7. The first model represents the reference model, which considers our main variables of interest (Res. Req. Ratio, PCG Ratio, binding and the interaction of the last two) and the lag of the dependent variable (lspread). Columns (2) to (5) show the results of gradually including independent variables at the macro, firm and bank level. Specifically, in column (3) we control for bank characteristics, such as solvency (Capital Adequacy Ratio, CAR), the situation of the institution in terms of liquid assets (30-day liquidity ratio), and its market power (Herfindahl–Hirschman index). In column (4) we include dummy variables associated to firms' size, while in column (5) we include a dummy indicating if the banking institution is the state-owned bank, with the objective of analysing whether the fact of being a state-owned bank implied a different behavior in terms of credit pricing for PCG operations.

TABLE 7

ESTIMATES OF SYSTEM GMM MODELS

	(1)	(2)	(3)	(4)	(5)
	GM M System	GMM System	GMM System	GMM System	GMM System
Spread $_{b,i,t-1}$	0.358***	0.326***	0.477***	0.431***	0.212***
	(0.073)	(0.064)	(0.066)	(0.073)	(0.065)
lExplnfl $_{t}$		0.386***	0.263**	0.208*	0.487***
		(0.138)	(0.128)	(0.119)	(0.134)
Loan Amount $_{b,i,t}$		-0.028***	-0.038***	-0.034***	-0.032***
		(0.008)	(0.008)	(0.007)	(0.008)
Res.Req. Ratio $_{b, t}$	-0.066***	-0.074***	-0.069***	-0.073***	-0.036**
	(0.021)	(0.023)	(0.020)	(0.021)	(0.017)
PCG Ratio $_{b, t}$	-0.036	0.243**	-0.374**	-0.283*	-0.823***
	(0.168)	(0.102)	(0.165)	(0.163)	(0.273)
Binding $_{b, i, t}$	-0.003	0.074***	0.059***	0.057***	0.038**
	(0.056)	(0.026)	(0.020)	(0.019)	(0.018)
Binding $_{b, i, t}$ · PCG $_{b, t}$	0.665	-1.121**	-0.618*	-0.618*	-0.594
	(0.807)	(0.516)	(0.355)	(0.340)	(0.408)
State Bank $_{b, t}$					-0.794***
					(0.089)
State Bank $_{b,t}$ · PCG $_{b, t}$					2.475***
					(0.324)
Binding $_{b, i, t}$ · Stałe Bank $_{b,t}$					3.484***
					(0.996)
Binding $_{b, I, t}$ · Stałe Bank $_{b, t}$					-28.737***
· PCG $_{b, t}$					(8.032)
Medium Sized Firm $_{b, i, t}$				0.176***	0.252***
				(0.043)	(0.047)
Small Sized Firm $_{b, i, t}$				0.327***	0.448***
				(0.082)	(0.082)
Micro Sized Firm $_{b, i, t}$				0.297***	0.407***
				(0.068)	(0.067)
CAR $_{b,t}$			-0.193**	-0.142	0.454***
			(0.088)	(0.092)	(0.108)
Liq.Ratio $_{b, t}$			0.425**	0.151	0.272
			(0.215)	(0.243)	(0.273)
HHI $_{b, t}$			0.013***	0.012***	0.004**
			(0.002)	(0.002)	(0.002)
Observations	7,553	7,553	7,553	7,553	7,553
Cluster	bank*industry	bank*industry	bank*industry	bank*industry	bank*industry
Number of id	953	953	953	953	953
Waald Test p-value	0.000	0.000	0.000	0.000	0.000
AR(1)	0.000	0.000	0.000	0.000	0.000
AR(2)	0.957	0.798	0.795	0.787	0.544
Hansen p value	0.001	0.124	0.300	0.296	0.161
Number of Instruments	28.000	61.000	70.000	73.000	73.000

As can be observed in Table 7, the coefficient associated with the lag of the spread of the interest rate is positive and highly statistically significant, which means that its variations can be persistent over time.

