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Public Guarantees, Relationship Lending and Bank Credit: Evidence from the COVID-19 Crisis

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Abstract

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JEL Classification: G01, G21, G38, E44, E62, H12, H81

Keywords: public guarantees, bank lending, COVID-19, Bank lending relationships, public and private risk substitution, Bank Competition

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Abstract

This paper analyzes the impact of public credit guarantee schemes on the allocation and performance of bank credit during the COVID-19 crisis. We exploit exhaustive loan-level data from the credit register with unique information on the provision of COVID-19 public loan guarantees in Spain. We find that firms are more likely to obtain a public guaranteed loan from banks to which they have larger pre-COVID credit exposures, measured as the share of the firm's total credit outstanding with the bank before the shock. This effect is more pronounced for risky firms and for firms in more pandemic-affected sectors, especially for weaker ex-ante banks, with lower capital and higher nonperforming loans. Effects operate both at the intensive and extensive margin of lending. Moreover, we show that the guarantee scheme results in credit substitution at the firm-bank level, with the share and amount of nonguaranteed (private) credit declining for firms that obtain guaranteed loans, in part reflecting early prepayment of outstanding private credit. Further, banks that grant guaranteed loans are less prone to recognize loan impairment, consistent with the public guarantee acting as a protection against (private) credit risk. Finally, we find that banks that participate more in the public credit guarantee scheme gain market share by increasing their portfolio of loans to existing but also to (less risky) new borrowers. These results show that government guaranteed credit has relevant economic effects on the structure of the banking system by affecting both existing and new borrower-lender relationships.

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1. Introduction

The COVID-19 pandemic and ensuing lockdowns halted large parts of the economy, causing a liquidity squeeze and dash for cash by firms (Eichenbaum et al., 2020; Guerrieri et al., 2020; Ding et al., 2020; Li et al., 2020; and Acharya et al., 2020). This prompted large-scale government interventions to keep firms afloat, including pay protection programs and loan guarantee schemes (Granja et al., 2020; Humphries et al., 2020; Chodorow-Reich et al., 2021; Baudino, 2020; and Falagiarda et al., 2020).

This paper analyzes the impact of public loan guarantee schemes on bank lending during COVID-19. We first analyze the determinants of public guaranteed loans, highlighting the relevance of pre-existing bank-firm credit exposures as a key driver of the allocation of public guaranteed credit. We then analyze the consequences of granting public guaranteed credit in terms of substitution between public guaranteed and non-guaranteed (private) credit, early repayments of loans, recognition of loan impairments, and bank competition, both for existing relationships and new borrowers.

Public guarantee schemes offer credit protection on part of the loan in exchange for a fee, which lenders pay to an administering agency in case they decide to disburse the loan, and typically come with eligibility criteria and lending requirements in terms of firm size and loan terms. While the guarantees are usually administered by government agencies on behalf of the government, the final lending decisions are delegated to financial intermediaries (lenders) and, hence, their disbursement depends on private banks' *incentives*. Loan guarantees act as credit enhancements, and as such are, from the perspective of the lenders, tantamount to a boost in creditworthiness of firms. The introduction of public loan guarantees aims to support the flow of credit by easing the tightening in firms' and banks' capital constraints originated by the decline in economic activity. The intended effects should be larger for firms with a larger capital tightening (more directly affected by the COVID-19 shock) and that were poorly capitalized to begin with (Holmström and Tirole, 1997). Moreover, public guarantees may not only be a boost to the creditworthiness of borrowers, but may also provide incentives to substitute private credit risk with public guarantees (Gale, 1991) as well as impact bank competition (Dell'Ariccia, Friedman and Marquez, 1999).

A key question is what the main mechanisms underlying banks' distribution of guaranteed credit are, as these can affect the effectiveness of the guarantee scheme. The government guarantees should ideally reach those firms that need it most, addressing the failure of the market to do so. However, in practice the allocation may be distorted by borrower and lender considerations. In this paper, we document how different firm and bank level fundamentals shape the distribution of guaranteed credit, focusing on the relevance of bank-firm pre-COVID credit exposures. We find that firms are more likely to obtain guaranteed credit from those banks to whom they have larger pre-existing credit exposures, measured as the share of the firm's total credit outstanding with the bank before the COVID-19. We also find that guaranteed loans are more likely to go to riskier firms (in terms of worse ex-ante credit scoring) and firms that are in sectors more negatively affected by the crisis (e.g. tourism, transport, hospitality), consistent with the relevance of balance sheet effects. Interestingly, these effects are increasing in the pre-existing exposure between the firm and the bank, consistent with the relevance of bank's incentives in disbursing guaranteed loans.

A second key question is what the effects of granting guaranteed loans are. We provide evidence on the relevance of guaranteed loans by first showing how the granting of public guaranteed loans by banks affect non-guaranteed private credit, resulting in credit substitution between public and private credit especially for riskier firms and by weaker banks which is suggestive of bank's incentives playing a key role. We then show how the granting of public guaranteed loans by a bank increases firms' private credit prepayment behavior to the bank, as well as reduces bank's recognition of non-performing loans (so-called stage 3) of the firm. We end by showing how public guaranteed loans affects the competitive structure of the banking market. We document how banks that participated more in the guarantee scheme are able to gain market share in the lending market, both by increasing their lending to borrowers with which they had pre-existing relationship (especially riskier, affected firms) and by tapping into less risky borrowers in new lending relationships.

The effect of loan guarantees on bank lending and its interaction with existing credit exposures is a priori not clear. In the absence of financial frictions, such as those arising from asymmetric information, moral hazard or bankruptcy costs, prior borrower-lender relationships should not affect the allocation of government guaranteed credit intermediated through financial intermediaries. However, in the presence of such financial frictions, banks may prefer to grant guaranteed credit to existing clients, either to preserve valuable relationships or to prevent defaults in their existing loan portfolios (Bolton et al., 2016). Firms may also turn to their main banks because of search costs involved in securing a guaranteed loan (Allen et al., 2019). Both channels would predict that guaranteed credit would disproportionately go to pre-existing clients and would suggest that this is more so the larger the exposure of a given bank to a firm. On the other hand, credit guarantees, by limiting potential losses on existing loan portfolios and by improving loan repayment for less creditworthy borrowers, may reduce adverse selection in credit markets, prompting banks to seek out new customers and diversify away from their large exposure clients (Mankiw (1986), Greenwald and Stiglitz (1986), de Meza and Webb (1987), Gale (1990), Innes (1991), and Dell'Ariccia, Friedman and Marquez (1999)). Guarantee schemes may also generate moral hazard by encouraging riskier lending at the margin (Kelly et al., 2016; Gropp et al., 2014). This effect should be especially stronger for weaker banks, with less skin in the game, i.e., those that are less capitalized and have more NPLs (Holmström and Tirole, 1997).

Our focus is on the Spanish public loan guarantee scheme established in March 2020 following the outbreak of COVID-19.[1] We focus on Spain for two reasons. First, the Spanish scheme was one of the largest public guarantee scheme programs in terms of take-up amounts relative to GDP, accounting for most of new business lending (Falagiarda et al., 2020). Second, we have rich data at the loan-level from the Spanish credit register with detailed data on bank-borrower credit exposures and unique information on the provision of public loan guarantees. In contrast to alternative datasets (e.g. the Euro Area Anacredit), our dataset allows us to uniquely identify loans with COVID-19 related public guarantees, rather than generic public loan guarantees.

We conduct our analysis using loan-level data at the firm-bank level over the period December 2019 to June 2021. We find that firms are more likely to obtain a public guaranteed (PG) loan from banks to which they have larger prior (pre-COVID) credit exposures, measured as the share of the firm's total credit outstanding with the bank as

[1] Although the Royal Decree Law 8/2020 of March 17 approved the guaranteed loans line, only 0.5% of the amount granted in 2020 correspond to March. Therefore, we do not expect to find any impact of the measure in March.

of December 2019. This effect is more pronounced for risky firms (based on ex-ante credit scoring) and firms in sectors whose turnover was hit harder by the pandemic, and these lending effects on riskier firms are even larger for banks with weaker balance sheets (lower bank capital ratio or higher NPLs). Effects operate both at the extensive and intensive margin of lending. Interestingly, differently from bank-firm exposure, we find that banks are less prone to grant guaranteed loans to firms with which they have a longer relationship. This suggests that the results of lending relationships are due to credit (volume) exposures as opposed to the duration of lending relationships per se.

The economic effects of our results are substantial. The results imply that an interquartile range increase in the firm's prior share of credit outstanding with the bank increases the probability of obtaining a PG loan by 24.4%, while this increase is only 4% for non-PG loans. Moreover, for guaranteed loans this increase is 32.5% if we focus on risky firms (interquartile rage increase), 27.4% for firms in (adversely) pandemic-affected sectors and 40% for risky firms in pandemic-affected sectors. Moreover, if the bank is lowly capitalized (interquartile range decrease) or has a high fraction of nonperforming loans (interquartile range increase), this increase grows to 43.6% and 42.9%, respectively. In terms of the size of the granted loans, we observe that PG loans have a higher amount (46% higher than non-PG loans), increasing to 66% higher if the firm's credit share with the bank is high (interquartile rage increase), the firm belongs to the sectors most affected by the pandemic and the firm is riskier (interquartile rage increase). Moreover, PG loans have a lower interest rate (2.3 percentage points on average) and a 163% longer maturity than non-PG loans.

