Business as Usual?: Bank Lending under Credit Relief Programs

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Abstract

This paper exploits target and blanket credit relief programs during the COVID-19 pandemic to study policy externalities. We ask whether policies designed to support credit flow in the targeted economy have spillover effects on the untargeted economy via the bank-lending channel. To answer this question, we explore the variation in bank's pre-pandemic loan portfolios that are eligible for the COVID-19 government guarantee schemes. Using instrumental variable techniques to address endogeneity concerns and Portuguese credit register data, we find that banks decrease loan supply to firms with government guarantees using their own funds to preserve lending to firms outside the program. Banks with high prior exposure to moratoriums have tighter lending conditions on new loans, while those with greater exposure to public guarantee schemes (PGS) offer better lending conditions. Finally, our triple differences results suggest higher/lower risk-taking in banks exposed to moratoriums/public guarantee schemes.

JEL classification: G21, G28, H30

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1 Introduction

The COVID-19 pandemic has forced a global business shut down and caused a liquidity crunch, which was especially acute among small businesses (SMEs) (e.g., Greenwald et al. (2020); Chodorow-Reich et al. (2021); Kapan and Minoiu (2021); Lagazio et al. (2021)). Restrictions on personal mobility and nonessential business operations strongly affected business revenues, causing a surge in firms' liquidity needs. At the same time, these containment measures caused a major global economic contraction. Banks, thus, simultaneously faced a surge in credit demand and the prospect of serious deterioration in asset quality and profitability. Unlike in the 2008 financial crisis, banks are not the source of the problem this time, but the financial sector plays a crucial role in determining how this crisis will unfold. Thanks to major reforms after the crisis of 2007-2009, banks are much better capitalized and more liquid, thus not under immediate stress (Schularick et al., 2020). As a result, they became more stable and able to effectively finance the needs of the real sector of the economy. Nevertheless, the financial sector is likely to face negative impacts from the pandemic, similar to other industries. Clogging banks' balance sheets with high amounts of non-performing loans would undermine the economic recovery, so proactive and strong credit risk management practices are vital. The biggest risk is that the economic crisis turns into a financial (banking or sovereign debt) crisis. To prevent this, initial policy reactions by monetary, prudential, and fiscal authorities were laid out rapidly. Central banks and supervisors have taken prompt action and implemented measures to sustain the economy. Central banks intervened in financial markets, both to maintain liquidity and bank lending through asset purchase programs or easing collateral requirements (e.g., Demirgüç-Kunt et al. (2020); Runkel (2022)). Regulatory authorities promptly addressed impending pressures and losses in the banking sector during and after the Great Lockdown by implementing measures such as reducing the counter-cyclical capital buffer to zero where appropriate, permitting banks to decrease capital below Pillar 2 guidance, and relaxing provisions rules to reduce their pro-cyclical impact (e.g., Altavilla et al. (2020); Core and De Marco (2020); Altavilla et al. (2021); Gourinchas et al. (2021); Cascarino et al. (2022)).

In addition, the COVID-19 pandemic and the associated social distancing measures represent a huge economic shock that has required a significant policy response. Governments have supported the economy with different measures to avoid inefficient bankruptcies and excessive destruction of relationships. Many of these measures relied on the banking system to act as a conduit of government-backed liquidity, whether through the use of public credit guarantees on new bank loans or the compulsory authorization to debtors to postpone loan payments. While these two measures provide a response to firms' liquidity needs, the mechanism through which they impact banks' business is distinct. Public credit guarantees on new bank loans generate a flow of credit and may lead to a substitution effect on new operations (Altavilla et al., 2021). It is also subject to banks' screening and is targeted at specific firms. On the other hand, authorizations to postpone loan payments (also known as moratorium), produce effects only on the pre-existent stock of credit and generally apply to all firms that ask for it. As a result, are referred to as blanket measures over which banks have no control. While the support policies, aimed at maintaining credit flow and supporting distressed borrowers, have been successful in preventing a complete collapse of the credit market, little is known about how banks have coped with these policies in extending new credit.

In this study, our goal is to fill this gap by investigating the impact of credit relief programs on bank lending during the COVID-19 pandemic. Specifically, we ask whether banks have been able to sustain lending to the economy and support viable distressed borrowers, netting out the effect of credit relief programs. Additionally, we address the question of whether policies aimed at supporting credit flow in the targeted economy can spill over to the untargeted economy via the bank-lending channel. To do this, we focus on the Portuguese case and use extensive credit register data. The Portuguese government launched its first package of support measures immediately after the first reported COVID-19 case and adjusted its strategy as the pandemic evolved. The biggest bulk of measures was implemented up to the second quarter of 2020. Two credit relief programs stand out as reliant on the banking system: public guarantee schemes (PGS) and moratoriums. Portugal, despite the size of the economy, was among the ones that have extensively used the PGS and moratorium programs. Up to June 2020, it was ranked the second highest euro area country in terms of the PGS share to total loans for newly extended credit and the third highest in terms of the moratorium credit to total credit. Notably, 34% of their reported loans to non-financial counterparties were under moratorium by the end of 2020 (Banco de Portugal, 2021). We apply a difference-in-differences approach to compare the lending of banks with different exposures to these two credit relief programs around the peak of policy uptakes. We also employ instrumental variables to address endogeneity concerns and control for potential confounding actors.

Our findings provide strong evidence of policy externalities. We find a reallocation effect from credit guarantee programs and a contraction effect from moratorium programs. Banks with high exposure to PGS increase lending in general but decrease lending using their own funds when compared to their counterparties. Moreover, the released lending capacities provided by the government guarantee were used to reallocate funds towards safer firms, at lower interest rates, and lower collateral. On the contrary, banks with high exposure to moratoriums charged higher interest rates and demanded higher collateral on new non-public guaranteed loans. This is consistent with a risk-shifting and profit-seeking behavior from banks with higher exposure to moratorium. Overall, these effects prevail, even knowing that bank loans during COVID-19 were not granted to riskier firms in general.

This paper contributes to several strands of literature. First, it adds to the literature studying the impact of COVID-19 pandemic on credit demand and supply by providing new evidence on the reallocation effect of credit guarantee programs. Several studies show that, induced by the outbreak of the pandemic and the uncertainty surrounding it, firms drew down bank credit lines and raised their cash levels in a reaction defined as a "dash for cash" (e.g.,Acharya and Steffen (2020); Greenwald et al. (2020); Li et al. (2020); Kapan and Minoiu (2021)). Yet, not all types of firms were allowed to do so; for instance, SMEs did not draw down as much as large firms did, due to lender discretion in granting credit lines ex-ante (Chodorow-Reich et al., 2021). Although, later, with the implementation of stabilization policies, the demand for bank credit by large and high-rating firms decreased, as firms looked for alternatives in the capital markets (Acharya and Steffen, 2020). On the supply side, banks were able to accommodate the liquidity demand at the expense of central banks' liquidity injection programs, the increase in depositors' savings, and high bank capital levels (Li et al., 2020). If not so, banks would be unwilling to meet credit demand by engaging in a pro-cyclical behavior to preserve capital ratios (Couaillier et al., 2022). Banks that were more exposed to drawdowns, reacted by tightening loan supply, particularly to smaller firms (e.g.,Greenwald et al. (2020); Kapan and Minoiu (2021)). All in all, banks' risk tolerance was reduced, even for most of the relationship borrowers (Berger et al., 2021).

Second, our study contributes to the literature on the execution of credit relief programs as instruments to overcome the negative effects of the pandemic. By investigating the impact of these programs on banks' ability to sustain lending to the economy and support viable distressed borrowers, this study adds to the understanding of how such policies affect credit flow and bank behavior, and sheds light on the externalities of these policies and their impact on the broader economy. Authorities enacted different support programs to ensure credit flow to the economy, including new public guarantee schemes(Gourinchas et al., 2021). These guarantee programs increase lending to constrained firms, allow them to stand up during crises (e.g., Custodio et al. (2022); de Blasio et al. (2018); Zecchini and Ventura (2009)), and reduce their cost of lending (e.g., Custodio et al. (2022); Zecchini and Ventura (2009)), although this last evidence is not unanimous as noticed by de Blasio et al. (2018). These programs tend to be more efficient when the guarantee coverage is more generous, promoting an effective increase in lending supply rather than just subsidizing lenders (Bachas et al., 2021). Nevertheless, loosening up the eligibility criteria of public guarantee schemes can endure the deterioration of firms' financial conditions in the long run Lagazio et al. (2021).

During the COVID-19 pandemic, the guaranteed loans were mostly extended to smaller firms in sectors severely affected by the pandemic and lesser to high-productivity firms, which is in line with the aim of the support programs (e.g., Altavilla et al. (2021); Kozeniauskas et al. (2022)). Yet, there is evidence of a substitution effect of non-guaranteed (pre-existent and new) with guaranteed credit — guaranteed loans did not represent a full increase in lending (Altavilla et al., 2021). On the lender side, capitalization played a determinant role, with well-capitalized banks being more available to grant credit (Altavilla et al., 2021). This result was amplified by a coordinated monetary and prudential intervention in Europe that reduced banks' funding costs and relieved capital requirements (Altavilla et al., 2020). Also, according to Core and De Marco (2020), banks with better information technology systems could react more quickly and were more able to lend.

Finally, on a broader scale, our study contributes to the literature on the nexus between sovereigns, banks, and firms by showing how a government policy on bank lending not only impacts the credit flow from exposed banks and the target firms but also changes the behavior of banks in their own credit allocation policies and risk-taking outside the scope of the government program. There is a well-established interdependence between governments and banks that goes beyond regulation. Governments aiming to maintain financial stability might consider bailing out banks in distress and internalizing part of their risk. In that case, other banks holding sovereign bonds will see their value eroded due to increased risk, which will weaken an already distressed financial sector (Acharya et al., 2014). The shock on the sovereign portfolio can lead banks to contract lending to firms — a risk-shifting strategy that is emphasized in low-capitalized banks (Acharya et al., 2018). However, the interconnection between governments and banks does rely exclusively on sovereign bonds. Leonello (2021) finds that sovereign credit guarantees can enact a risk-shifting behavior by banks, even when they do not hold sovereign bonds.Bonfim et al. (2022) add that this effect can also be amplified by banks' credit exposure to firms with government procurement contracts.

2 Institutional Framework

The government launched its first package of measures to support businesses eleven days after the first reported COVID-19 case. Most initiatives were intended to provide liquidity to firms, protect jobs, and avoid credit default. As the pandemic situation evolved and the first lockdown ended, the government adjusted its strategy and announced the *Economic and Social Stabilization Program (PEES)*. In the words of the government:

" (...) if at first, the objective was to control the pandemic without killing the economy, it is now important to resume the economy without unraveling the pandemic".

Presidency of the Council of Ministers (2020) — June 6, 2020

This structural program was built to last until the end of 2020, but the dynamic nature of the COVID-19 shock required an adaptive response by the authorities. On the credit side, there were two types of credit relief programs: public guarantee schemes (PGS) and moratoriums.

The Portuguese authorities frequently adopt PGS to aid SMEs in securing bank loans, but never on the scale observed during the COVID-19 pandemic. The frequent adjustments to the program make it complex to follow the announcement and implementation of every single credit line. Globally, the announced programs comply with EU regulations and are executed by an independent body. The guaranteed fraction of the loan range from 80 to 90 percent, the maximum maturity is 3 to 6 years, and the guarantee cost is 25-175 basis points. To be eligible, firms need to comply with five criteria:

1. Have positive equity by the end of 2019 (except if created in the last two years)
2. Not having active default incidents
3. Not having active debts to the Social Security and Tax Authority
4. Not classified as "undertaking in difficulty" as defined in the Commission Regulation (EU) No 651/2014 article 2 number 18
5. Register a homologous decrease in sales of at least 40% between March and May 2020.[1]

The applications for the PGS followed a double-screening process. First, firms applied to the program through a partner bank, which assessed the risk of the loan and decided on the credit conditions (including

[1] Criterium relaxed in later programs.

the price). Second, the guarantor entity analyzed the application and made the final decision. The Portuguese government announced a total of 8.4 million euros of available PGS under the COVID-19 pandemic, representing more than 10% of the existent credit to firms by the end of 2020. Most credit lines were granted during the second quarter.[2]

To tackle firms' liquidity constraints, the government simultaneously implemented a moratorium program allowing firms to request loan payment suspensions, independently of their size. To be eligible, firms could not be in a credit default situation or owe debt to the Social Security and Tax Authority. The moratorium deadline was successively extended until September or December 2021. By the end of 2020, 34% of the existent credit to firms was under moratorium (Banco de Portugal, 2021). As in PGS, almost all moratorium requests happened during the second quarter.