In addition, the coefficients associated with the variables PCG and reserve requirements are statistically significant and the signs are the expected; we find that the PCG policy has a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy. Specifically, although in the more general model the variable $PCGRatio_{b,t}$ has a positive coefficient, when we control for loan and bank characteristics the sign of the coefficient is always negative. In addition, the coefficient of the interaction term with the $Binding_{b,t}$ dummy variable is higher and negative, which means that when the cap established on PCG rates is binding, banks that granted loans under the public guarantees policy charged lower interest rates. This result also shows the effectiveness of the interest rate cap introduced in the PCG policy, since the cap level could not be binding. These results also hold for the most saturated specifications.

Given that we performed the two-step estimation (heteroscedastic weight matrix), we focus in the Hansen´s overidentification test, which shows that our overidentification restrictions are valid (Table 7). As for the Arellano-Bond test for serial correlation, we reject the null hypothesis of no autocorrelation of order 1 and cannot reject the hypothesis of no autocorrelation of order 2, which implies that there is evidence that the Arellano-Bond model assumptions are satisfied.

Finally, we defined dummy variables to identify heterogeneus effects over the interest rate charged by banks under the PCG and the Reserve Requirements policies. Specifically, we run specifications including a dummy indicating whether the bank was private or state-owned, a dummy indicating if the banking institution was significantly active in the supply of PCG loans, as well as a dummy indicating whether the loan was granted to an industry affected by the pandemic. We did not find heterogeneous behaviors in terms of the effect of the analysed policies over interest rates charged by banks.

6. Final remarks

Following the COVID-19 shock, several governments around the globe implemented a set of policies in order to cope with the contraction in the supply of credit. Uruguay was no exception; among other policy measures, between March and April 2020 the Uruguayan Government expanded an existing public credit guarantee and introduced deductions in local currency reserve requirements.

We analyse the impact of this type of policies on loans' interest rate spread over the interbank rate. Uruguay offers an ideal setup for this study since we have both type of policies implemented in conjunction with detailed data on loan contracts. We find that the PCG policy had a relatively higher effect on loans' interest rates in comparison to the reserve requirements policy.

The design of the PCG policy seems to have been adequate as the restriction of the maximum allowed interest rate was binding in one third of the local currency loan operations. As we have said before, during 2020 PCG operations represented only 8.5% of new loans granted to MSMEs per month. However, the results found in this research indicate that not only this 9% was favored by this policy, since its effect on the interest rate seems to have spread to the remaining lending operations.

Given the widespread application of the analysed policies around the world in the context of the pandemic, this study not only contributes with evidence on the performance of recent policies but also for policymakers' discussion on the design of policies as a quick response to a negative shock.

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APPENDIX

CREDIT RATINGS IN URUGUAY

According to Uruguayan regulation, borrowers are classified with a rating scale that reflects their payment capacity.[10]

Rating 1A: back-to-back loans, that is, loans fully covered by very liquid collaterals.

Rating 1C: borrowers with strong payment capacity (i.e. less than 10 days past due).

Rating 2A: borrowers with an adequate payment capacity (i.e. less than 30 days past due).

Rating 2B: borrowers with potential problems in their payment capacity (i.e. less than 60 days past due).

Rating 3: borrowers with a compromised payment capacity (i.e. less than 120 days past due).

Rating 4: borrowers with a very compromised payment capacity (i.e. less than 180 days past due).

Rating 5: unrecoverable borrowers (more than 180 days past due).

TABLE A1

DEFINITION OF THE VARIABLES

Loan-Contract Variables	
ISpread $_{b,i,t-1}$	Monthly average lending interest rate minus monthly average rate of interbank call operations
Loan Amount $_{b,i,t}$	Loan amount (in logs)
Res.Req. Ratio $_{b,t}$	Reserve requirements deductions to total loans granted by month
PCG Ratio $_{b,t}$	Ratio between the amount of loans backed with PCG guarantees and the total amount of new loans granted for bank b in month t
Binding $_{b,i,t}$	Dummy that takes the value of 1 when the max cap for the siga rate is binding
Bank Variables	
CAR $_{b,t}$	Capital adequacy ratio
HI-Il $_{b,t}$	Bank's market power in loan market (measured by the HH Index)
State Bank $_{b,t}$	Dummy that takes the value of 1 when the banking institution is the state-owned bank
Macroeconomic Variables	
IExplnf $_{t}$	Anual inflation expectations

[10] For more detail: Comunicación No 2019/001, Superintendencia de Servicios Financieros, BCU.