We then turn to document the effects of the public guarantee scheme. We first show that the public guarantee scheme results in credit substitution at the firm-bank level. In particular, we show that the credit share and the granted amount of nonguaranteed (private) credit from a bank to a firm both decline if the bank grants a PG loan to the firm, while the total credit from the bank to the firm increases. The economic effects are substantial: firms that have a PG loan with a bank decrease their credit share of non-PG loans with the bank by 7.8 percentage points and decrease their total amount of non-government guaranteed credit amount with the bank by 15.4 percentage points, from December 2019 to June 2021. Moreover, we find that banks that grant a PG loan to a firm increase their overall credit exposure to the firm by 116.8 percentage points, resulting in a higher total credit share of the bank with that firm by 21.6 percentage points.

As shorter residual maturity of existing private credit may affect credit substitution between public and private guaranteed loans, we analyze how the residual maturity of the loans affects credit substitution. For firms with lower residual maturity prior to the COVID-19 shock (equivalent to a decrease in its interquartile range), the share of total loans increases by 22.7 percentage points and by 26 percentage points if, additionally, the firm is riskier (interquartile increase) or belongs to the more affected sectors. The credit share in terms of non-PG (private) loans decreases by 15.9 percentage points for firms with debt with shorter residual maturity, and further decreases to 17.5 percentage points for riskier firms in more affected sectors and borrowing from lowly capitalized banks. This suggests that banks take advantage of the public guaranteed loan scheme to substitute their private credit, especially to riskier firms (worse ex-ante credit scoring) in more affected sectors and by weaker banks (lower capital ratio).

We then turn to analyze how the repayment patterns of firms are affected by the public guarantee scheme. We document that firms that receive a PG loan are more prone to early prepay previous outstanding private (non-PG) loans from banks that grant the PG loan. The effect is economically relevant as it increases the early repayment amount (over firm total assets) by 26.4% in the next six months since the PG loan is granted. This figure jumps to 51.5% for firms with shorter residual maturity, to 76% when, in addition, the credit share between the banks and the firm is high, to 108.9% when the firm is riskier and to 194.9% when the bank is lowly capitalized. These results imply that granting a PG loan can effectively reduce the overall risk exposure of the bank to the firm, as it helps banks receive early prepayments of their previously outstanding (nonguaranteed) loans.

We then document that banks that grant a PG loan are less prone to classify a given firm's loan impairment status as stage 3 (denoting impaired loans) when compared to other banks that have outstanding loans with such firm. This suggests that banks that grant PG loans are reluctant to classify firms as nonperforming even if other banks have already done so. This is consistent with the public guarantee acting as a protection against potential losses should the firm fail. For instance, to have a PG loan with a bank reduces the likelihood to be classified as stage 3 by 63.1%. Moreover, this decrease reaches 72.6%

when, additionally, the share between the firm and the bank is high (interquartile range increase), if the firm is risky (interquartile range increase) to 90.4% or if the firm belongs to a pandemic-affected sector to 95.3% and, in addition, if the bank is lowly capitalized (interquartile range decrease) to a 143.6% reduction.

Finally, our results indicate that banks take advantage of the use of the public guarantee scheme to increase their market share in the market for corporate loans. Banks that use the public scheme more intensively increase their market share in the medium run by 9%. Moreover, they achieve this by expanding their credit portfolio towards both old (those with pre-existing loans) and new borrowers, being pre-existing firms those that contribute at least the double than newly ones to this change. While our previous results show that existing relationships help more riskier firms in negatively affected sectors, the extensive margin analysis indicates that those new firms tend to have a low risk profile and belong to industries that are less hit by the pandemic. This implies that the bank-intermediated government-guarantee scheme brings about a change in market structure, with potential adverse consequences for market contestability, by allowing more active banks to gain market share at the expense of other banks. Indeed, over the period studied, from December 2019 to June 2021, the Herfindahl-Hirschman index (HHI) of market concentration increased from 968 to 1102. We also show that among the more active banks it is larger banks that gain more market share, as these banks have a technological advantage in (quickly) processing guaranteed credit during the lockdowns in the pandemic.

Our paper relates to a large literature on the value and effects of lending relationships. The theoretical models in Sharpe (1990) and Rajan (1992) imply that lending relationships emerge to overcome informational asymmetries. These lending relationships can bring benefits to firms in terms of preferential access to credit, but they can also bring costs in the form of enhanced bargaining power of banks and associated hold-up problems. Consistent with this view, Berger and Udell (1995) using survey data from the U.S. Small Business Administration find that small firms with longer relationships enjoy more favorable lending terms, while Petersen and Rajan (1994) using the same dataset find that benefits accrue primarily in terms of the quantity as opposed to the price of credit. This literature has also shown that the value of relationship lending becomes pertinent during episodes of financial distress. Dahiya et al. (2003) using syndicated loan data show that the valuation of lending banks declines when their borrowers experience financial distress, while Bae et al. (2002) in the case of Korea find that the value of firms is adversely affected when their main bank experiences adverse shocks. Similarly, Carvalho et al. (2015) find, using syndicated loan data from 34 countries, that bank distress adversely affects the market values of firms with strong lending relationships. Bolton et al. (2016) using Italian credit register data find that relationship banks charge less favorable terms in normal times but offer larger quantities and more favorable terms to their relationship customers during crises. Schwert (2017) using syndicated loans data finds that better capitalized banks engage more in relationship lending. We contribute to this literature by showing that lending relationships are valuable in securing public loan guarantees during an exogenous economic downturn, and how this is especially true the higher the exposure of a bank to a given firm is, especially for riskier and more negatively impacted firms.

Our paper is also related to the literature that analyzes the role of information asymmetries in shaping the lending decisions of financial intermediaries. Holmström and Tirole (1997) shows how the optimal lending structure depends on the severity of the informational asymmetry (moral hazard) faced by the lenders. In particular, the share of lending from informed lenders is higher when such informational asymmetry heightens. Sufi (2007) finds evidence supporting this theory and documents how, in the syndicated market, lead banks retain a larger share of the loan and form a more concentrated syndicate when the borrower requires more intense monitoring. We contribute to this literature by showing that during a negative aggregate shock, which increases uncertainty and informational asymmetries, banks with higher exposure to a firm increase the granting of publicly guaranteed loans and via this channel the total lending to such firms.

Our paper also relates to the literature on the role of government interventions in credit markets. In the presence of information asymmetries between borrowers and their lenders, government intervention can result in a more efficient allocation of resources, even if the government has no informational advantage over the lenders (Mankiw, 1986; Philippon and Schnabl, 2013; and Philippon, 2021). The reason is that without government intervention, credit rationing can occur, and government interventions could correct this market failure. Public loan guarantees are an important government intervention tool.[2] Their introduction can reduce the credit rationing that would otherwise occur when firms are hit by a negative shock. Consistent with this view, Bachas et al. (2021) find that more generous loan guarantees under the U.S Small Business Administration (SBA) boost bank lending volumes. Related work has studied the implications of government-sponsored credit by studying the role of government-sponsored enterprises (GSEs) in U.S. mortgage markets. Loutskina and Strahan (2009) show that the secondary market activities of GSEs have boosted the securitization of mortgage loans, making mortgage markets more liquid. Elenev et al. (2016) develop a model where guaranteed mortgages are underpriced and enjoy favorable capital requirements to show that an increase in the price of the guarantee would result in fewer but safer mortgages, benefitting financial stability. Similarly, Jeske et al. (2013) develop a model with heterogeneous households to show that a reduction in the interest rate subsidy associated with the government bailout guarantee for GSEs would increase inequality by discouraging home ownership for poor households. Hurst et al. (2016) find that interest rates on mortgage loans securitized by GSEs are insensitive to regional variation in default risk, in contrast to non-GSE loans that are securitize in the private market. We contribute to this literature by showing that public loan guarantees disproportionately accrue to more vulnerable firms (riskier, smaller firms, and firms whose turnover is harder hit by the pandemic), thus providing implicit evidence of these government interventions partly correcting market failures. Importantly, we also contribute by showing that the allocation of public loan guarantees also depends on bank lending relationships, especially to riskier, more negatively affected firms, consistent with the notion that government support measures interact with private information asymmetries through bank lending relationships and bank incentives to shape the allocation of credit.

The literature on government interventions in the credit market has also highlighted how the introduction of government guarantees can, in some cases, distort the allocation of credit in a negative way by inducing excessive risk taking. The reason is that public guarantees, by affecting the valuation of bank investors and making them less subject to

[2] Other examples include government-sponsored debt restructuring programs, such as the 2009 U.S. Home Affordable Modification Program (HAMP) which offered incentives to lenders to renegotiate mortgages and prevented foreclosures of highly indebted households (Agarwal et al. (2017), or direct lending by state-owned banks (Jimenez et al., 2020).

the negative consequences of declines in output (Merton, 1977), can increase the risk-taking incentives of banks. Gropp et al. (2014) show evidence of this effect analyzing the removal of deposit insurance guarantees for a subset of banks in Germany and how such banks differentially increase the risk of their loans. Wilcox and Yasuda (2019) analyze the impact of the introduction of loan guarantees for small business loans in Japan and find that they increase the risk taking of banks. We contribute to this literature by showing that the credit exposure of a firm to a given bank before the shock is a key determinant of the granting of public guaranteed loans. This lending effect is stronger for riskier firms, and this riskier lending effect in turn is stronger for banks with weaker balance sheet strength (as measured by low capital ratio or high NPL ratio), consistent with the view that these banks are more subject to moral hazard issues (Holmström and Tirole, 1997).