3 Identification Strategy

3.1 Bank's Exposure to Credit Relief Programs

Our identification focuses on banks' exposure to the two disclosed credit relief programs. We define bank's exposure to public guarantee schemes (*PG Exp.*) as the ratio of public-guaranteed bank credit at the onset of the COVID-19 crisis (i.e., in March, April, and May 2020) to the total bank assets. Following the same rationale, bank's exposure to moratorium programs ($Morat.$ *Exp.*) is the ratio of the credit under the moratorium up to May 2020 to the total bank assets. These programs have different eligibility criteria and, thus, different exposure expressions as presented in equations 1 and 2, in which the subscript b refers to bank and f to firm. Bank assets are measured at the end of 2019 to unveil bank's position prior to the exogenous shock caused by the COVID-19 crisis.

$$PG\ Exp_b = \frac{\sum_{f=1}^{n} PG_{fb,March-May\,2020}}{Assets_{b,2019}} \tag{1}$$

$$Morat\ Exp_b = \frac{\sum_{f=1}^{n} Morat_{fb,March-May\,2020}}{Assets_{b,2019}} \tag{2}$$

[2]According to Tribunal de Contas (2021), 6.9 million euros were executed by the end of the third quarter of 2020.

3.2 Empirical Specification

This paper aims to study policy externalities and understand whether a policy directed at a targeted sector can spill over and affect elsewhere, e.g., sectors not targeted by the policy. More specifically, we ask whether banks sustain lending to the economy and provide support to viable distressed borrowers as intended, netting on the direct impact of government support.

To address this question, we apply difference-in-differences to compare the lending of banks with different exposure to credit relief programs around the onset of COVID-19. We follow Degryse et al. (2019) to include industry-location-size-time fixed effects (γ_{ilst}) for the purpose of capturing time-varying firm credit demand.[3]

$$\begin{aligned} Credit_{fbt} = & \sum_{t=1}^{n} \boldsymbol{\beta}_{1,t} Period_t \times PG\ Exp_b + \\ & \sum_{t=1}^{n} \boldsymbol{\beta}_{2,t} Period_t \times Morat\ Exp_b + \\ & \sum_{t=1}^{n} \boldsymbol{\alpha}_t Period_t \times \mathbf{BankChars}_b + \\ & \gamma_{ilst} + \omega_{fb} + \epsilon_{fbt} \end{aligned} \tag{3}$$

where the subscript f refer to firm, b to bank and t to period. The dependent variable $Credit_{f,b,t}$ takes one of two values: the log-transformed credit amount of firm f to bank b in period t or the log-transformed non-guarantee credit exposure of firm f to bank b in period t. $Period_t$ is a dummy variable that equals 1 in the period under investigation, and 0 otherwise.[4]

The pre-pandemic bank controls interacted with time dummies are included to capture differences in bank lending behavior that are specific to bank characteristics. Precisely, we include bank size, liquidity, capital ratio, non-performing loans, and foreign bank dummy, all measured as of 2019. Banks' balance sheet strength and financial health influence the willingness of banks to grant credit using their own funds. Large banks have the advantage of screening, and monitoring (Diamond, 1984) and have, in theory, better technology to respond to the implementation of a new credit relief program. Banks that are more liquid rely less on external support to guarantee credit flow to the economy and less capitalized banks are more constrained in using their

[3] The results are similar using firm-quarter fixed effects (Khwaja and Mian (2008)), which we present in Table 8 as a robustness check.

[4] The subscript t could represent either a quarter, as shown in the regression coefficients plots, or the collapsed pre-/post-pandemic periods, as shown in the regression tables.

own funds. Banks with lower non-performing ratios are better equipped to deal with the negative impacts of lockdowns and to handle the pressure from moratorium programs. We include a dummy variable to account for foreign banks' differing incentives, which have recently increased their participation in the Portuguese credit market. It is important to note that we take into account banks' exposure to the most affected industry (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile) to account for the direct impact of the COVID-19 shock on banks' lending decisions (Akgunduz et al., 2022). Finally, we control for unobservables related to bank-firm relationships by including bank-firm fixed effects (ω_{fb}). Detailed variable definitions are provided in Appendix A.

The primary identification challenge we face is the endogeneity concern that policy measures are likely not randomly assigned and/or simultaneously determined with bank lending decisions. For this purpose, we performed balance checks in Table 3 which shows differences in means between banks more and less exposed to the two credit relief programs. The results, taken together, confirm our idea of controlling for bank's characteristics in the regressions and simultaneously accounting for the exposure to PGS when studying the effect of the exposure to the moratorium programs. As the table shows, banks more exposed to the moratorium programs look similar to less exposed banks except for size and exposure to PGS - more exposed banks are relatively bigger and more likely to engage in PGS. However, banks exposed to PGS are different in many dimensions from less exposed banks, which raises endogeneity concerns.

We use the Bartik instrument to endogenize the exposure to PGS in the spirit of Goldsmith-Pinkham et al. (2020) and Granja et al. (2022). The Bartik instrument is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry over the bank's total assets, as shown in equation 4.

$$Bartik_b = \frac{Pre - Pandemic\,PG\,Credit\,Share_{b,2019} \times Nationwide\,PG\,Credit\,Shifter}{Assets_{b,2019}} \tag{4}$$

The $Pre - Pandemic\,PG\,Credit\,Share_{b,2019}$ is the bank's credit share by the municipality and the 3-digit sector at the end of 2019. The $Nationwide\,PG\,Credit\,Shifter$ is the growth in public guarantees by industry and location from March 2020 to April 2020.

We then apply the Two-Stage Least Squares (2SLS) regression analysis. We first regress the bank's exposure to PGS on the Bartik instrument along with the other controls included in equation 3, and plug into the predicted value from the first stage (denoted below as $\widehat{PG\,Exp_b}$) as illustrated in the following specification.

$$
\begin{aligned}
Credit_{fbt} = &\sum_{t=1}^{n} \boldsymbol{\beta}_{1,t} Period_t \times \widehat{PG\,Exp_b} + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{2,t} Period_t \times Morat\,Exp_b + \\
&\sum_{t=1}^{n} \boldsymbol{\alpha}_t Period_t \times \mathbf{BankChars}_b + \\
&\gamma_{ilst} + \omega_{fb} + \epsilon_{fbt}
\end{aligned} \tag{5}
$$

Our parameters of interest are β_1, t and β_2, t. A positive β_1, t (β_2, t) indicates that banks with higher exposure to PGS (moratorium) increased lending more than banks with lower exposure.

3.3 Data

We use various datasets to gather credit, firm, and bank data. We obtain loan-level information from the Portuguese Central Credit Responsibility (CRC) database, which provides credit exposures reported by all lending institutions operating in Portugal, covering all loans issued by banks with a reporting threshold of 50 euros on a monthly basis. CRC contains numerous loan attributes, such as amount, origination, maturity, interest rate, collateral, guarantees, default flag, moratorium flag, and issuing bank. Besides, we can also identify loans granted under the PGS and loans subject to the moratorium.

We focus on the period from 2019q3 to 2020q4 and merge loan data with the 2019 firm balance sheet information from the Central Balance Sheet (CB) database, which provides annual administrative financial data for all firms in Portugal.[5] To fully describe firms, we also add details on the judicial restructuring process from the CITIUS database and the firms' default probability from Banco de Portugal's in-house credit assessment system (SIAC). We exclude firms that have simultaneously received guaranteed credit and requested a moratorium period to ensure appropriate identification for our research questions. As for the bank data, we obtain bank balance sheet information as of December 2019 from supervisory reports and monetary

[5]Our choice of the sample period is largely dependent on data availability and quality. The Portuguese Central Credit Register underwent a major revision in September 2018 with the new reporting system starting to collect granular credit data at the instrument level. There are, however, important series breaks in the beginning, essentially because the changes in reporting standards required an infrastructural update on the participating institutions, leading to the gradual implementation of the instruction.

and financial statistics (MFI Statistics). Finally, we complete banks' and firms' geodemographic information from Banco de Portugal's proprietary database (SPAI).

Our sample contains a total of 248,501 solvent firms existing in 2019, 55 banks, and 2,079,823 bank-firm-quarter observations from July 2019 to December 2020. Unlike other data sources, the CRC records loans above €50 and, thus, allows for a broad study of SME credit activity. The sample used in this study represents more than 90 of the Portuguese credit market to non-financial firms. Table 1 presents descriptive statistics, and Table 2 shows the characteristics of firms under the different credit relief programs.

4 Results

In this section, we present the results for our four research questions and introduce some additional checks.

4.1 Do banks more exposed to credit relief programs exhibit differences in credit supply?

From a dynamic perspective presented in Figure 3, the impact of exposure to the credit relief programs on the bank credit supply was negligible prior to the shock, for both total and non-public guaranteed credit, suggesting parallel trends. However, after 2020q2 there is a significant difference in credit supply for banks more exposed to PGS, as well as for banks more exposed to moratoriums.

Panel (a) of Figure 3 shows that banks with higher exposure to PGS granted more credit in the aftermath of the COVID-19 pandemic, with lending rates accelerating until the third quarter of 2020 (positive and increasing $\beta_{1,t}$). Upon examining the type of credit, we find that these lending levels were achieved by using state-guaranteed credit lines. Banks more exposed to PGS leveraged credit relief programs to reduce their risk exposure and preserve their own funds. This result is in line with Altavilla et al. (2021) findings on the substitution of non-guaranteed with guarantee credit. However, the total credit increase was more substantial immediately after the shock compared to the decrease in non-guaranteed credit, indicating that these banks were better positioned to maintain credit to sectors excluded from PGS.[6]

As for moratorium exposure, Panel (b) of Figure 3 shows that banks with higher exposure reduced their lending activity (negative $\beta_{2,t}$). This result supports the argument that banks with higher exposure to

[6] As mentioned in the section 2, these credit line programs were gradually becoming more inclusive, initially only covering specific sectors and excluding bigger firms, leaving a substantial fraction of the economy without access to guaranteed credit.

moratoriums faced an involuntary increase in credit risk in their loan portfolios, making them less likely to grant new loans. It is worth noting that moratorium is a blanket measure applied at the firm's request; therefore, banks experienced an exogenous shock that could not have been anticipated or avoided, given the specificity of the COVID-19 pandemic.

To tackle the endogeneity concerns on the exposure indicators, Figure 4 presents the results of the IV model. The coefficients obtained are similar to the ones from the OLS approach, reinforcing the previous conclusions. One notable difference is that before the introduction of the credit relief programs, the parallel trend between total and non-guarantee credit, as well as the insignificance of the coefficients, becomes even clearer.

To estimate the average treatment effect, we perform sub-sample regressions for both types of credit (total and non-public guaranteed) and firm profiles (using public-guaranteed credit or moratorium) over the entire sample period. The sub-sample results are shown in Table 4 & Table 5.

Overall, the conclusions from the dynamic perspective remain unchanged. On average, a one–standard deviation increase in a bank's exposure to PGS is associated with a 5.4% increase in total credit and a 4.8% decrease in non-public guaranteed credit in the aftermath of COVID-19. A one–standard deviation increase in a bank's exposure to moratoriums is associated with a 2.8% decrease in total credit. In addition, we find that banks with higher exposure to PGS granted more credit to firms without public-guaranteed credit, supporting the argument that these banks could sustain credit to the economy using the released lending capacity.

4.2 Are firms able to maintain/substitute credit when their banks are more exposed to credit relief programs?

A natural next step is to investigate if firms were able to substitute potential adverse effects on access to credit with loans from other less-affected banks. To evaluate the aggregate impact on access to credit at the firm level, we estimate the following firm-level regression:

$$
\begin{aligned}
Credit_{ft} = & \sum_{t=1}^{n} \boldsymbol{\beta}_{1,t} Period_t \times \widehat{PG\,Exp}_f + \\
& \sum_{t=1}^{n} \boldsymbol{\beta}_{2,t} Period_t \times Morat\,Exp_f + \\
& \sum_{t=1}^{n} \boldsymbol{\alpha}_{t} Period_t \times \mathbf{BankChars}_f + \\
& \sum_{t=1}^{n} \boldsymbol{\rho}_{t} Period_t \times \mathbf{FirmChars}_f + \\
& \gamma_{ilst} + \omega_f + \epsilon_{fbt}
\end{aligned} \tag{6}
$$

where the subscript f refer to firm and t to period. The credit relief program exposures ($\widehat{PG\,Exp}_f$ and $Morat.Exp_f$) and banks' characteristics ($\mathbf{BankChars}_f$) are now measured at the firm level as the weighted average values. We also add firms' characteristics ($\mathbf{FirmChars}_f$) to capture firms' profiles and their ability to obtain credit. Industry-location-size-quarter fixed effects and firm fixed effects are again included to control for any time-varying and time-invariant firm credit demand. The exposure to PGS follows the IV approach previously presented.

Table 6 shows the results from the firm's perspective, where two main findings stand out. First, firms more dependent on banks with higher exposure to PGS observed a reduction in the non-public guaranteed credit ($\beta_1 = 0.123^{**}$), while maintaining the total credit level. This means that firms were compelled to substitute credit and opt for loans that reduce the risk of the bank's portfolio and require less capital. In this case, we can question if the PGS complied with their goals, given that there was no flow of credit.

Second, firms more reliant on banks with higher exposure to moratoriums faced a reduction in credit levels (β_2 significantly lower than zero). As a result, firms more exposed to banks with high levels of moratoriums suffered a shortage of credit. Exceptionally, firms with public-guaranteed credit were able to maintain the credit levels without substituting non-guaranteed with guaranteed credit. This result provides important information on the adverse impacts of credit relief programs, as protecting firms through loan payment suspensions has the reverse effect of reducing the supply of credit due to the risk increase in banks' loans portfolio.

4.3 Do banks' exposure to credit relief programs affect the characteristics of the new credit granted after the shock?

We next investigate if banks exposed to credit relief programs grant new loans with different interest rates and levels of collateralization. We use the following specification:

$$
\begin{aligned}
Condition_{lfbt} = & \sum_{t=1}^{n} \boldsymbol{\beta}_{1,t} Period_t \times \widehat{PG\,Exp}_b + \\
& \sum_{t=1}^{n} \boldsymbol{\beta}_{2,t} Period_t \times Morat\,Exp_b + \\
& \sum_{t=1}^{n} \boldsymbol{\alpha}_t Period_t \times \mathbf{BankChars}_b + \\
& \sum_{t=1}^{n} \boldsymbol{\rho}_t Period_t \times \mathbf{FirmChars}_f + \\
& \sum_{t=1}^{n} \boldsymbol{\lambda_t} Period_t \times LoanMat_l + \omega_{fb} + \theta_t + \epsilon_{lfbt}
\end{aligned}
\tag{7}
$$

where the subscript l refer to loans, f refer to firm, b to bank and t to period. *Condition* can be either the interest rate or the collateralization of the loan. As in the bank-firm credit supply specification, both the PGS and the moratorium exposure are measured at the bank level. In addition to bank and firm characteristics, we further incorporate loan maturity ($LoanMat$), as it can influence both lending conditions. The exposure to PGS follows the IV approach previously presented.

Table 7 presents the regression results. As for pricing, we observe an opposite effect between banks that are more exposed to PGS and moratoriums. Banks with more exposure to PGS use less own funds to grant loans and, thus, are more likely to provide new non-public guaranteed loans with lower interest rates than banks with more extensive capital requirements on their loan portfolio ($\beta_1 = -0.952^{***}$). On the other hand, banks with more exposure to moratoriums are more likely to grant new non-public guaranteed loans with higher interest rates ($\beta_2 = 0.627^{***}$). It applies to all subsamples of firms and indicates that given the increase in the risk of their portfolio, banks call for compensation on new operations. This finding adds to the adverse effects of moratoriums on the credit market.

Concerning collateralization levels, we also find opposite effects, except for firms that obtained both new non-public guaranteed loans and new public guaranteed loans, for which there is no discernible impact from the banks' exposures. The results align with the relationship between interest rates and collateralization levels, as banks that put a higher price on risk also demand more collateral in case of default.

4.4 Do banks involved in credit relief programs shift their risk appetite?

So far, we have examined the impact of credit relief programs on the credit level of the average firm. Yet, several results suggest that the risks associated with these programs (reduction of credit risk in PGS and increase in moratoriums) might have shifted the banks' business. To assess changes in banks' risk appetite, we analyze the behavior of banks based on the risk of the firm. We follow the specification in equation 5 and add a triple difference structure at the bank-firm level, where the variable $Treat$ is the tercile group based on firm risk, measured by the firm's probability of default.

$$
\begin{aligned}
Credit_{fbt} = &\sum_{t=1}^{n} \boldsymbol{\beta}_{1,t}^{treatgroup} Period_t \times Treat_i^{treatgroup} \times \widehat{PG\,Exp}_b + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{1,t}^{treat} Treat_i^{treatgroup} \times \widehat{PG\,Exp}_b + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{1,t}^{period} Period_t \times \widehat{PG\,Exp}_b + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{2,t}^{treatgroup} Period_t \times Treat_i^{treatgroup} \times Morat\,Exp_b + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{2,t}^{treat} Treat_i^{treatgroup} \times Morat\,Exp_b + \\
&\sum_{t=1}^{n} \boldsymbol{\beta}_{2,t}^{period} Period_t \times Morat\,Exp_b + \\
&\sum_{t=1}^{n} \boldsymbol{\alpha}_t Period_t \times \mathbf{BankChars}_b + \gamma_{ilst} + \omega_{fb} + \epsilon_{fbt}
\end{aligned}
\tag{8}
$$

Regarding firm risk, Figure 5 shows that banks with higher exposure to PGS changed their risk appetite by granting more credit to low-risk firms and significantly reducing credit to riskier firms. Yet, the increase in credit to low-risk firms is materialized through public-guaranteed credit. Differently, banks with higher exposure to moratoriums seem to have changed their risk appetite towards riskier firms and, in fact, reduced credit to low-risk firms.

Analogously, Figure 6 shows that banks with higher exposure to PGS favor productive firms (productivity measured as value-added per employee) in granting NPG credit. On the contrary, banks with more exposure to moratoriums cut even more lending to productive firms.

Figure 7 and Figure 8 examine the role of industry shock with the triple differences specification in which the variable $Treat$ is the dummy for zombie firms with interest coverage ratios lower than 1 for equal to or more than three years or the dummy for COVID-affected industries for which the decrease in the aggregate output from 2019 to 2020 in the third tertile. On the one hand, we observe that banks with higher exposure to PGS are more likely to decrease NPG loans to zombie firms and firms in affected industries, probably due to the subsititution with public-guranteed loans. On the other hand, banks with higher moratorium exposures increased lending to zombies, in line with credit externalities.

Again, these findings are consistent with the results for the characteristics of new loans, reinforcing the idea that exposure to PGS caused banks to adopt safer business practices, while exposure to moratoriums led banks to riskier business. The exact mechanism by which this occurred (whether it was a deliberate strategic decision or a result of the impact of credit reliefs on a bank's balance sheet) is still an open question for future research. What we do know is that business was not as usual, and banks with different exposures showed behavior that is consistent with a shift in risk.

4.5 Additional Checks

In this subsection, we present a set of robustness tests that support our previous results and provide additional insights. First, we investigate the mechanism underlying our bank-firm credit supply results, considering the rollover decisions at the onset of the pandemic. At loan maturity, a firm might want to renew its debt, and the bank can decide whether to grant a new loan or not. If a new loan is granted, the bank can also steer the firm towards guaranteed or non-guaranteed credit. We define a dummy for situations when a firm faced rollover decisions from its relationship bank during the peak of the COVID-19 pandemic (i.e. fraction of credit that became due before June 2020 is in the third tercile).

Figure 9 illustrates how rollover decisions interfere with the lending decisions of banks exposed to credit relief programs. The results show that the contraction in credit supply is more acute near a rollover event. This is true for banks with higher exposure to PGS as well as for banks with higher exposure to moratoriums.

Second, we use the Khwaja and Mian (2008) estimator by including firm-quarter fixed effects. Although this framework captures time-varying firm demand better, there is a cost of dropping single bank relationship firms. Table 8 confirms the robustness of our main results.

Finally, we examine the attribution of public guaranteed and non-public guaranteed credit from March 2020 to December 2020 based on a linear probability model. More specifically, we investigate how these two types of loans are distributed among firms with different risk and productivity profiles. The results presented in Figure 10 suggest that the distribution of public- guaranteed and non-public guaranteed loans are similar in the lower risk deciles but diverge in the higher risk deciles. Non-public guaranteed credit is more likely to be allocated to high-risk firms and firms with higher productivity, again consistent with risk-shifting.

5 Conclusion

In order to respond to the financial impact of the COVID-19 pandemic, governments implemented credit relief programs such as public guarantee schemes and moratoriums. This study aimed to examine the effect of these programs on bank lending. In particular, we investigate whether banks have been able to maintain lending to the economy and assist viable distressed borrowers, despite the influence of credit relief programs. Additionally, we examine whether policies aimed at promoting credit flow in the intended economy can have an indirect effect on the broader economy through the bank-lending channel.

Our findings provide strong evidence of policy externalities, with a reallocation effect from credit guarantee programs and a contraction effect from moratorium programs. Banks with high exposure to public guarantee schemes increase lending in general, but decrease lending using their own funds when compared to their peers. The decrease in lending is widespread and is sharper among firms with higher risk. When extending new loans, banks with higher exposure to PGS are more likely to offer lower interest rates than banks that have lower exposure. Also, these banks demand less collateral on new non-public guaranteed loans to firms with no existing PGS. On the other hand, banks with high exposure to moratorium programs show a contraction effect, implying the importance of targeted liquidity provision or prudential policies to these banks. Additionally, these banks are more likely to offer new non-public guaranteed loans at higher interest rates and demand more collateral. This shows that, due to the heightened risk in their portfolio, banks demand compensation for new transactions. This outcome highlights the adverse effects of moratoriums on the credit market and uncovers a risk-shifting and profit-seeking behavior.

The results of this study have important policy implications for policymakers and regulators. The externalities of credit relief programs need to be considered when designing policies aimed at supporting credit flow in the targeted economy. To sustain lending to the economy and support viable distressed borrowers, policymakers should consider the spillover effects of their policies and the behavior of banks exposed to various credit relief programs that are designed differently in their nature. Given the findings of this study, it is crucial for policymakers to design targeted liquidity provisions or prudential policies for banks exposed to massive forbearance, as well as to ensure that credit externalities are priced in a manner that aligns with the goals of the policy.

The results of this study are based on extensive credit register data from the Portuguese economy and a difference-in-differences approach to evaluate the impact of policies. In addition, to enhance the robustness of our results, we employed instrumental variables to address endogeneity concerns about bank's decision to participate in public guaranteed credit programs and control for potential confounding factors.

In conclusion, this study contributes to our understanding of the impact of credit relief programs on bank lending during the COVID-19 pandemic and provides important insights for policymakers and regulators. The findings highlight the importance of considering the spillover effects of credit relief programs, as well as the behavior of banks exposed to such programs, in order to sustain lending to the economy and support viable distressed borrowers.