A related literature has assessed the competitive distortions resulting from government interventions in credit markets (Matutes and Vives 1996). The empirical literature analyzing this issue has produced conflicting results. For instance, Berger and Roman (2015) find that banks that received capital injections from the US Troubled Assets Relief Program increased market shares and market power, while Calderon and Schaeck (2016) find in a cross-country setting that government interventions are associated with a decrease in market power of recipient banks. We contribute to this literature by showing that public loan guarantees affect the competitive structure of the banking industry, by increasing the market share of those banks that use them more. Our results show that government guaranteed credit has relevant economic effects on the structure of the banking system, both via their distribution being determined by existing borrower-lender relationships especially for more affected riskier borrowers, and via establishing new bank-firm relationships for less risky firms.

Finally, our paper is part of an emerging literature on the effects and implications of government interventions using loan guarantees during the COVID-19 crisis. This literature has found conflicting results, with the effectiveness of guarantee programs in reaching the most vulnerable firms varying across papers. Several papers assess the impact of the U.S. pay protection scheme, which provided SBA-guaranteed loans to businesses to keep workers employed during the crisis. Granja et al. (2020) using loan-level data on PPP loans find that some funds flowed to geographic areas that were less affected by the crisis and that many firms used the funds for other than intended purposes.

Using survey data, Humphries et al. (2020) find that PPP loans accrued disproportionally to larger firms instead of the intended more vulnerable smaller firms, reducing its effectiveness. Chodorow-Reich et al. (2021) using supervisory loan-level data find that smaller firms received PPP loans on less favorable terms. In a contemporaneous paper, Altavilla et al. (2021) using European credit register data find that public loan guarantees were predominantly extended to smaller firms and led to a substitution of guaranteed for non-guaranteed loans. We contribute to this literature by focusing on the effects of *existing credit exposures and lending relationships*, which have not been previously considered. We show that the allocation of public loan guarantees depends on the magnitude of pre-existing credit exposures and that the substitution of public guarantee loans for non-public guaranteed loans results in a change in overall credit exposures between bank-firm pairs. We also provide novel evidence that granting a guaranteed loan increases the prepayment of pre-existing loans to the banks that grant it, and that loans to firms are less prone to be reported as impaired by banks that grant the firm a guaranteed loan. Both results suggest that the granting of guaranteed loans affects the repayment behavior of a given firm, reducing the perceived credit risk for the bank. Finally, we contribute to this literature by analyzing how government credit guarantees schemes have affected the competitive structure of the banking system, showing that banks that use these schemes more increase their market share both in pre-existing and new borrowers. Taken together, our results indicate that the loan guarantee scheme benefitted banks with pre-existing credit exposures, by allowing them to substitute nonguaranteed credit with less risky guaranteed credit, especially for the riskier, more negatively affected borrowers, and by enhancing the loan repayment capacity of existing borrowers. Moreover, in the extensive margin they also help them to gain new borrowers, especially less risky borrowers in less-affected sectors. Consequently, these banks increase their market shares, giving them potentially competitive advantages over other banks.

The paper continues as follows. Section 2 provides institutional details on the Spanish loan guarantee scheme. Section 3 describes the data. Section 4 describes the empirical strategy. Section 5 presents the empirical results. Section 6 concludes.

2. The Spanish Loan Guarantee Scheme

The Spanish loan guarantee scheme was announced and implemented in March 2020, following the outbreak of COVID-19 in the country. The government-sponsored program was set in place under the Royal Decree Law 8/2020 of March 17, with the aim to enable firms to draw on the funds needed to deal with the fall-out of the crisis brought about by the sudden emergence of COVID-19.[3] The state guarantee was intended to support the provision of guaranteed credit up to 100 billion euros. Both companies and self-employed workers could access these guarantees through their financial institutions, either by taking out new loans or by renewing existing ones. The state guarantee covered up to 80% of the amount lent in the case of new loans and 70% of the amount lent for the renewal of existing loans. The guaranteed loans cover a broad range of financing needs, including salary payments, vendor invoices pending settlement, rental of premises, and liquidity needs arising from the expiration of financial or tax obligations. Demand for PG loans was high from inception of the program, with 70 percent of all PG loans granted between April and June 2020.

The guarantees are provided by the ICO (Institute of Official Credit) to the financial institutions that grant the funding. ICO is a state-owned bank, with an independent legal status, linked to Spain's Ministry of Economy and Business. It finances itself on the national and international capital markets. The debt commitments and financial obligations it enters into with third parties benefit from the explicit, irrevocable, unconditional and direct guarantee of the Spanish State. In exchange for issuing the government guarantee, the bank pays ICO a fee amounting to 20 to 120 basis points of the loan amount. Figure 1 offers a schematic overview of the financial commitments and flows of the loan guarantee scheme among the various parties involved.

There are several exclusion criteria for participation in the public guarantee scheme.[4] Loans intended for the consolidation and restructuring of existing loans, as well

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[3] See "Real Decreto-ley 8/2020, de 17 de marzo, de medidas urgentes extraordinarias para hacer frente al impacto económico y social del COVID-19", available in Spanish at: https://www.boe.es/eli/es/rdl/2020/03/17/8/con and https://www.boe.es/buscar/pdf/2020/BOE-A-2020-3824-consolidado.pdf.

[4] See ICO website for further details on the guarantee scheme: https://www.ico.es/en-US/web/ico_en/ico/press_room/press_release/the-government-launches-the-guarantee-line-to-guarantee-the-liquidity-of-the-self-employed-and-companies.

as the cancellation or early repayment of pre-existing debts, are excluded from participation in the scheme. In addition, firms that had loans in arrears according to Spanish Credit Register (CIR) as of December 31, 2019, or that were subject to bankruptcy proceedings as of March 17, 2020, are excluded from these loans. Regarding the loan terms, the maximum eligible amount is 1.5 million euros in most occasions, the maximum loan maturity is 5 years (subsequently extended to 8 years with the Royal Decree 34/2020 of November 17, 2020) and the debtor's payment holiday is up to 12 months (subsequently extended to 24 months with Royal Decree 34/2020). The guarantees are not free for banks and their customers. The cost of the guarantee amounts to between 20 and 120 basis points and is to be assumed by the lending bank through the payment of a fee to ICO. Moreover, the financial institutions commit to maintaining the conditions of the new loans and renewals under the guarantee scheme at the same level as applied before the COVID-19 crisis. With respect to interest rates, banks have an obligation to ensure that the costs of new loans benefiting from these guarantees will remain in line with the costs charged before the start of the pandemic. This implies that the interest rate on loans that are renewed cannot be increased even if borrower risk has increased. The lending entities also commit to maintaining, at least until 30 September 2020, the limits of the revolving credit lines granted to all clients and, particularly, to those clients whose loans are guaranteed. Finally, the coverage of the guarantee varies according to the size of the firm, going from 80% for SMEs to 70% or 60% for large companies, depending on whether it is a new operation or a refinancing, respectively.

3. Data

We combine four different data sources: (i) the Spanish Credit Register (CIR), (ii) loan application data of firms to non-current banks, (iii) supervisory bank balance sheet information, and (iv) firm balance-sheet information from the Spanish Mercantile Registers collected by the Banco de España.

Our main database come from the credit register owned by Banco de España which contains granular information at loan level since 1984 and at a monthly frequency of all type of loans, firms and banks operating in Spain. The CIR is a comprehensive database with a very low threshold (almost 0, which makes it a census) that includes information of the loan such as the type of instrument, amount (drawn and undrawn), degree of collateralization, maturity, currency, interest rate, grace period, default status. From the CIR we are able to construct exhaustive information on the credit exposure of all firms with all of its banks. This is particularly relevant as our variable of interest is the share of total credit outstanding that the firm has with a bank just before the eruption of the COVID-19 pandemic and its evolution over time. The CIR also provides some information about the borrower such us its identity, industry (at NACE 3 digits), location (at zip-code level), size and date of the establishment. In terms of the lender, the CIR has information on the bank identity. This allows us to match each loan to firm and bank characteristics. An advantage of the CIR database is that it contains a numerical credit score of each borrower, which provides an ex-ante measure of credit risk.

Importantly for our purposes, the CIR has detailed information on any loan guarantees, and in particular on whether the loan has an ICO guarantee as part of the Spanish pandemic loan guarantee program. This information is a clear advantage of the Spanish credit register as we use it to construct an indicator variable for whether the loan has an ICO guarantee or not.

We also exploit information on loan applications from the CIR. At monthly frequency, a bank receives automatically from the Banco de España information about their current borrowers' exposure. Additionally, banks can request this information from the Banco de España for their potential borrowers with their consent (Jiménez et al. 2012; Jiménez et al. 2014). We take such individual requests from banks on potential borrowers as a clear indication that, in general, the firm is searching for a loan and that, specifically, it has asked the bank for a loan. This information is stored monthly by the Banco de España since 2002. We include this information on loan applications in the data set to account for selection issues in the loan application process.

The economic and financial information of firms is collected from the balance sheets and income statements that Spanish firms must submit yearly to the Spanish Mercantile Register, which is collected by the Central Balance Sheet Office (the unit in the Bank of Spain in charge of collecting and cleaning these datasets). We use the unique firm identifier (CIF) to perform this merge. Additionally, we also have information at bank level of the balance sheets and income statements that banks are required to report monthly to the Banco de España in its role as banking supervisor. We match this information using the bank identifier that is present in both databases.

We restrict our analysis to non-financial corporations and the sample period to 2019:12-2021:06, so that we contrast the evolution of lending immediately before and after the introduction of the Spanish loan guarantee scheme in March 2020. We exclude from the sample firms that are not eligible for participation in the ICO guarantee scheme, either because they were undergoing loan restructurings or bankruptcy proceedings, or because they had loans in arrears as of December 31, 2019. Including such firms would contaminate our analysis.