Tables

Table 1: Descriptive Statistics

	Mean	Q1	Median	Q3	Std. Dev.
Bank Sample					
PG Exp.	0.23	0.56	0.00	0.00	0.91
Morat Exp.	6.57	5.99	0.00	5.83	13.99
Bartik Instrument	0.03	0.09	0.00	0.00	0.13
Previous PG Exp.	0.20	0.73	0.00	0.00	0.42
Bank Assets (Billion)	7.53	18.47	0.09	0.68	27.95
Foreign Bank	0.36	0.49	0.00	0.00	1.00
Bank Liquidity	0.02	0.04	0.00	0.00	0.08
NPLs	0.03	0.06	0.00	0.01	0.07
Capital Ratio	0.17	0.20	0.01	0.11	0.39
Credit Ratio	0.69	0.23	0.39	0.73	0.95
Observations	55				
Firm Sample					
Total Credit (thousand)	404.27	4,510.99	1.50	24.23	430.52
Total assets (thousand)	2,104.32	59,569.58	22.42	197.95	2,077.63
Firm Risk	0.11	0.24	0.01	0.03	0.16
Leverage	3.06	652.45	0.00	0.18	0.73
Profitability	-0.64	137.57	-0.22	0.03	0.23
Industry Shock	0.12	0.30	-0.09	0.06	0.46
Regional Shock	0.07	0.12	-0.03	0.05	0.21
Firms with Public Guarantee	0.06	0.23	0.00	0.00	0.00
Firms with Moratorium	0.16	0.37	0.00	0.00	1.00
Firms with No Credit Relief Programs	0.73	0.44	0.00	1.00	1.00
Observations	218,407				

This table shows descriptive statistics on the bank, firm, and loan samples. Loan data are from Central Credit Responsibility (CRC), covering the years 2019 and 2020. Firm-specific data, as of the end of 2019, are from the Central Balance Sheet of Banco de Portugal. Data on firms' default probability are from Banco de Portugal's in-house credit assessment system (SIAC). Banks' balance sheet data, as of December 2019, are from supervisory reports and monetary and financial statistics (MFI Statistics). All variables are defined in Appendix A.

Table 2: Firms under Different Credit Relief Programs

	with PGS	with Moratorium	None	Total
Bank Chars				
PG Exp.	1.25	1.03	1.10	1.10
Morat Exp.	10.91	10.52	10.40	10.47
Bartik Instrument	0.21	0.17	0.18	0.18
Previous PG Exp.	0.95	0.84	0.82	0.84
Bank Assets (Billion)	45.38	40.98	43.71	43.25
Foreign Bank	0.10	0.10	0.09	0.09
Bank Liquidity	0.04	0.04	0.04	0.04
NPLs	0.03	0.03	0.03	0.03
Capital Ratio	0.11	0.11	0.11	0.11
Credit Ratio	0.64	0.65	0.64	0.64
Firm Chars				
Total Credit (thousand)	450.23	676.57	275.53	354.52
Total assets (thousand)	1,556.88	2,749.16	1,923.89	2,043.19
Firm Risk	0.04	0.09	0.12	0.11
Leverage	0.23	0.58	4.02	3.20
Profitability	0.06	-0.11	-0.86	-0.68
Industry Shock	0.15	0.17	0.10	0.12
Regional Shock	0.07	0.08	0.07	0.07

This table shows mean values for the subsamples of firms with PGS, moratorium, or none of the credit relief programs. Loan data are from Central Credit Responsibility (CRC), covering the years 2019 and 2020. Firm-specific data, as of the end of 2019, are from the Central Balance Sheet of Banco de Portugal. Data on firms' default probability are from Banco de Portugal's in-house credit assessment system (SIAC). Banks' balance sheet data, as of December 2019, are from supervisory reports and monetary and financial statistics (MFI Statistics). All variables are defined in Appendix A.

Table 3: Balance Checks

Exposure to Public Guarantee Programs				
	Exposed Banks	Non-Exposed Banks	Diff.	S.E.
Observations	13	42		
PG Exp.	0.991	0.000	0.991***	(0.216)
Morat. Exp.	10.102	5.480	4.622***	(1.473)
Previous PG Exp.	0.857	0.002	0.855**	(0.369)
Bank Size	9.338	5.984	3.354***	(0.570)
Foreign Bank	0.154	0.429	-0.275**	(0.130)
Bank Liquidity	0.046	0.015	0.032***	(0.010)
NPLs	0.042	0.029	0.013	(0.015)
Capital Ratio	0.113	0.185	-0.072*	(0.038)
CreditRatio	0.685	0.690	-0.005	(0.059)
Covid Exp.	37.088	33.324	3.764	(5.074)
Exposure to Moratorium Programs				
	High Exposure Banks	Low Exposure Banks	Diff.	S.E.
Observations	27	28		
PG Exp.	0.429	0.047	0.382**	(0.146)
Morat. Exp.	10.943	2.357	8.586***	(1.142)
Previous PG Exp.	0.366	0.047	0.319	(0.196)
Bank Size	7.376	6.200	1.176**	(0.566)
Foreign Bank	0.370	0.357	0.013	(0.132)
Bank Liquidity	0.030	0.015	0.015	(0.010)
NPLs	0.023	0.042	-0.019	(0.015)
Capital Ratio	0.146	0.189	-0.044	(0.054)
CreditRatio	0.716	0.662	0.054	(0.062)
Covid Exp.	39.443	29.170	10.273	(6.908)

This table shows differences in means between banks more and less exposed to Public Guarantee Schemes and more and less exposed to Moratorium Programs. Banks exposed to PGS are those with PG Exp. above the median, where PG Exp. is the ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Banks exposed to Moratorium are those with Morat Exp. above the median, where Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Loan data are from Central Credit Responsibility (CRC), covering the years 2019 and 2020. Banks' balance sheet data, as of December 2019, are from supervisory reports and monetary and financial statistics (MFI Statistics). All variables are defined in Appendix A. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Table 4: Bank-Firm Credit Supply: OLS Results

	Total Credit All Firms	NPG Credit All Firms	Total Credit With PG	NPG Credit With PG	Total Credit Without PG	Total Credit With Moratorium	Total Credit None
Post × PG Exp.	0.055***	-0.023***	0.215***	-0.058***	0.028***	0.012**	0.005
	(0.002)	(0.003)	(0.012)	(0.015)	(0.002)	(0.005)	(0.003)
Post × Morat. Exp.	-0.028***	-0.031***	-0.028***	-0.032***	-0.026***	-0.014***	-0.029***
	(0.002)	(0.002)	(0.008)	(0.009)	(0.002)	(0.003)	(0.002)
Post × Covid Exp.	-0.022***	-0.021***	-0.027***	-0.018*	-0.024***	-0.020***	-0.030***
	(0.002)	(0.002)	(0.009)	(0.010)	(0.002)	(0.003)	(0.002)
Bank Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILST FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,079,823	2,079,823	155,639	155,639	1,908,207	397,481	1,258,426
Adjusted R^2	0.915	0.919	0.864	0.906	0.919	0.917	0.909

This table shows the results from OLS regressions using bank-firm data. The dependent variable is (i) the log-transformed amount of total credit; (ii) the log-transformed amount of non-public guaranteed credit. Post is a dummy variable equal to 1 for quarters later than 2020q1. PG Exp. is the ratio of public-guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. Morat Exp. is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets. Covid Exp. is the ratio of credit to firms that operated in sectors most affected by the COVID-19 Pandemic (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile), over bank's total assets. Bank characteristics, as of the end of 2019, include log(bank assets), foreign bank dummy, bank liquidity, non-performing loans, and capital ratio. All regressions include industry-location-size-quarter fixed effects and bank-firm fixed effects. All variables are defined in Appendix A. Robust standard errors, clustered at the bank-quarter level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Table 5: Bank-Firm Credit Supply: IV Results

	Total Credit All Firms	NPG Credit All Firms	Total Credit With PG	NPG Credit With PG	Total Credit Without PG	Total Credit Without Moratorium	Total Credit None
Post × PG Exp.	0.054***	-0.048***	0.268***	-0.110***	0.020***	0.002	-0.007*
	(0.003)	(0.003)	(0.015)	(0.017)	(0.003)	(0.006)	(0.004)
Post × Morat. Exp.	-0.028***	-0.022***	-0.045***	-0.015	-0.023***	-0.012***	-0.026***
	(0.002)	(0.002)	(0.008)	(0.010)	(0.002)	(0.003)	(0.002)
Post × Covid Exp.	-0.022***	-0.027***	-0.010	-0.034***	-0.026***	-0.022***	-0.033***
	(0.002)	(0.002)	(0.009)	(0.011)	(0.002)	(0.004)	(0.002)
First Stage							
Post × Bartik	6.063***	6.063***	6.192***	6.192***	6.055***	6.073***	6.036***
	(0.007)	(0.007)	(0.033)	(0.033)	(0.007)	(0.016)	(0.009)
Bank Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILST FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,079,823	2,079,823	155,639	155,639	1,908,207	397,481	1,258,426
F	819.405	192.384	342.443	9.448	526.333	109.926	253.816

This table shows the results from IV regressions using bank-firm data. The dependent variable is (i) the log-transformed amount of total credit; (ii) the log-transformed amount of non-public guaranteed credit. Post is a dummy variable equal to 1 for quarters later than 2020q1. In the first-stage of our IV model, we use the Bartik instrument to endogenize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. PG Exp. is the predicted ratio of public-guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. Morat Exp. is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets. Covid Exp. is the ratio of credit to firms that operated in sectors most affected by the COVID-19 Pandemic (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile), over bank's total assets. Bank characteristics, as of the end of 2019, include log(bank assets), foreign bank dummy, bank liquidity, non-performing loans, and capital ratio. All regressions include industry-location-size-quarter fixed effects and bank-firm fixed effects. All variables are defined in Appendix A. Robust standard errors, clustered at the bank-quarter level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Table 6: Firm Credit Results

	Total Credit All Firms	NPG Credit All Firms	Total Credit With PG	NPG Credit With PG	Total Credit Without PG	Total Credit With Moratorium	Total Credit None
Post × PG Exp.	0.023***	-0.035***	0.056	-0.123**	-0.005	0.002	-0.005
	(0.004)	(0.005)	(0.034)	(0.051)	(0.004)	(0.009)	(0.005)
Post × Morat. Exp.	-0.013***	-0.013***	0.002	0.027	-0.010***	-0.021***	-0.010***
	(0.003)	(0.003)	(0.024)	(0.032)	(0.003)	(0.006)	(0.003)
Post × Covid Exp.	-0.003	-0.020***	0.054**	-0.036	-0.012***	0.003	-0.014***
	(0.003)	(0.003)	(0.027)	(0.034)	(0.003)	(0.005)	(0.003)
First Stage							
Post × Bartik	6.781***	6.781***	6.977***	6.977***	6.778***	6.875***	6.775***
	(0.012)	(0.012)	(0.081)	(0.081)	(0.013)	(0.041)	(0.014)
Bank Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILST FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,055,095	1,055,095	40,203	40,203	984,512	136,374	789,992

This table shows the firm-level credit results. The dependent variable is (i) the log-transformed amount of total credit; (ii) the log-transformed amount of non-public guaranteed credit, all aggregated at the firm level. Bank exposures and characteristics are the weighted averages by the share of credit of firm's relationship banks in 2019q4. Post is a dummy variable equal to 1 for quarters later than 2020q1. In the first-stage of our IV model, we use the Bartik instrument to endogenize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. PG Exp. is the predicted ratio of public-guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. Morat Exp. is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets. Covid Exp. is the ratio of credit to firms that operated in sectors most affected by the COVID-19 Pandemic (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile), over bank's total assets. Bank characteristics, as of the end of 2019, include log(bank assets), foreign bank dummy, bank liquidity, non-performing loans, and capital ratio. Firm characteristics, measured in 2019, include firm size, risk, and profitability. All regressions include industry-location-size-quarter fixed effects and firm fixed effects. All variables are defined in Appendix A. Robust standard errors, clustered at the firm level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Table 7: Lending Conditions

	Pricing				Collateral			
	All Firms	With PG	With Moratorium	None	All Firms	With PG	With Moratorium	None
Post × PG Exp.	-0.952***	-1.646**	-1.017***	-0.570***	-0.051**	0.106	-0.069**	-0.082***
	(0.148)	(0.763)	(0.273)	(0.150)	(0.020)	(0.146)	(0.031)	(0.025)
Post × Morat. Exp.	0.627***	1.058**	0.655***	0.371***	0.047***	-0.052	0.054***	0.063***
	(0.100)	(0.502)	(0.185)	(0.097)	(0.013)	(0.096)	(0.020)	(0.016)
Post × Covid Exp.	-0.376***	-0.678**	-0.275**	-0.237***	-0.021**	0.023	-0.038***	-0.027**
	(0.062)	(0.278)	(0.115)	(0.066)	(0.008)	(0.057)	(0.013)	(0.011)
First Stage								
Post × Bartik	0.602***	0.308***	0.732***	0.685***	0.602***	0.308***	0.732***	0.685***
	(0.038)	(0.061)	(0.069)	(0.040)	(0.038)	(0.061)	(0.069)	(0.040)
Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,460	8,656	15,761	16,073	70,460	8,656	15,761	16,073
Adjusted R^2	0.014	0.008	0.021	0.009	0.007	0.004	0.012	0.008
F	20.410	2.062	10.992	6.237	8.040	1.843	3.773	3.015

This table shows the regression results on lending conditions of newly issued loans. The dependent variable is i) annual interest rate (pricing); ii) a dummy variable for a secured loan (collateralization). We run the same model on different subsamples: all firms, firms with PG credit, firms with Moratorium, or none. Post is a dummy variable equal to 1 for quarters later than 2020q1. In the first-stage of our IV model, we use the Bartik instrument to endogenize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. PG Exp. is the predicted ratio of public guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. Morat Exp. is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets. Covid Exp. is the ratio of credit to firms that operated in sectors most affected by the COVID-19 Pandemic (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile), over bank's total assets. Control variables include bank characteristics as of Dec. 2019 (log(bank assets), foreign bank dummy, bank liquidity, non-performing loans, and capital ratio) and firm characteristics as of 2019 (firm size, risk, and profitability), and loan maturity. All regressions include bank-firm and time fixed effects. All variables are defined in Appendix A. Robust standard errors, clustered at the bank-firm level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Table 8: Robustness Tests: Khwaja and Mian (2008)

	Total Credit All Firms	NPG Credit All Firms	Total Credit With PG	NPG Credit With PG	Total Credit Without PG	Total Credit With Moratorium	Total Credit None
Post × PG Exp.	0.086***	-0.038***	0.303***	-0.085***	0.053***	0.017**	0.013*
	(0.004)	(0.005)	(0.016)	(0.019)	(0.005)	(0.008)	(0.007)
Post × Morat. Exp.	-0.034***	-0.023***	-0.056***	-0.021*	-0.029***	-0.012***	-0.030***
	(0.002)	(0.003)	(0.009)	(0.011)	(0.002)	(0.004)	(0.004)
Post × Covid Exp.	-0.020***	-0.028***	-0.001	-0.031**	-0.022***	-0.020***	-0.029***
	(0.003)	(0.003)	(0.010)	(0.012)	(0.003)	(0.004)	(0.004)
First Stage							
Post × Bartik	6.051***	6.051***	6.211***	6.211***	6.040***	6.050***	6.008***
	(0.010)	(0.010)	(0.036)	(0.036)	(0.010)	(0.019)	(0.013)
Bank Chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,332,334	1,332,334	135,923	135,923	1,196,411	329,039	663,229
F	567.671	105.236	282.944	6.967	377.935	76.915	136.110

This table shows the robustness of bank-firm regression results presented in Table 5 using the Khwaja and Mian (2008) estimator instead of the ILST estimator. The dependent variable is (i) the log-transformed amount of total credit; (ii) the log-transformed amount of non-public guaranteed credit. Post is a dummy variable equal to 1 for quarters later than 2020q1. In the first-stage of our IV model, we use the Bartik instrument to endogenize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. PG Exp. is the predicted ratio of public-guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. Morat Exp. is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets. Covid Exp. is the ratio of credit to firms that operated in sectors most affected by the COVID-19 Pandemic (i.e. industries which value-added decreased most from 2019 to 2020 based on the third tercile), over bank's total assets. Bank characteristics, as of the end of 2019, include log(bank assets), foreign bank dummy, bank liquidity, non-performing loans, and capital ratio. All regressions include firm-quarter and bank-firm fixed effects. All variables are defined in Appendix A. Robust standard errors, clustered at the bank-quarter level, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance levels.

Figures

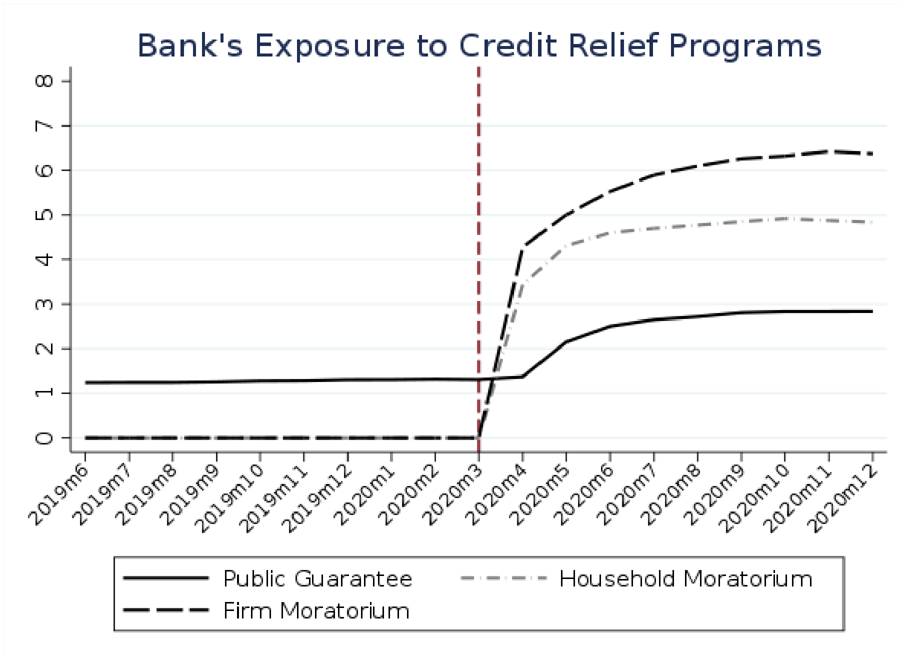


Figure 1: Bank's Exposure to Credit Relief Programs

This figure shows the aggregate bank exposures to the credit relief programs, as a percentage of bank assets, from June 2019 to December 2020. The red dashed-line represents the outbreak of the COVID-19 crisis in Portugal.

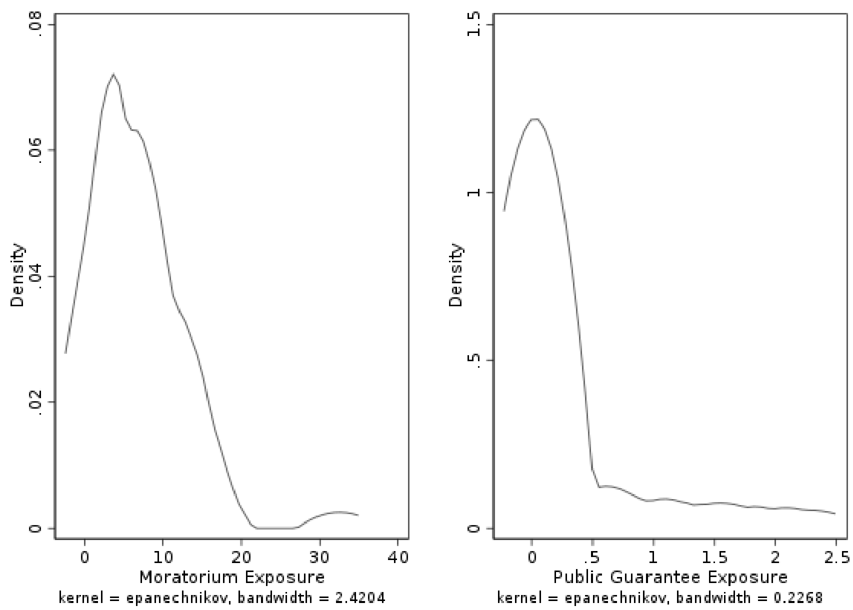
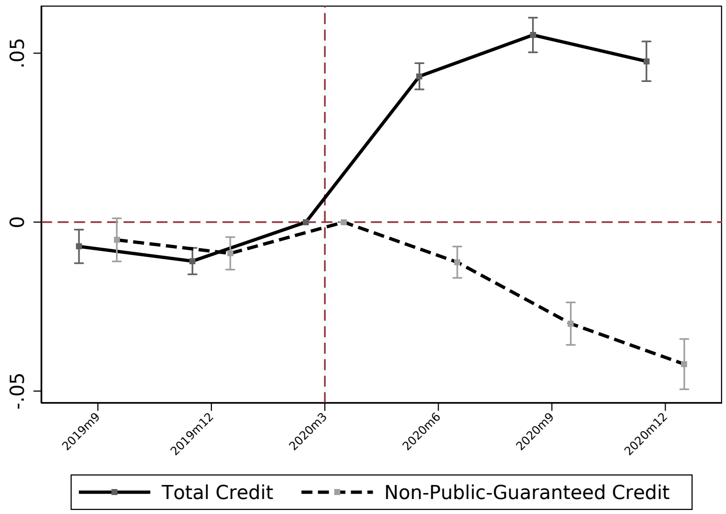
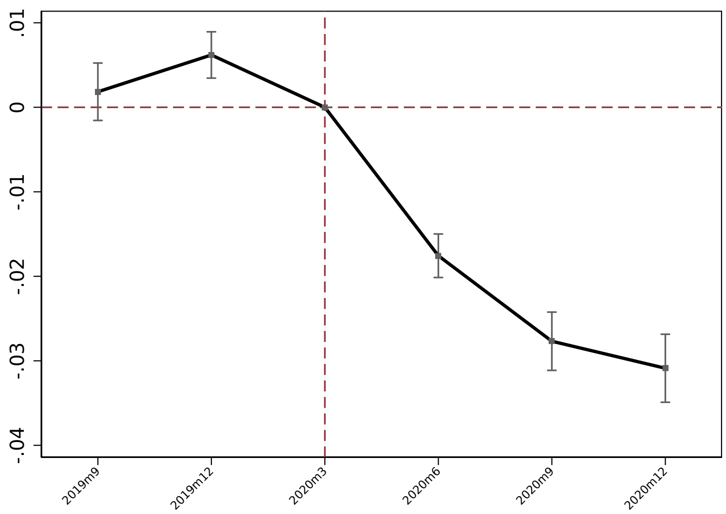


Figure 2: Distribution of Bank Exposure to Credit Relief Programs

This figure plots the distribution of bank exposure to PGS and moratorium programs. The PGS exposure is the ratio of public-guaranteed credit granted to firms in March, April, and May 2020 over bank's total assets. The moratorium exposure is the ratio of credit to firms under moratorium in March, April, and May 2020 over bank's total assets.



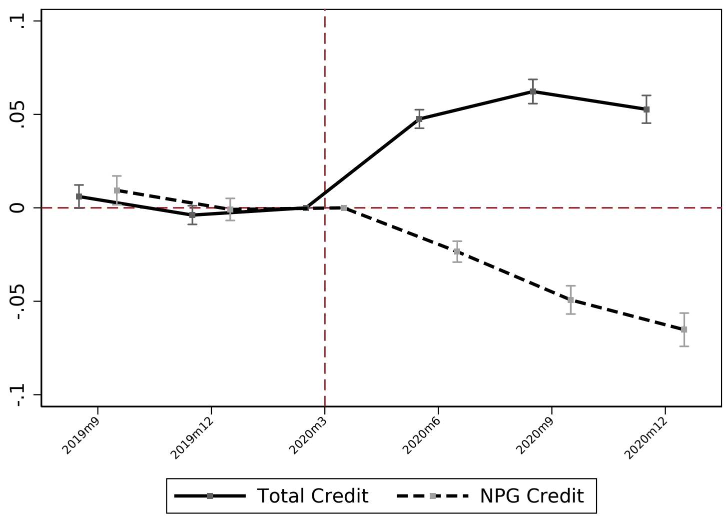
(a) Bank's Exposure to Public Guarantee Programs



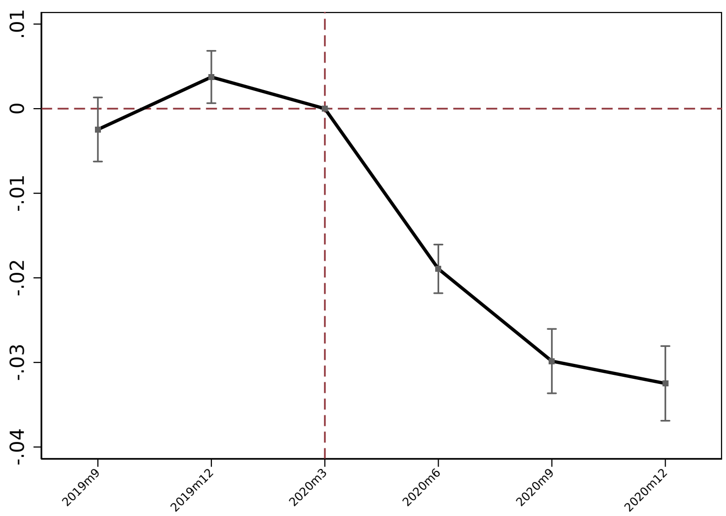
(b) Bank's Exposure to Moratorium Programs

Figure 3: Bank-Firm Credit Supply: OLS Results

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply in our baseline OLS specification. Standard errors are clustered at the bank-quarter level. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets.