3. Empirical Strategy

We perform alternative empirical analyses to provide answers to the following four sets of questions: i) What firms/banks are more likely to participate in the public guarantee scheme? For instance, are riskier firms and less healthy banks more likely to participate?; ii) Are the conditions of public-guaranteed loans different from those of non-public guaranteed ones, in particular in terms of loan amounts?; iii) Is there a substitution of non-public guaranteed for public-guaranteed loans among banks that grant a public guaranteed loan to a firm?; iv) How do banks recognize the loan impairment of firms that receive guaranteed loans?

Importantly, in each of these analyses we analyze the relevance of pre-existing lending relationships in shaping the observed relations. Specifically, we focus our analysis on the relevance of the ex-ante loan exposure that a firm has with a bank, proxied by the share in terms of the firm's total loans as of December 2019. As an example, we will analyze what is the role of pre-existing lending relationships in obtaining guaranteed loans and if this role varies depending on bank and firm characteristics.

To answer the first question, we construct a dataset at the firm-bank level to capture firms that have actively sought funding during this particular time period. We first identify all firm-bank pairs in the CIR in terms of new financing transactions granted or loan applications made to non-current banks between March and December 2020. Then, for those firms identified in the previous step we also consider all banking relationships as of December 2019, to account for the possibility that if a company seeks a loan, then it will likely probe the banks with which it has a prior relationship. We pool the observations at firm-bank level for the considered period, so that we have only firm-bank pairs in the sample. This database includes 128 banks and around 200,000 firms, and results in 718,000 (firm-bank) observations. With this database we are able to investigate what are the firm, bank and firm-bank characteristics that makes a company more likely to get a public guaranteed loan (PGL) from a bank between March and December 2020, focusing on the credit exposure of the firm with a given bank just before the pandemic.

We consider the following regression specification to analyze the extensive margin estimated by OLS as a linear probability model:

$$PGL_{ij} = \beta_0 Share_{ij} + \beta_1 Firm_i + \beta_2 Bank_j + \beta_3 Firm\text{-}Bank_{ij} + \eta_i + \eta_j + \varepsilon_{ij} \quad (1)$$

where PGL_{ij} is an indicator variable denoting whether the firm has a public guaranteed loan with the bank or not, i refers to firms and j refers to banks. We are interested in the coefficient on the $Share_{ij}$ variable, which captures the share of the firm with the bank in terms of the amount of the firm's credit as of December 2019, to understand whether prior lending relationships are a key driver to obtain a PGL. Share is predetermined to the COVID shock and, in line with the literature on banking relationships, is stable over time before this shock. We are exploiting the shock on this "predetermined" variable to analyze how bank lending relationships affect lending and risk taking differentially for public guaranteed loans and non-guaranteed loans. $Firm_i$ is a vector of firm controls which includes the size of the firm (proxied by a SMEs dummy[5]), its credit risk (captured by a scoring measure with higher values meaning more risk[6]), its liquidity (as the fraction between cash and other liquid assets over total assets of the firm), its growth opportunities (as proxied by the growth rate of firm sales between 2018 and 2019), and a dummy for more severely affected sectors by the pandemic (defined as those whose turnover

[5] Based on the definition of the Commission Regulation (EU) No. 651/2014, of June 17, 2014.

[6] The scoring function synthesizes a battery of firm financial and non-financial ratios in a sufficient statistic of the solvency of a firm. based on 18 firm variables such as debt-term structure; average cost of debt; capital ratio, ROE, ROA and sales' profitability; industry; age; bank loan defaults, etc. Each of the firms' variables is assigned to a specific area: financial indebtedness, solvency, liquidity, profitability, business information, and default history. Moreover, each variable is categorized in six intervals and a different rating value is assigned depending on the allocation to each of the buckets. Then, each rating value is weighted inside its corresponding area, and each of the six areas is again weighted to get the final score, which is the weighted sum of the ratings assigned to the different characteristics. Ratings are such that the (risk) score is increasing in the firm's credit risk.

decreased by more than 15% in 2020). *Bank*$_j$ refers to a set of bank controls that includes the size of the bank (defined as the log of total assets), its capital ratio (defined as the ratio of own funds over total assets), its liquidity position (defined as the ratio of liquid assets over total assets) and the NPL ratio (defined as the ratio of non-performing loans, doubtful and 90 days overdue, over total loans of the bank). We also include the average residual maturity of loans outstanding between the firm and the bank as an additional control in the *Firm-Bank*$_{ij}$ vector. In some specifications we also control for firm (η_i) and bank (η_j) fixed effects that account for observable and unobservable time-invariant firm and bank factors, and that absorb all firm and bank controls à la Khwaja and Mian (2008). This is particularly important to be able to give a supply side interpretation of the effects: the inclusion of firm fixed effects ensures that we are comparing the same firm with at least two different banks and, therefore, absorb any demand factors. Thus, if the estimated β_0 is positive and statistically significant when firm and bank fixed effects are introduced, then this can be interpreted as evidence that banks favored in their distribution of public guarantees those firms to which they were more exposed. Finally, ε_{ij} is the error term. To reduce endogeneity concerns all firm and bank explanatory variables are measured as of December 2019. Standard errors are multi-clustered at the firm and bank level to allow for serial correlation across firms and banks.

To analyze differences in the likelihood to obtain non-PG loans, we run the same exercise but replace the dependent variable by one capturing whether the firm only obtained a non-PG loan during the sample period. In the Appendix, we also check the stability of the results conditioning on banks that granted a loan (PGL or not) to a firm.

We are also interested in analyzing whether the effect of the loan share variable on the likelihood to obtain a PGL is more pronounced for riskier firms and/or less healthy banks. To capture this possibility, we estimate a model where we include double and triple interactions terms of the *Share* variable with the scoring variable and the severely affected sector dummy, from the firm side, and the capital ratio and NPL ratio, form the bank side. The enriched regression specification is as follows:

$$PGL_{ij} = \beta_0 Share_{ij} + \beta_1 Share_{ij} * \begin{pmatrix} Risk_i \\ Affct.sector_i \end{pmatrix} + \beta_2 Share_{ij} * Risk_i *$$

$$Affct.sector_i + \beta_3 Share_{ij} * Risk_i * Affct.sector_i * \begin{pmatrix} Bank\ capital\ ratio_j \\ Bank\ NPL_j \end{pmatrix} +$$

$$+\varphi_{ij} + \eta_i + \eta_j + \varepsilon_{ij} \ (2)$$

where φ_{ij} is a vector of variables that contains the rest of the interactive terms of lower degree not showed. Moreover, it also includes quadruple interactions of the other bank controls (including lower degree terms) to mitigate concerns about omitted variables. With this specification we can evaluate the possible existence of a selection bias whereby worse-quality firms match with worse-quality banks when the exposure of the firm with the bank is large. If this were the case, we would expect the estimated betas to be all positive and statistically significant but the one on Share*Risk*Affected sector*Bank capital, would be negative and significant.

In the Appendix, we show some robustness exercises on the share and risk variables. First, we replace the share variable, inter alia, with a long-term share computed since 1999 or with a dummy variable that captures whether the bank is the main lender of the firm as of December 2019 to show that the relationship of the *Share* variable is robust. Second, we replace the risk variable with the credit history of the firm. We also study if the results are robust to focusing on high risk firms, defined as those in the higher decile of the distribution of the risk variable. Finally, it is possible that the results were affected by some seasonal effect that occurred on a recurring basis after March. We therefore analyze the likelihood of getting a new credit in 2019 for different treatment periods, as a falsification test. Moreover, we show that the effect of the *Share* variable on the likelihood to grant a loan does not change in March, on average.

Table 1 presents summary statistics of the main regression variables in the extensive margin analysis. Little more than a third of the observations (37.8%) have a PGL during the analyzed period while 28.7% of all firm-bank couples only have non-PG loans. A total of 95% of all observations corresponds to small and medium-size firms (SMEs) and 62% belong to the sectors considered as severely affected by the pandemic. The average value of the Share variable is 26.6% and its median is 13.6%.

Turning to the intensive margin analysis, i.e., the amount granted, we construct a database of new loans granted from 2020:03 to 2020:12. For every firm and bank we collapse all new loans in two types: PG and non-PG loans. As a result, we obtain a database at the firm-bank-type of loan level. The dataset has more than 620.000 observations and allows us to control for firm*bank fixed effects. This is quite relevant if the allocation of public guarantee loans is not random. Therefore, we estimate the following equation:

$$Committed\ amount_{ijk} = \beta PGL_{ijk} + \eta_{ij} + \varepsilon_{ijk} \quad (3)$$

where k refers to the loan type and PGL is a dummy that equals 1 for public guaranteed loans, and 0 otherwise. The previous equation is the most saturated one due to the inclusion of firm-bank fixed effects. In the tables we also show the estimation results of similar models that includes only zip code fixed effects, industry fixed effects, bank or firm fixed effects. Following Altonji et al. (2005) and Oster (2019) we evaluate the sensitivity of our estimation results to the inclusion of observable and unobservable controls by testing the stability of the estimated β to significant increases in the R^2 when new fixed effects are included. On the one hand, those models have the advantage that they do not require working with firms that have received the two types of loans in the time period of study, which implies working with more observations; and that we are able to include as explanatory variable *Share*, which allow us to evaluate the direct impact of this variable on the loan amount granted apart from its indirect effect through the PGL. On the other hand, they have the disadvantage of not allowing us to measure how the amount of the guaranteed loans compares to that of non-guaranteed loans, from the same firm with the same bank. Therefore, in Eq. (3) the coefficient on PGL (β) is capturing the differential effect on the committed amount of having a public guaranteed loan. Eq. (3) is estimated using a Poisson model in order to reduce possible biases arising from a classical log linear estimation (see Santos Silva and Tenreyro, 2006). As before standard errors are clustered at the firm and bank level.