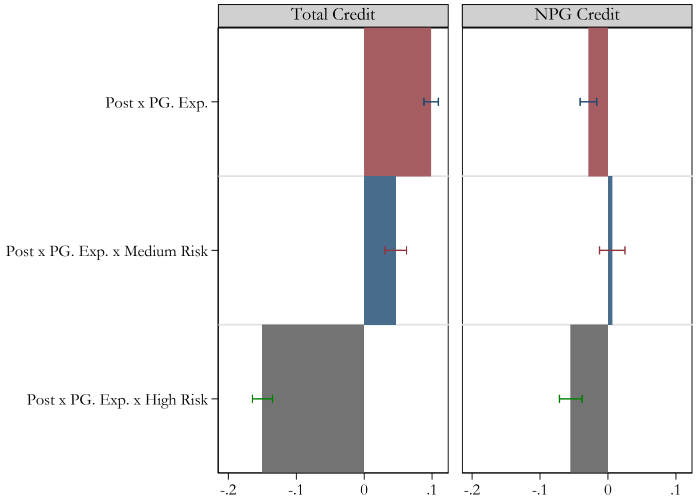
(a) Bank's Exposure to Public Guarantee Programs



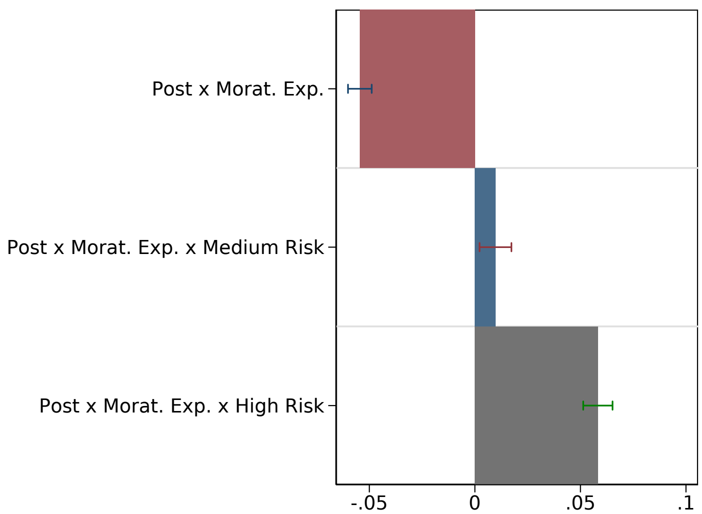
(b) Bank's Exposure to Moratorium Programs

Figure 4: Bank-Firm Credit Supply: IV Results

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply in our baseline IV specification. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



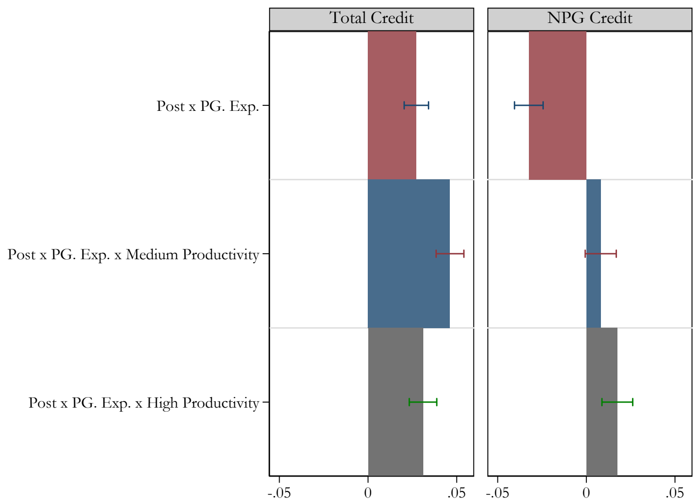
(a) Bank's Exposure to Public Guarantee Programs



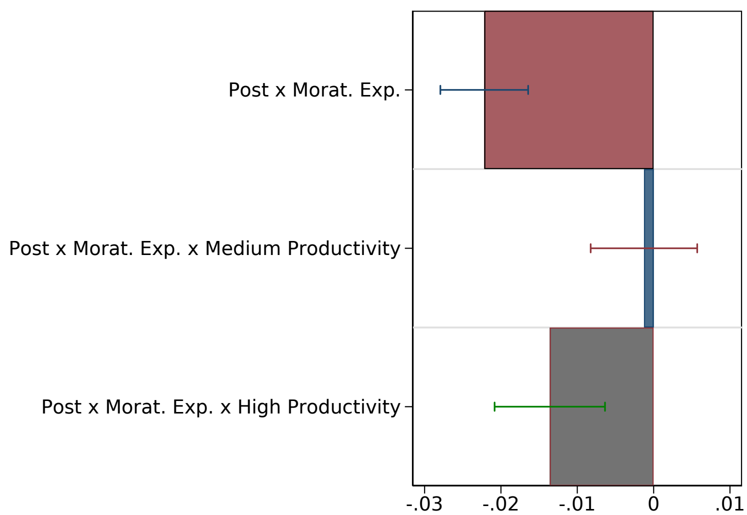
(b) Bank's Exposure to Moratorium Programs

Figure 5: Firm Risk

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply, applying the triple difference estimator. We classify firms into three risk groups: low-risk firms (probability of default in the first tercile), medium-risk (probability of default in the second tercile), and high-risk (probability of default in the third tercile). Insolvent firms with negative equities are also classified as high-risk firms. We then define two dummy variables for the medium-risk and the high-risk group which we then interact with PG Exp., Morat Exp., and the double difference terms. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



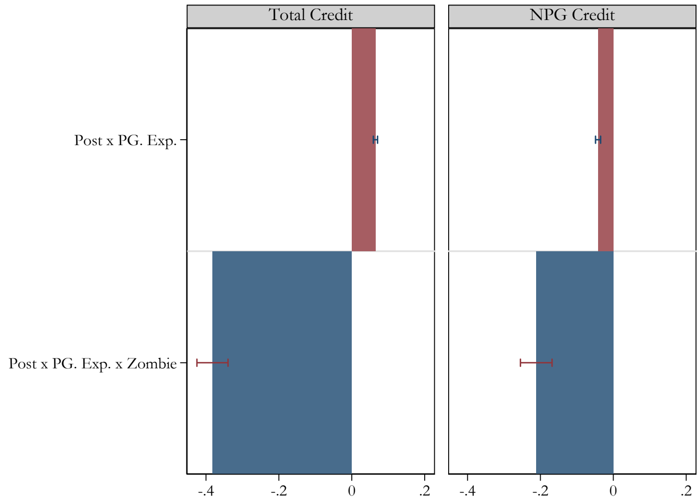
(a) Bank's Exposure to Public Guarantee Programs



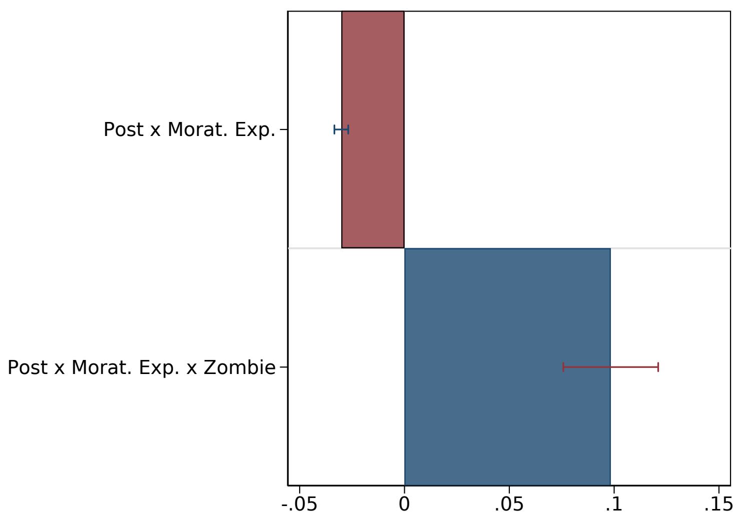
(b) Bank's Exposure to Moratorium Programs

Figure 6: Firm Productivity

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply, applying the triple difference estimator. We classify firms into three groups based on productivity terciles. We then define two dummy variables for the medium-productivity and the high-productivity group which we then interact with PG Exp., Morat Exp., and the double difference terms. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



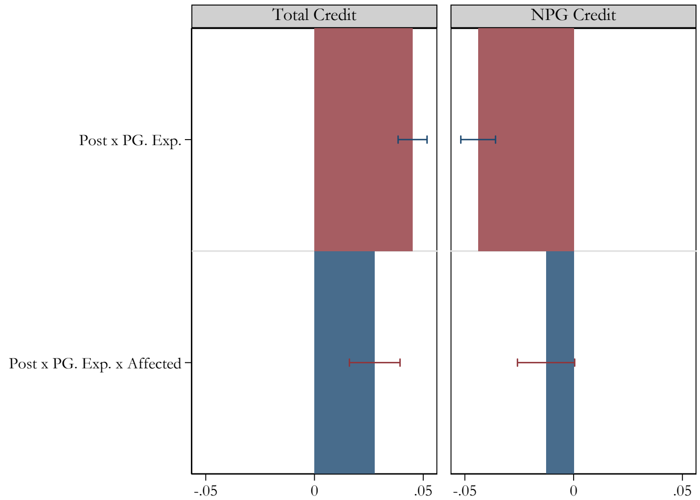
(a) Bank's Exposure to Public Guarantee Programs



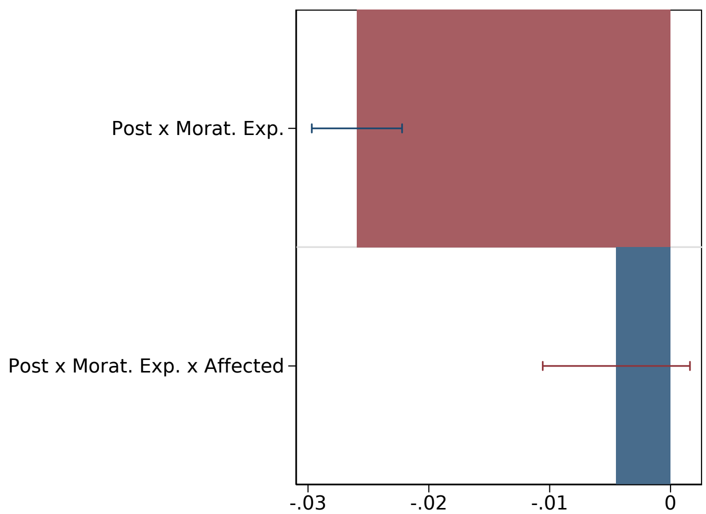
(b) Bank's Exposure to Moratorium Programs

Figure 7: Zombie Firms

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply, applying the triple difference estimator. We identify zombies as firms with an interest coverage ratio of less than 1 over three years. We then define a dummy variable for zombie firms which we then interact with PG Exp., Morat Exp., and the double difference terms. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



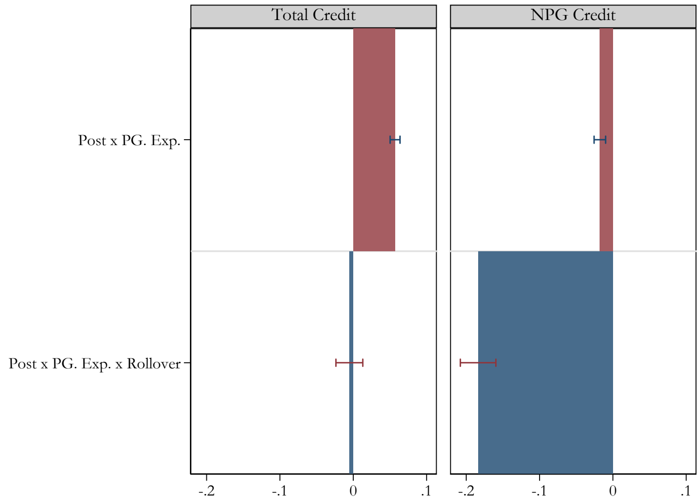
(a) Bank's Exposure to Public Guarantee Programs