In the same vein as before, we also investigate the heterogeneity of the results in three dimensions: the exposure with the bank, the risk of the firm, and the viability of the bank. This is captured in the following equation:

$$Committed\ amount_{ijk} = \beta_0 PGL_{ijk} * Share_{ij} + \beta_1 PGL_{ijk} * Share_{ij} * \begin{pmatrix} Risk_i \\ Affct.sector_i \end{pmatrix} + \beta_2 PGL_{ijk} * Share_{ij} * Risk_i * Affct.sector_i + \beta_3 PGL_{ijk} * Share_{ij} * Risk_i * Affct.sector_i * \begin{pmatrix} Bank\ capital\ ratio_j \\ Bank\ NPL_j \end{pmatrix} + \varphi_{ijk} + \eta_i + \eta_j + \varepsilon_{ijk} \quad (4)$$

where φ_{ijk} is a vector of variables that contains the rest of interactive terms of lower degree not shown as well as the quadruple (and lower degree terms) interactions with the rest of bank controls.

Additionally, to estimate the effects on other relevant loan related variables, including the interest rate and maturity (in months), we replace the left-hand side variable of the above equations by each of the aforementioned loan terms. Table 1 also provides the descriptive statistics of these dependent variables. The loan amount has an average value of 129,649 euros with a median of around 60,000 euros. Finally, the average new loan has an interest rate of 3.3% and a maturity of 26 months.

The public guarantee scheme was not the only measure that the Spanish government or financial regulator took to safeguard the functioning of the financial system during the pandemic. Following the European Central Bank's supervisory recommendation on the distribution of dividends (ECB/2020/19, ECB/2020/35 and ECB/2020/62), the Spanish banks limited the distribution of the dividends in 2020, thus strengthening their capital base. However, some banks were allowed to distribute dividends if, before the recommendation, this distribution was already committed at the general meeting of shareholders (see Martinez-Miera and Vegas, 2021). As a result, one group of dividend-paying banks was affected by the policy and another group was not. In a robustness check, we therefore control for whether the distribution of dividends was affected or not.[7]

Turning to the question of whether banks that grant a PGL decide to reduce their exposure to non-PG loans, we propose a different approach that needs its own database. To estimate this substitution effect, we follow a standard difference-in-difference setting with two periods (2019:12 and 2021:06), an event (the COVID-19 pandemic that started in March 2020) and a treated group (those firms that get a PGL from a bank). Using this approach we measure the change in the share of the firm with a bank (for both non-PG loans and total loans) caused by the differential effect of the introduction of the loan guarantee program due to the pandemic. We do so by comparing the evolution of the *Share* variable in firm-bank pairs that get a PGL loan. As before, the *Share* variable is computed using the credit amount of a firm with all its banks in two periods of time: before and during the pandemic. We compute the change in share based either on total loans or on non-PG loans only. All in all, we have a dataset at firm-bank level with around 6,700,000 observations, covering 178,000 firms and 130 banks, that allow us to estimate by OLS the following difference-in-difference model:

[7] The Spanish government also imposed a moratorium on mortgage loans, but this only applied to household loans, not firm loans, which are the focus of our study.

$$\Delta Share_{ijt} = \beta PGL_{ij} + \eta_i + \eta_j + \varepsilon_{ijt} \qquad (6)$$

We construct the treatment variable as the product of a time dummy (which refers to the start of the pandemic, March 2020, and later dates), and a treated dummy (which refers to a firm *i* that obtained a PG loan from bank *j* before *t*). It is captured by the PGL dummy variable (which for simplicity does not have the subscript *t*). In fact, we start by estimating the model with only zip code fixed effects, to progressively saturate it with more and more fixed effects until we arrive at Eq. (6), which includes bank and firm fixed effects, to check the stability of the estimated coefficient. The coefficient β on PGL captures the impact on the change in the share (of non-PG loans and total loans) of a firm with a bank caused by the public guarantee program established after the onset of the pandemic for firms that obtained a PG loan with respect to those firms that did not receive any. We also exploit the differential intensity in treatment since PG loans have different amounts. Moreover, we also analyze the direct change in the credit of the firm with the bank, to ensure that the previously analyzed change in the share is not driven just by changes in the composition of credit from other banks. In this specification we are able to include *Share* as an additional dependent variable (doing so in Eq. (6) would give rise to an endogeneity problem), which gives us the opportunity to evaluate the direct and indirect effects, through PG loans, of the share with the bank.

In this difference-in-difference model, the underlying assumption is that, in the absence of a shock, the treated firms behave in a similar way as the untreated ones. To be able to interpret the estimated coefficients as the causal impact of the introduction of the program on the change of share, it is crucial to test this parallel trend assumption. We do this by reporting the estimated coefficient of β for different time periods.

We also study the heterogeneous effects across different firm/bank characteristics in our variable of interest. We do this by estimating the analogue of Eq. (6) that includes additional interaction terms. The equation then takes the following form:

$$\Delta Share_{ijt} = \beta_0 PGL_{ij} + \beta_1 PGL_{ij} * Firm\text{-}Bank_{ij} + \varphi_{ij} + \eta_i + \eta_j + \varepsilon_{ijt} \qquad (7)$$

where $Firm\text{-}Bank_{ij}$ is a vector of firm, bank and firm-bank characteristics similar to that introduced in Eqs. (2) and (4).

Additionally, to better understand how this substitution is taking place, we carry out an analysis of the extent to which non-PG loans are repaid in advance after obtaining a PG loan. To this end, we construct a variable that measures the early repayment amount of a bank with a firm in the next months following the granting of the PG loan. This analysis is conducted on a database that is constructed at the firm-bank-year:month level for the period 2020:03 to 2021:06. In particular, we estimate by OLS the following equation:

$$Cumulative\ early\, \frac{repayment}{Assets}_{ijt} = \beta PGL_{ij} + \gamma Share_{ij} + \ \eta_{it} + \eta_{jt} + \varepsilon_{ijt} \quad (8)$$

where the cumulative amount of early repayment in the next *x* months (from 1 to 6) is expressed in terms of the firm's total assets as of December 2019; η_{it} are firm*year:month fixed effects; and η_{jt} are bank*year:month fixed effects, which controls for both time-invariant and time-varying observed and unobserved firm and bank characteristics, respectively. If the estimated coefficient on β is positive and significant it would be evidence that banks are early amortizing unsecured operations after obtaining a public guaranteed loan. For robustness, we also compare the early repayment after a PGL with that produced after a non-PGL. The heterogeneity of these effects is explored using the following equation:

$$Cumulative\ early\ repayment/Assets_{ijt} = \beta_0 PGL_{ij} + \beta_1 PGL_{ij} * Firm\text{-}Bank_{ij} + \varphi_{ij} + \eta_{it} + \eta_{jt} + \varepsilon_{ijt} \quad (9)$$

Regarding the question of how banks handle the recognition of impaired loans of firms that obtained a PGL, we carry out a separate analysis that exploits the same data set used for the substitution analysis. We are interested in investigating whether banks that granted a PGL to a firm are more reluctant to classify the firm as having impaired loans (i.e., stage 3 loans) or not. Under IFRS 9 accounting, banks are supposed to recognize the impairment of loans in three stages of increasing credit risk: stage 1 denotes that the loan has seen a significant increase in credit risk since inception, stage 2 indicates that the increase in credit risk is considered high, and stage 3 indicates that credit risk has increased to the point that the loan is impaired. Such loan classification should be done on a forward-looking basis, but existing accounting rules leave ample discretion to the bank in terms of the criteria used to classify loans into these three buckets of credit risk (e.g., Huizinga and Laeven, 2012). To the extent that the guarantee offers credit protection to banks, banks with PGL may use their discretion to not classify the firm as being impaired even if other banks do so. The proposed model takes the form:

$$Stage3_{ij} = \beta PGL_{ij} + \eta_i + \eta_j + \varepsilon_{ijt} \qquad (10)$$

where *Stage 3* is a dummy that equals 1 if the bank classified a firm as having stage 3 loans sometime from 2020:03 to 2021:06, and 0 otherwise. We estimate Eq. (10) by OLS as a linear probability model. Given that we are including firm fixed effects, we can compare the same firm with at least two different banks. Therefore, if the β is negative and statistically significant there is evidence of different loan impairment recognition behavior depending on whether the bank granted a PG loan to the firm or not. As before, the heterogeneity is captured by enriching Eq. (10) as follows:

$$Stage3_{ij} = \beta_0 PGL_{ij} + \beta_1 PGL_{ij} * Firm\text{-}Bank_{ij} + \varphi_{ij} + \eta_j + \varepsilon_{ijt} \qquad (11)$$

Finally, we are interested in analyzing whether the guaranteed loan scheme had any effect on the banks' aggregate portfolio and, ultimately, on the concentration of credit in the Spanish banking system. In particular, we test if the banks that were most active in extending guaranteed credit gained market share. If this is the case, we want to analyze how this was achieved, whether by extending loans to new borrowers or by increasing exposure to existing borrowers. In this regard, we use a panel database at the bank-time level that includes 139 banks (including commercial banks, credit co-operatives and financial credit establishments) for the period between December 2019 and June 2021. We then estimate the following difference-in-difference model:

$$y_{it} = \beta PGL_i * \mathrm{Post}_t + Bank_i * \mathrm{Post}_t + \eta_i + \eta_t + \varepsilon_{it} \qquad (12)$$

where the subscript *i* refers to bank and *t* to time; PGL_i is a continuous variable capturing the weight of the public guarantee scheme during the period over total loans of the bank as of December 2019; $Post_t$ is a dummy variable that takes the value of one after March 2020, and 0 otherwise; *Bank* is a set of bank controls (the same as in the other models); η_i are bank fixed effects; η_t time fixed effects; and y_{it} is the dependent variable that can be the bank's credit market share at *t*, or the weight of new borrowers in the bank's loan portfolio (either in terms of the number of firms or the volume of their credit). As we expect the β coefficient to vary over time we also estimate Eq. (12) for the different cross-sections, substituting the *Post* dummy by time dummies. Standard errors are robust at bank level. In the case of analyzing the effect of the guarantee regime on the variation in market share, a positive and significant β coefficient would indicate that the banks that extended credit guarantees the most, were the ones that gained market share.

4. Empirical Results

This section provides the results of our analysis. We first document what are the key determinants driving the allocation of public guaranteed loans both at the extensive (Section 4.1) and intensive margin (Section 4.2). We then document the economics effects of such allocation of public guaranteed loans in terms of credit substitution (Section 4.3), early repayment (Section 4.4), loan impairment recognition (Section 4.5) and market shares (Section 4.6).

4.1 Allocation of credit: Extensive margin

The results on the extensive margin of obtaining a new PGL loan are presented in panel A of Table 2. The analysis is conducted at the bank-firm level, and the sample includes loan applications. Regressions include an increasingly richer set of fixed effects as one moves across the table columns, with the regression in column (5) including firm and bank fixed effects to absorb credit demand and supply effects.

We find that PG loans are more likely to be granted to SMEs, risky firms, less liquid firms, firms with positive past sales growth, and firms in affected sectors. In terms of bank characteristics, we find that PG loans are more likely to be extended by banks that have a higher ex ante loan share in the firm, and that have higher residual maturity on outstanding loans with the firm. Both are measures of a bank's credit exposure to the firm and capture the role of existing lending relationships. Moreover, we find that PG loans are more likely to be extended by bigger banks, banks with lower capital ratios and lower return on assets (ROA), and by banks with higher NPL ratios, indicating that there is an association between PGL loan extension and bank weakness, consistent with risk shifting behavior.

Panel B of Table 2 presents results for non-guaranteed loans. We find that the *Share* variable obtains a much smaller coefficient (0.03 versus 0.22) when compared with the results for PG loans in panel A. Most other variables of interest either obtain the opposite sign or do not enter with a statistically significant coefficient when compared to the PGL results. In particular, the signs on the risk-related variables are reversed.

Results presented thus far include loan applications that did not result in the granting of loans. We obtain similar results when limiting the sample by conditioning on granted loans, presented in Appendix Table A1. These estimates show the differential effects between granted public guaranteed loans and non-guaranteed loans and highlight the different loan granting strategies followed in PGL and Non-PG loans.

In Table 3, we estimate heterogeneous effects of the *Share* variable depending on pre-determined bank and firm characteristics. Results are as before estimated when including loan applications. The differential effects after excluding loan applications are presented in Appendix Table A2. The heterogeneous results for the granting of PG loans indicate that the positive effects of the *Share* variable are more pronounced for risky firms and for firms in affected sectors, as well as for banks with lower capital ratios and higher NPL ratios. The regressions for non-PG loans presented in panel B obtain much smaller effects of the *Share* variable and the opposite sign for its interaction with Affected sector variable. These results can be interpreted as evidence of a risk-taking channel operating through PG loans by banks that are more exposed to risky firms.

Results in Appendix Table A3 show that the results so far are robust to alternative measures of the exposure of a bank to a firm (the *Share* variable), to how we measure firm risk, and to the inclusion of the length of the firm-bank relationship (since 1999). In particular, results are qualitatively unaltered when replacing the loan share of the firm with the bank measured at 2019:12 with a long-term share variable computed over the period 1999:1 to 2019:12. These results, presented in panel A, also imply that the *Share* variable is stable over time, in line with the existing literature on lending relationships showing that firms infrequently switch their main bank. In panel B, we replace the *Share* variable with a main bank dummy, which equals 1 if the bank was the main lender of the firm in 2019:12 (in terms of total amount of credit committed) and 0 otherwise. The results in panel C are obtained after replacing the risk variable with Bad credit history, which is a dummy variable that takes a value of 1 if the firm experienced some loan default in the past and 0 otherwise. Panel D replaces the risk variable by its highest decile (denoted High risk). In each of these cases we obtain qualitatively similar results as in our baseline specification. In Panel E, we include as regressor the length (in logs) of the relationship between the firm and the bank computed since 1999, and horserace this measure against the share variable. We find that the length of the relationship is not increasing the likelihood to get a PGL and that our results are robust to this control. In other words, the effect operates through the magnitude of the lending relationship, not the duration of the lending relationship.

Taken together, the results indicate that pre-existing credit exposures, as measured by the Share variable, matter for obtaining PG loans and it does so much more than for non-guaranteed loans. Moreover, the effect of loan relationships as measured by the *Share* variable is more pronounced for risky and more affected firms, and for weaker banks, as captured by banks' capital and NPL ratios, which suggests the existence of a risk-taking channel in granting PG loans.

The economic effects of the results in Tables 2 and 3 are substantial. The results in Table 2 imply that an interquartile range increase in the firm's share of credit outstanding with the bank increases the probability of obtaining a guaranteed loan by 24.4 percentage points (0.216*(.429-.003)/0.378*100), while this increase is only 4 percentage points for non-guaranteed loans (0.027*(.429-.003)/0.287*100). Moreover, the heterogeneous effects estimated in Table 3 imply that for guaranteed loans this increase is 32.5 percentage points if we focus on risky firms, 27.4 percentage points for pandemic-affected sectors and 40 percentage points for risky firms in more affected sectors. If the bank is lowly capitalized or has a high fraction of nonperforming loans, this increase grows to 43.6 percentage points and 42.9 percentage points, respectively. These are large effects compared to the average probability of having a loan guarantee of 38 percent.

In Appendix Table A4, we perform a falsification test to make sure that the effect of the *Share* variable is specific to PG loans and derives from the pandemic period, and not outer periods. Specifically, this table reports regression results of a linear probability model at firm-bank level of the probability of a firm to get a loan (of any type, being guaranteed or not). We consider different time periods to address concerns that the effect of the *Share* variable analyzed in the period 2020:03-2020:12 is picking up seasonal effects other than the COVID-19 pandemic. Post is a dummy that equals 1 for the months after the reference date until December of that year. We find that there is no significantly different effect of the *Share* variable on the likelihood of receiving a loan between the periods before and after COVID-19. This implies that the overall effect of the *Share* variable is not changing although we know (from Table 2 and 3) that the pandemic has had a differential impact on PG loans and non-PG loans.

We also test the non-linear effects of the *Share* variable in Table A5 in the Appendix. We find that our main results are maintained when we allow credit to new borrowers to behave differently by introducing a zero-share dummy (denoting firm-bank pairs without an existing credit relationship) in the regression. We also note that the zero-share dummy is positive and significant for both PG and non-PG loans, and it is more so among low-risk firms in the case of publicly guaranteed loans, and more so among less affected and less risky firms for the rest of the loans.

4.2 Allocation of credit: Intensive margin

In Table 4, we estimate the implications of the public guarantee scheme for the intensive margin of loan granting and we horserace it with the effect of the *Share* variable, by estimating the effect on loan amounts. We first find that the share of the firm with the bank is correlated with unobservable firm characteristics, as can be seen comparing column (4), without firm fixed effects, with column (5), which includes firm unobserved heterogeneity. Once the firm fixed effects are controlled for, the *Share* variable has a positive effect on the loan amount and this effect does not vanish when we control for the fact that the loan is government-guaranteed or not. Moreover, we find that PG loans are on average larger in magnitude. Adding progressively richer sets of fixed effects increases the R-squared of the regressions but does not substantially alter the size of the estimated coefficient (if anything it increases a bit in size). In line with this, the regressions also pass the Oster (2019) test, allaying concerns of omitted variables regarding the *PGL* variable. We observe that PG loans has a higher amount (46% higher than non-PG loans).

In Table 5, we assess the differential effect of relationship lending, as captured by the *Share* variable, on the granting of public guaranteed loans at the intensive margin by including an interaction between the *Share* variable and the *PGL* dummy variable.

We find that the positive effect of PG loans on loan size is more pronounced when the loan share is higher (by 58.8%) and especially so in affected sectors. Moreover, we find that the differential effect of the loan share variable is more pronounced for riskier firms in affected sectors (by 66%). The variables capturing the differential effects of bank balance sheet strength (capital and NPL ratios) do not enter significantly.

In panel A of Table 6, we estimate intensive margin effects for other loan terms, including the interest rate and loan maturity. In addition to implying larger loans, we find that PG loans also tend to command lower interest rates and longer maturities than non-guaranteed loans. PG loans have a lower interest rate (2.3 percentage points on average) and a 162% higher maturity than non-PG loans. We also find that a higher *Share* reduces the interest rate and the maturity of the granted loans. These results imply that, in line with them being guaranteed, PG loans enjoy more favorable lending terms, both in terms of size, interest rate and maturity.