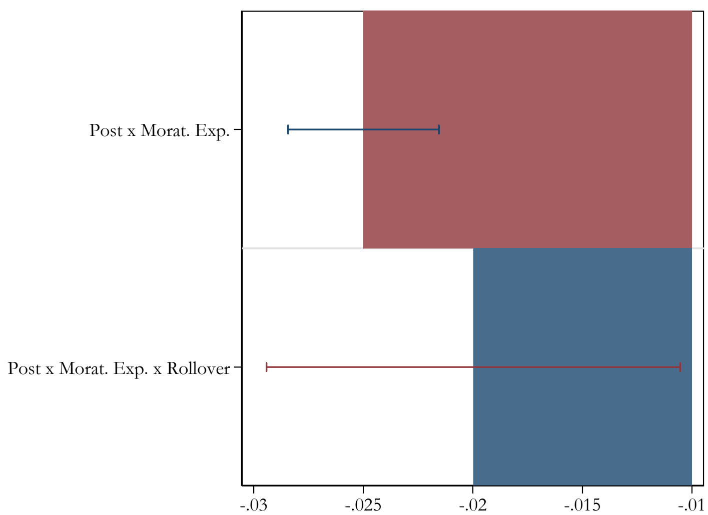
(b) Bank's Exposure to Moratorium Programs

Figure 8: Affected Industry

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply, applying the triple difference estimator. We classify firms into two groups based on the extent to which their business sectors are affected by the COVID-19 pandemic: affected firms (sectorial value-added decrease from 2019 to 2020 is in the third tercile) and unaffected firms (sectorial value-added decrease from 2019 to 2020 is in the first and the second terciles). We then define a dummy variable for affected firms which we then interact with PG Exp., Morat Exp., and the double difference terms. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



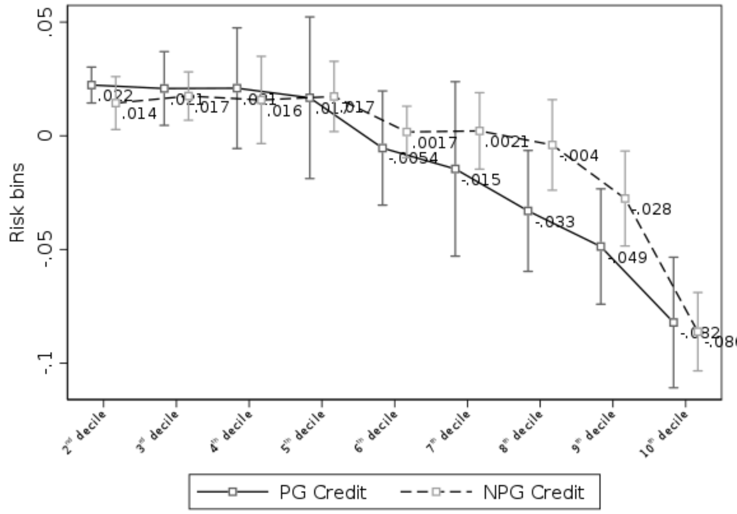
(a) Bank's Exposure to Public Guarantee Programs



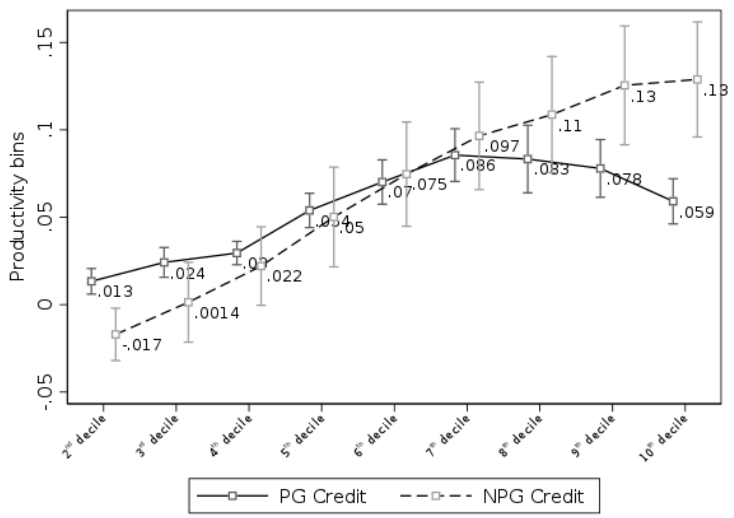
(b) Bank's Exposure to Moratorium Programs

Figure 9: Replacement

This figure shows point estimates and 95% confidence intervals for the dynamic effect of bank's exposure to credit relief programs on credit supply, applying the triple difference estimator. We define a dummy variable for situations when a firm faced rollover decisions from its relationship bank during the peak of the COVID-19 pandemic (fraction of credit that became due before June 2020 is in the third tercile) which we then interact with PG Exp., Morat Exp., and the double difference terms. As in Table 5, we use the Bartik instrument to endogeneize the exposure to public guarantee credit. Bartik is computed as the shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry. Panel A plots the coefficients on PG Exp. when the dependent variable is either total credit or non-Public-Guaranteed credit. PG Exp. is the predicted ratio of PGS granted to firms in March, April, and May 2020 over bank's total assets. Panel B plots the coefficients on Morat Exp where the dependent variable is the total credit. Morat Exp. is the ratio of credit to firms under moratorium programs in March, April, and May 2020 over bank's total assets. Standard errors are clustered at the bank-quarter level.



(a) Firm Risk Deciles



(b) Firm Productivity Deciles

Figure 10: Which Firms Were Granted Public Guaranteed and Non-Public Guaranteed Credit?

This figure shows point estimates and 95% confidence intervals for the coefficients of the risk deciles in panel (a) and the productivity deciles in panel (b) based on a linear probability model of obtaining a public guaranteed credit (PG Credit) or non-public guaranteed credit (NPG Credit). The first decile serves as the reference group and is omitted from the estimation. The dependent variable is i) a dummy variable that takes a value of one if a firm obtained public guaranteed credit in 2020, ii) a dummy variable that takes a value of one if a firm obtained non-public guaranteed bank credit in 2020. Control variables include firm size, risk, profitability, age, cash holding, leverage, insolvency, a dummy for zombie firms, and a dummy for firms with pre-pandemic public guarantee credit. We control for sector and location fixed effects. Standard errors are clustered at the sector level.

References

Acharya, V., Dreschsler, I., and Schnabl, P. (2014). A pyrrhic victory? bank bailouts and sovereign credit risk. *The Journal of Finance*, 69(6):2689–2739.

Acharya, V., Eisert, T., Eufinger, C., and Hirsch, C. (2018). Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans. *Review of Financial Studies*, 31(8):2855–2896.

Acharya, V. V. and Steffen, S. (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *Review of Corporate Finance Studies*, 9(3):430–471.

Akgunduz, Y. E., Cilasun, S. M., Dursun-de Neef, , Hacihasanoglu, Y., and Yarba, (2022). How do Banks Propagate Economic Shocks? *SSRN Working Paper*.

Altavilla, C., Barbiero, F., Boucinha, M., and Burlon, L. (2020). The Great Lockdown: Pandemic Response Policies and Bank Lending Conditions. *ECB Working Paper*, 2465.

Altavilla, C., Ellul, A., Pagano, M., Polo, A., and Vlassopoulos, T. (2021). Loan Guarantees, Bank Lending and Credit Risk Reallocation. *SSRN Electronic Journal*.

Bachas, N., Kim, O. S., and Yannelis, C. (2021). Loan guarantees and credit supply. *Journal of Financial Economics*, 139(3):872–894.

Banco de Portugal (2021). Nota de informação estatística – moratórias de crédito – novembro de 2021.

Berger, A. N., Bouwman, C. H. S., Norden, L., Roman, R. A., Udell, G. F., and Wang, T. (2021). Is a Friend in Need a Friend Indeed? How Relationship Borrowers Fare during the COVID-19 Crisis. *Federal Reserve Bank of Philadelphia Working Paper*, 21-13.

Bonfim, D., Ferreira, M. A., Queiro, F., and Sujiao, Z. (2022). Sovereign-Bank Diabolic Loop: The Government Procurement Channel. *Nova SBE Working Paper Series*.

Cascarino, G., Gallo, R., Palazzo, F., and Sette, E. (2022). Public guarantees and credit additionality during the Covid-19 pandemic. *MOFiR Working Paper*, 172.

Chodorow-Reich, G., Darmouni, O., Luck, S., and Plosser, M. (2021). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*.

Core, F. and De Marco, F. (2020). Public Guarantees for Small Businesses in Italy during Covid-19*. *Working Paper*.

Couaillier, C., Lo Duca, M., Reghezza, A., and D'Acri, C. R. (2022). Caution: Do Not Cross! Capital Buffers and Lending in COVID-19 Times. *ECB Working Paper*, (2644).

Custodio, C., , Bonfim, D., and Raposo, C. C. (2022). Supporting small firms through recessions and recoveries. *Working Paper*.

de Blasio, G., De Mitri, S., D'Ignazio, A., Finaldi Russo, P., and Stoppani, L. (2018). Public guarantees to SME borrowing. A RDD evaluation. *Journal of Banking and Finance*, 96:73–86.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.

Demirgüç-Kunt, A., Horváth, B. L., and Huizinga, H. (2020). Which firms benefit from corporate qe during the covid-19 crisis? the case of the ecb's pandemic emergency purchase program.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review*, 110(8):2586–2624.

Gourinchas, P.-O., Kalemli-Özcan, , Penciakova, V., and Sander, N. (2021). COVID-19 and Small- and Medium-Sized Enterprises: A 2021 "Time Bomb"? *AEA Papers and Proceedings*, 111:282–286.

Granja, J., Makridis, C., Yannelis, C., and Zwick, E. (2022). Did the paycheck protection program hit the target? *Journal of Financial Economics*, 145(3):725–761.

Greenwald, D. L., Krainer, J., and Paul, P. (2020). The Credit Line Channel. *Federal Reserve Bank of San Francisco Working Paper*, 26.

Kapan, T. and Minoiu, C. (2021). Liquidity Insurance vs. Credit Provision: Evidence from the COVID-19 Crisis. *SSRN Electronic Journal*, 3773328(October).

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

Kozeniauskas, N., Moreira, P., and Santos, C. (2022). On the cleansing effect of recessions and government policy: Evidence from Covid-19. *European Economic Review*, 144:104097.

Lagazio, C., Persico, L., and Querci, F. (2021). Public guarantees to SME lending: Do broader eligibility criteria pay off? *Journal of Banking Finance*, 133:106287.

Leonello, A. (2021). Government guarantees and the two-way feedback between banking and sovereign debt crises. *Journal of Financial Economics*, 130(3):592–619.

Li, L., Strahan, P. E., and Zhang, S. (2020). Banks as lenders of first resort : evidence from the covid-21 crisis. *NBER working papaer series*, 27256(may):1 − 37.

Presidency of the Council of Ministers (2020). Resolution of the council of ministers no.41/2020.

Runkel, C. (2022). Eurozone: Pandemic emergency purchase program. *Runkel, Corey*, (2022):1569–1600.

Schularick, M., Steffen, S., and Troeger, T. H. (2020). Bank capital and the european recovery from the covid-19 crisis.

Tribunal de Contas (2021). Covid-19 - execução orçamental, dívidas e garantias a 30 de setembro de 2020.