In panel B of Table 6, we consider heterogenous effects through the inclusion of interactions terms between the *PGL* dummy variable and firm or bank characteristics. These regressions capture the differential effects between granted PG loans and granted non-PG loans and control for potential selection issues through the inclusion of firm*bank fixed effects. We find that banks give cheaper loans if the loan is a PG loan and especially so when their lending share in the firm is larger. This differential effect of the *Share* variable for PG loans is stronger for firms in an affected sector, for riskier firms (albeit with a t-statistic of 1.61), and for banks with higher NPL ratios. These results indicate that lending relationships turn valuable in a crisis, because they allow firms to receive guaranteed credit on more favorable loan rate terms. These results are also consistent with the existence of a bank risk taking channel for the distribution of public guaranteed loans because the effect is stronger (i.e. lower loan rates) for riskier firms and weaker banks.

The results on loan maturities indicate that PG loans on average enjoy longer maturities, but that maturities on PG loans tend to be shorter for firms with a high loan share. Moreover, the maturity of PG loans of firms with a higher loan share tends to be longer if these firms are riskier and from more affected sectors, and this effect is more pronounced when these firms borrow from banks with higher NPL ratios. A lengthening of maturity is particularly valuable during a rollover crisis, as in the case of the COVID-19 liquidity squeeze. Therefore, these results suggest that one value of lending relationships is that riskier firms can disproportionately lengthen the maturity of their debt claims during a liquidity squeeze. Moreover, the fact that this effect is stronger for weaker banks, as captured by higher NPL ratios, is evidence of a risk-taking channel whereby weaker banks are more likely to engage in maturity transformation for riskier relationship firms when granting public guaranteed loans.

We also analyze whether the impact of *Share* on the probability to grant a loan is non-linear. The loan guarantee scheme could allow banks to gain market share. In particular, any gain in capital savings from the use of the scheme could be used to extend loans to new borrowers, be it through PG or non-PG loans. This is what we show in Table A5 of the Appendix. First, we observe that the zero-share dummy is positive and significant not only for PG but also for non-PG loans. Second, the previous results remain unaltered once this non-linearity is considered. Third, we find that, while banks increase their new loans to companies, they are doing so among low-risk firms in the case of publicly guaranteed loans, and among less affected and less risky firms for the rest of the loans. In the next section, we study whether the Spanish loan guarantee scheme resulted in banks that were most active in its use gaining market share, and we assess if they do so by, among other strategies, looking for new borrowers.

The Spanish loan guarantee scheme was not the only measure taken to support Spanish firms during the pandemic. The European Central Bank (ECB) also responded to the COVID-19 crisis by imposing dividend restrictions on banks to preserve bank capital, with a view to supporting the flow of credit to the real economy. Specifically, the ECB recommended on March 27, 2020, that banks do not pay dividends for financial years 2019 and 2020 during the pandemic, or at least not until October 1, 2020, and also refrain from share buy-backs over this period. This recommendation did not apply to 2019 dividends already paid out before the announcement date. These dividend restrictions applied to all Spanish banks that are directly or indirectly supervised by the ECB.

We want to make sure that our main results on the extensive and intensive margin are not confounded by the imposition of dividend restrictions. To this end, we repeat the analyses of the extensive and intensive margins while accounting for whether the bank faced a restriction on the payments of dividends or not. The results are presented in Appendix Table A6. Specifically, this table reports regressions results of a linear probability model at the firm-bank level (Panel A) or at the firm-bank-type of loan (public guaranteed loan or not) level (Panel B) of the role of dividend restrictions on the probability of granting loans with public guarantee as well as on the amount granted between 2020:03 to 2020:12. Dividend restricted is a dummy equal to 1 if the bank restricted dividends following the ECB's recommendation and 0 otherwise.

We do not observe a relevant role of dividend restrictions for PGL granting in the extensive margin results presented in panel A. The results on the amount of loan granted, i.e., the intensive margin results in panel B, indicate that there is a level effect of dividend restrictions on the amount granted but this effect is not significantly different for PG loans. Taken together, we do not find any evidence that our main analysis on the extensive and intensive margins of lending is contaminated by the imposition of dividend restrictions.

4.3 Substitution

Next, we investigate the effect of the public guarantee scheme on the allocation of loans, focusing on whether the granting of public guarantee loans results in a substitution of public guarantee loans for non-public guaranteed loans and in a change in overall credit exposures between bank-firm pairs.

First, we assess to what extent the granting of public guaranteed loans results in a substitution of public guaranteed loans for nonguaranteed loans. We do so by estimating a difference-in-difference model at the firm-bank level of the effect of the existence of public guaranteed loans on the change in the credit share of nonguaranteed loans at the bank-firm level over the period December 2019 to June 2021. The dependent variable is *ΔShare*, which is the change in the bank's share in the firm's nonguaranteed loans, based on loan amounts, over the period December 2019 to June 2021. The variable of interest is PGL, which is a dummy equal to 1 if the firm received a public guaranteed loan from the bank over the period December 2019 to June 2021, and 0 otherwise. We resort to this specification in first differences because there were no public guaranteed loans prior to March 2020 (i.e., PGL takes a value of zero before March 2020). The model is estimated at the firm-bank level using OLS, with multi-clustering of standard errors at the firm and bank level. The results are presented in columns 1 to 5 of Panel A of Table 7, which vary in terms of the fixed effects included, with the specification in column 5 included the richest set of fixed effects at the firm and bank level to absorb demand and supply effects.

We find that firm-bank pairs with public guaranteed loans tend to reduce the share of nonpublic guaranteed loans. This suggests that the public guarantee scheme contributed to a substitution of public guaranteed loans for nonguaranteed loans. The effect is economically meaningful. Based on the estimates in column 5, firm-bank pairs with PG loans experience a decrease of 7.8 percentage points in the share of nonguaranteed loans over the analyzed period. Results are qualitatively unaltered when replacing the PGL dummy with PGL amount/Assets (column 6) and when replacing ΔShare with ΔCredit, computed based on nonguaranteed loans only (Panel B). Specifically, in column 1 of Panel B we find that the total volume of non-public guaranteed loans declines by 15.4% for banks that grant PG loans to the firm.

In column 6, we assess the sensitivity of this result to replacing the PGL dummy variable with a variable capturing the quantity of PG loans. Specifically, we replace the PGL dummy with PGL amount/Assets, which is the ratio of the total amount of public guaranteed loans that the firm received from the bank over the period December 2019 to June 2021, divided by the firm's total assets at year-end 2019. The results are qualitatively robust to this change.

We also analyze the sensitivity of this result to using an alternative measure of lending relationships based on gross flows (instead of shares) of credit, in the spirit of Davis and Haltiwanger (1992) who study employment changes using gross measures of job flows. Specifically, in panel B of Table 7 we replace the ΔShare variable with ΔCredit, which is the log change in total loans between the firm and the bank, computed over the period December 2019 to June 2021. Panel B also controls for the direct effect of the *Share* variable. Results are robust to these changes, and there is no significant direct effect of the *Share* variable.

Next, we analyze the impact of public guaranteed loans on the total credit exposures between bank and firm pairs. We do so by changing the ΔShare variable based on nonguaranteed loans with a variable that measures the change in the bank's share in the firm's total loans over the same period. Otherwise, the specifications are the same as before. The results are presented in Table 8 (panel A and B as before).

In contrast to the effects on nonguaranteed loans in the previous table, we find that firm-bank pairs with public guaranteed loans tend to strengthen their lending relationships, in the sense that they increase the share of total loans between the firm and the bank. This suggests that the public guarantee scheme contributed to an increase in the concentration of credit among pre-existing lending relationships. In section 4.6 we perform an analysis along these lines in which we provide evidence on how the public guarantee scheme affected the concentration of the credit market.

The economic effects of the results are substantial. Firm-bank pairs with PG loans experience an increase of 21.6 percentage points in the loan shares over the analyzed period (column 5 of Panel A) and overall credit for these firm-bank pairs increases by 116.8 percentage points (column 1 of Panel B). The direct impact of the share of the firm with the bank becomes negative once PGL variable is also included (panel B), which implies that banks increase their total share with the firm, but they do so more for firms with which they have less exposure once the effect of PG loans is taken into account.

In Tables 9 and 10, we investigate whether there are heterogeneous effects along bank and firm characteristics of the substitution effects identified in Tables 7 and 8. A key driver of substitution could be the loan maturity. To the extent that the guarantee scheme protects against rollover risk, banks will have an incentive to replace nonguaranteed loans with guaranteed loans as they expire. This would imply that the substitution effect should be stronger for bank-firm pairs with a shorter residual maturity of outstanding loans. Moreover, to the extent that risk-shifting is at place, this effect should be stronger for riskier firms and weaker banks. In line with this hypothesis, we find in Table 9 that granting a PGL is associated with a reduction in the share of non-public guaranteed loans, and that this substitution effect is more pronounced for firm-bank pairs with a shorter residual maturity of outstanding loans. Moreover, this impact of maturity on the substitution channel is more pronounced for riskier firms (column 2) and for firms that are more affected by the crisis (column (5), and this risk shifting effect is more pronounced for banks with less capital (column 6). This evidence suggests that risk shifting is a key driver of the substitution channel.

In line with the strong substitution effects associated with loan maturity in Table 9, we find the opposite results in Table 10 where we assess the impact on total loans. Specifically, we find that banks that banks grant a PGL loan increase their overall share of loans in the firm, and this effect is stronger if the residual maturity of outstanding loans is shorter. Moreover, this impact of residual maturity is less pronounced for riskier firms (column 2) and firms in affected sectors (column 4).