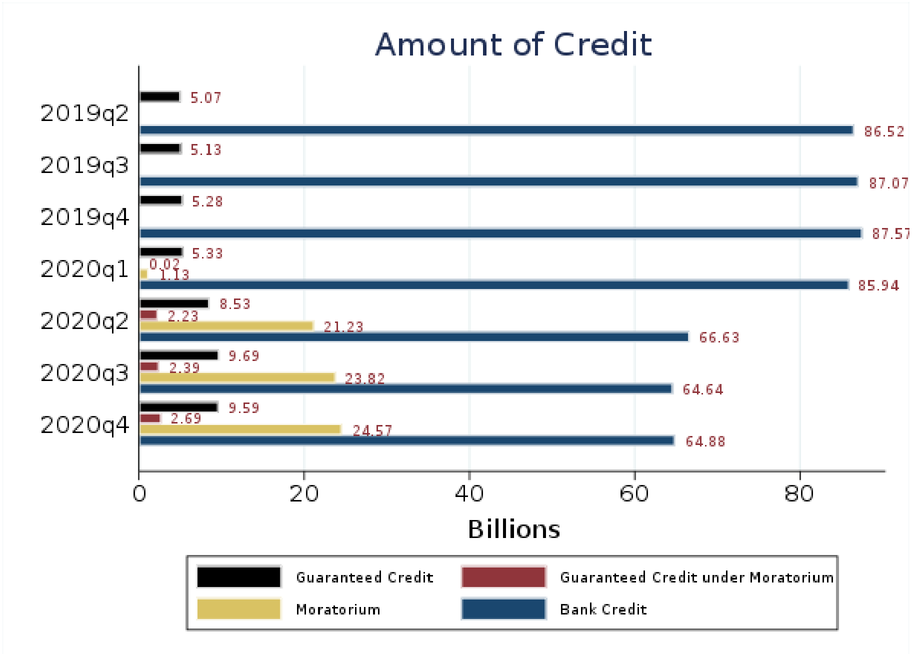
Zecchini, S. and Ventura, M. (2009). The impact of public guarantees on credit to SMEs. *Small Business Economics*, 32(2):191–206.

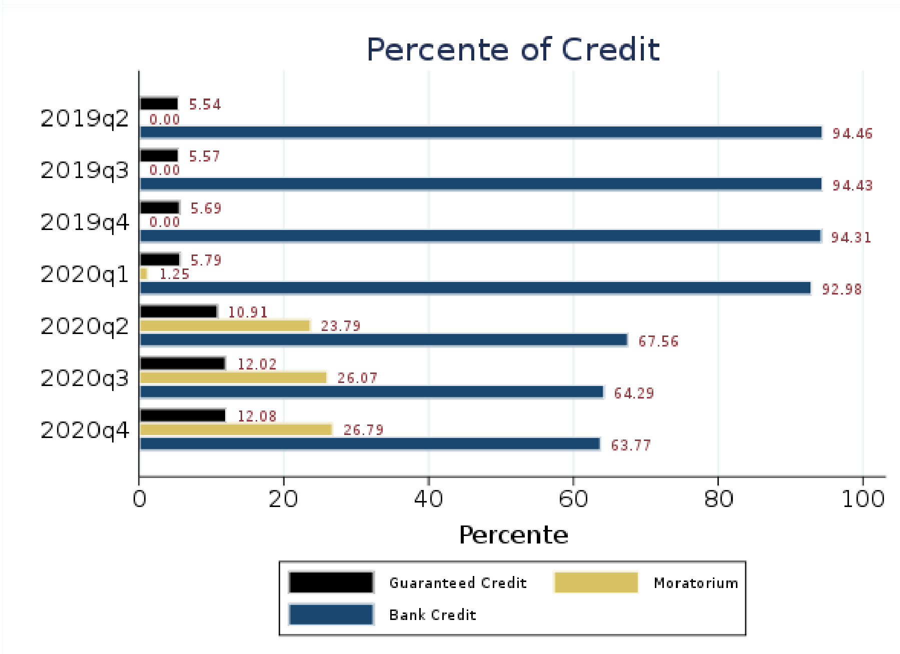
Appendices

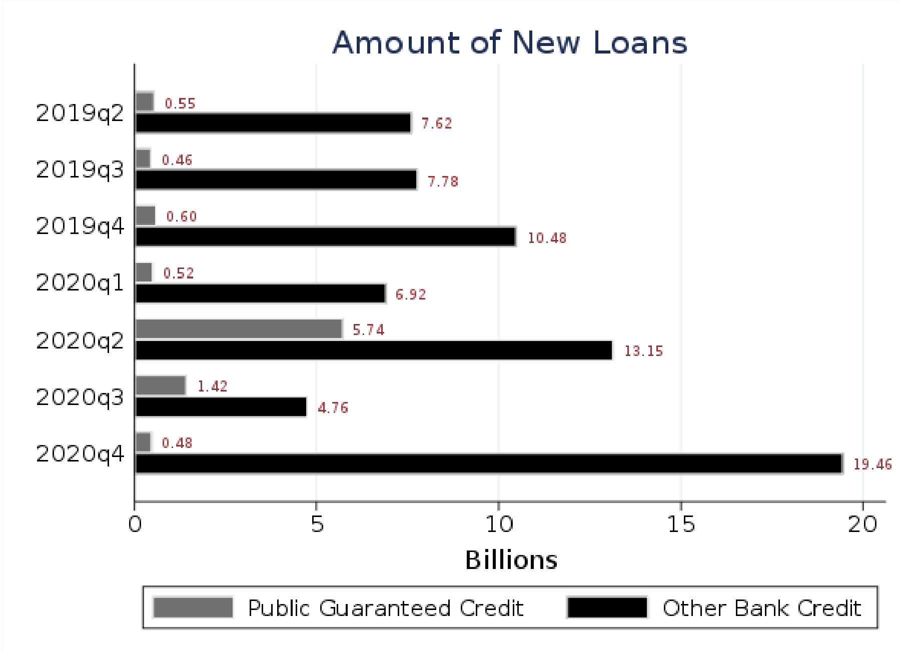
Appendix A Variable Definitions

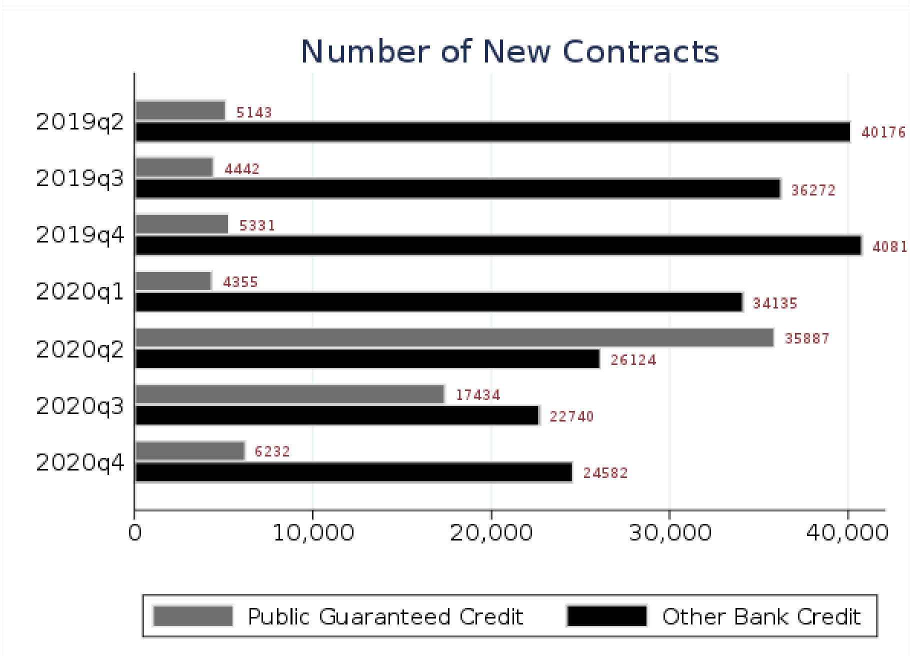
Bank-Firm Variables	
Total Credit	Firm's total credit outstanding in each bank
NPG Credit	Firm's non-public guaranteed credit outstanding in each bank
Bank Variables	
PG Exp.	Credit to firms under the public guarantee schemes granted in March, April, and May 2020, as a fraction of total bank assets
Morat Exp.	Credit to firms under the moratorium programs in March, April, and May 2020, as a fraction of total bank assets
Bartik Instrument	Shift-share predictor of public guarantee growth from March 2020 to May 2020 by municipality and industry
Covid Exp.	Credit to firms who operated in sectors that are most affected by the COVID-19 Pandemic, as a fraction of total bank assets
Previous PG Exp.	Credit to firms under the public guarantee schemes granted before March 2020, as a fraction of total bank assets
Bank Assets	Book value of total bank assets
Foreign Bank	Dummy variable that takes the value of one if a majority of the bank's equity is owned by a foreign bank
Bank Liquidity	Ratio of liquid to total assets
NPLs	Ratio of non-performing to total corporate loans
Capital Ratio	Ratio of bank equity to total assets
Credit Ratio	Ratio of corporate credit to total assets
Firm Variables	
Total Assets	Book value of firm total assets
Firm Risk	Firm probability of default
Leverage	Firm total debts as a fraction of total assets
Profitability	Firm EBIT as a fraction of total assets
Industry Shock	Symmetric drop in sectorial (3-digit) value-added from 2019 to 2020
Regional Shock	Symmetric drop in municipality value-added from 2019 to 2020
Loan Variables	
Loan Amount	Amount of a new loan
Annual Interest Rate	Nominal annual interest rate
Collateral Dummy	Dummy variable that takes the value of one if the loan is secured by collateral
Maturity	Maturity (in years) of the loan on which a borrower's final loan payment is due.

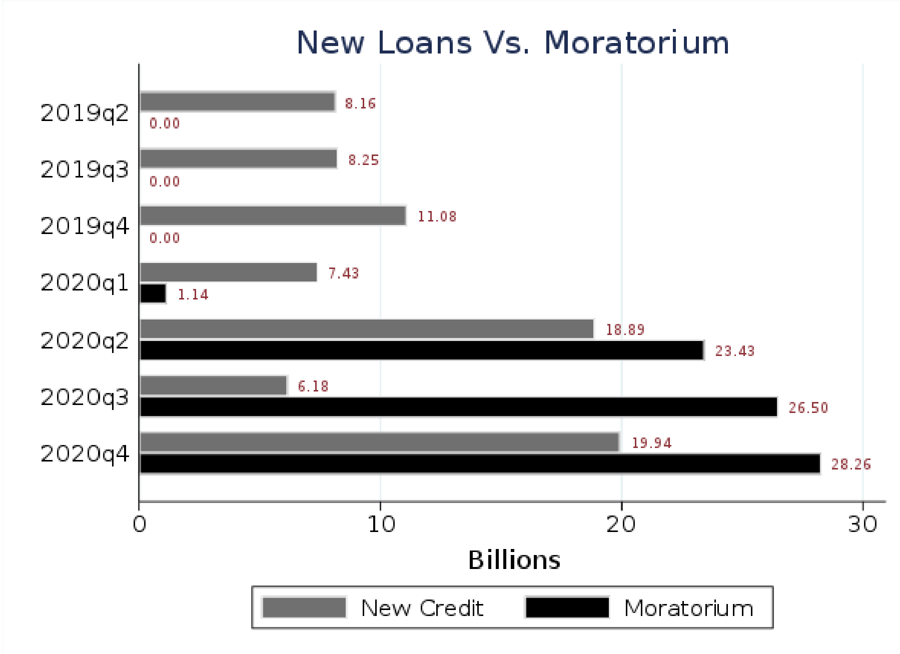
Appendix B Credit Evolution around the COVID-19 Recession in the Corporate Sector






Amount of New Loans
2019q2
2019q3
2019q4
2020q1
2020q2
2020q3
2020q4
0.55
7.62
0.46
7.78
0.60
10.48
0.52
6.92
5.74
13.15
1.42
4.76
0.48
19.46
0
5
10
15
20
Billions
Public Guaranteed Credit
Other Bank Credit


Number of New Contracts
2019q2
2019q3
2019q4
2020q1
2020q2
2020q3
2020q4
5143
40176
4442
36272
5331
4081
4355
34135
35887
26124
17434
22740
6232
24582
0
10,000
20,000
30,000
40,000
Public Guaranteed Credit
Other Bank Credit


New Loans Vs. Moratorium
2019q2
2019q3
2019q4
2020q1
2020q2
2020q3
2020q4
8.16
0.00
8.25
0.00
11.08
0.00
7.43
1.14
18.89
23.43
6.18
26.50
19.94
28.26
0
10
20
30
Billions
New Credit
Moratorium