In terms of the economic impact, for firms with lower residual maturity in December 2019 (a decreases in the interquartile range), the share of total loans increases by 22.7 percentage points and by 26 percentage points if, additionally, the firm is risky (interquartile increase) or belongs to the more affected sectors. Analyzing the share in terms of non-PG loans, firms with debt with shorter residual maturity decreases it by 15.9 percentage points and even by 17.5 percentage points for riskier firms in more affected sectors and working with lowly capitalized banks.

A key assumption underlying the substitution results presented thus far is that of parallel trends in the behavior of PGL and non-PG loans before the inception of the guarantee scheme. Figures 2 and 3 provide evidence in support of this parallel trend assumption. The sample period of these figures starts in March 2020 which coincides with the inception of the guarantee scheme. Obviously, we cannot extend the sample period further back in time because there were no PG loans before March 2020.

Panel A of Figure 2 presents time-varying coefficients of the effect of public guaranteed loans on the firm's non-public guaranteed loan share in a bank, derived from the estimation of the regression specification in column 5 of Table 7 using different end points of the sample period. Panel B of Figure 2 presents similar time-varying coefficients but estimated for total loans instead of non-public guaranteed loans based on the specification in column 5 of Table 8. In both cases, confidence bands are presented based on 95% confidence levels. In terms of interpretation, it is important to point out that the majority of PG loans were granted in the first quarter following the inception of the guarantee scheme (i.e., between April and June 2020, 70% of all PG loans were granted, and only 0.5% of all PG loans were granted in March). Figure 2 shows that there was no change in loan share for non-PG loans (panel A) and for total loans (panel B) in the first month (March 2020) of the guarantee scheme. Thus, the behavior at the time of the inception of the guarantee scheme was similar between bank-firm pairs with PG loans and bank-firm pairs without PG loans. It is only in the subsequent two months, until June 2020, when the majority of PG loans were granted, that a substantial difference emerges between PGL and non-PG loans. Specifically, there is no change in loan share for non-PG loans also in this subsequent period (panel A), while the change in loan share of total loans increases sharply from zero.

Figure 3 extends the analysis in Figure 2 by estimating the time-varying effects of PGL on the change in loan shares for different dates of origination of the PGL (as opposed to different sample periods). In line with the previous results, we find that firms that obtained a PGL experienced a decline in the share of non-PG loans only after the first month since origination and this decline lasts for about two months (panel A). For total loans, we do not find a significant variation of the effect of PGL across different times since origination.

4.4 Early repayment

Next, we further analyze the mechanisms by which the substitution of loans took place, and in particular we test whether the proceeds from public guaranteed loans are used for the early repayment of outstanding loans. To this end, we estimate a linear regression model at the firm-bank-month level of the effect of public guaranteed loans on the early repayment of loans between March 2020 and June 2021. We measure the early repayment of loans by the total amount of loans that are repaid in full prior to their expiration date, scaled by the firm's total assets. The regression includes a PGL dummy variable, which equals 1 if the firm received a public guaranteed loan by the bank in month 0 (i.e., March 2020), and 0 otherwise. We estimate the effect of the granting of a public guaranteed loan on the cumulative early repayment amounts computed over subsequent months, using separate regressions for months 1 through 6. Regressions include firm*year:month and bank*year:month fixed effects to absorb demand and supply effects, and standard errors are corrected for multi-clustering at the firm and bank level. The results are presented in panel A of Table 11.

We find that pre-existing loans from banks that grant a PG loan are more prone to be early repaid. This suggests that the guarantee scheme was used by banks to facilitate the recovery of their pre-existing loans. These findings should be seen against the background that under the guarantee scheme, loan restructurings were not permitted. The effect is economically relevant as it increases the early repayment amount (over firm total assets) by 26.4% in the next six months since the PG loan was granted.

Appendix Table A7 shows that results are robust when the early repayment of loans from an institution that grants PG loans are compared to early repayment of loans from institutions that granted non-PG loans, as opposed to all loans. We make this change to address the concern that the results may simply be capturing a new bank loan effect whereby firms early repay more to banks after the bank grants them new loans, independently of it being PG loan or not. In this case, we find that the repayment channel kicks in only starting after 4 months, while for all loans we found that it started already after 2 months.

A key driver of early repayment could be the residual maturity of the loan. Maturing loans face higher rollover risk and are therefore more likely to be the target of prepayment by banks. In panel B of Table 11, we therefore consider heterogeneous effects of early repayment, focusing on loan maturity as a key driver of early repayment. As dependent variable, we use the cumulative early repayment amount computed over the first 6 months (i.e., the same variable as used in column (6) of panel A). Consistent with our priors, we find that early repayment is especially the case when the outstanding loans have short (residual) maturity, and that this effect is stronger for banks with a higher loan share, for riskier firms, and for less capitalized banks. These results indicate that existing bank lending relationships tend to promote the early repayment of loans with higher rollover risk and does so in a way that is in line with risk shifting. From an economic point of view, the effect of PGL on the early repayment increases to 51.5% for firms with shorter residual maturity, to 76% when, in addition, the share between the banks and the firm is high, and to 108.9% when the firm is riskier and to 194.9% when the bank is lowly capitalized.

4.5 Bank management of loan impairment

The results on early repayment are indicative of active bank management of outstanding loans. A more direct test of the active bank management of credit risk using the credit guarantee scheme is whether the scheme influenced the classification of past due and impaired loans. Existing accounting rules leave ample discretion to banks in the classification of credit exposures and nonperforming loans (e.g., Huizinga and Laeven (2012). Specifically, under IFRS 9 accounting, banks are supposed to recognize the impairment of loans in three stages of increasing credit risk, with stage 3 classification denoting that credit risk has increased to the point that the loan is impaired.

We test whether banks that granted a PGL to a firm are more reluctant to classify loans as Stage 3 loans using a linear probability model at the firm-bank level estimated over the period March 2020 and June 2021. Such use of discretion by the bank could denote regulatory arbitrage but could also reflect the banks perception that the guarantee offers protection to the banks in case of past due payments or different payment patterns of the firm. The dependent variable is Stage 3, which is a dummy variable that equals 1 if the bank classified the firm as having stage 3 loans during the period analyzed, and 0 otherwise. Our variable of interest is PGL, which is a dummy variable equal to 1 if the firm received a public guaranteed loan by a bank, and 0 otherwise. In addition to estimating the average effect of PGL, we also consider heterogeneous effects of PGL depending on bank-firm lending relationships (share), firm characteristics (risk, affected sector) and bank characteristics (bank capital, NPL ratio). Regressions include firm and bank fixed effects to absorb demand and supply effects, and standard errors are adjusted for multi-clustering at the firm and bank level. The results are presented in Table 12.

We find that banks that grant PG loans are less prone to classify firms as having Stage 3 loans, after accounting for other channels through the inclusion of firm and bank fixed effects (column 1). This effect is particularly pronounced for firm-bank pairs with strong pre-existing lending relationships (column 2), especially for risky firms and/or firms in affected sectors. The effects are economically meaningful. The presence of PG loans reducing the probability of classifying stage 3 loans by 1.3 percentage points, which is a large effect given that firms with stage 3 loans on average represent only 2.1% of the sample. Therefore, if a firm has a PG loan with a bank the likelihood to be classified as stage 3 decreases by 63.1%. Moreover, this decrease reaches 72.6% when the share between the firm and the bank is high (interquartile range increase), to 90.4% for riskier firms (interquartile range increase) or to 95.3% when the firm belong to a pandemic-affected sector, and, if, in addition, the bank is lowly capitalized the decrease is 143.6%. These results indicate that banks use the credit guarantee scheme to actively engage in credit management by increasing the prepayment of non-PG loans and by reducing the classification of loans into the category of impaired loans, especially when the firm has pre-existing lending relationships with the bank. Moreover, column (8) shows that our results are robust to restricting our sample to firm-bank pairs that at the end of the period have non-PG loans (we lose 36% of the sample). Results are unaltered, suggesting that the effect is not driven by the mechanical effect of the substitution of PG loans for non-PG loans.

4.6 The effect on bank market share

The use of public guaranteed scheme can favor the increase the credit supply of a given bank. On the one hand, if PG credit is partly subsidized this can increase bank's supply of loans by increasing the value for the bank of a PG loan, and the other hand, banks can exploit the capital gain from substituting PG loans for non-PG loans, due to the lower required capital for PG loans, to increase their market share. This increase in market share could be achieved not only through the extension of PG loans but also by granting non-PG loans.

Table 13 shows the results of the estimation of Eq. (12), capturing the effect on bank market shares, for different dependent variables and two different explanatory variables. Thus, we analyze whether banks that use more intensively the public guarantee scheme (measured using the volume of guaranteed credit over bank total assets at the end of 2019, or with a dummy that takes the value 1 if the bank is above the third quartile of the distribution of the usage, respectively) change their firm market share, or whether this has an impact on the bank's decision to grant loans to new borrowers or to borrowers with which the bank has already a pre-existing loan. In columns (1) and (2) of Table 13, we find that those banks that lent a larger volume of PG loans, relative to their size, increase their share in the long-run by around 0.06 percentage points, which represents a 9% increase with respect the average market share. This behaviour is especially true (three times higher) for the largest banks, as can be seen when analysing the heterogeneity of the results with respect to the size of the bank. This is particularly relevant, because it informs us about the importance of bank size as an indicator of better technology. Thus, the largest banks were technologically more capable than the rest in handling and processing a large amount of information in a short period of time. Moreover, it follows that they achieve this by expanding their credit portfolio both towards pre-existing firms and towards new borrowers (see columns (4) and (5) and (6) to (9), respectively). We know, from Table A5 of the Appendix, that those new firms are less risky or belong to industries that are less hit by the pandemic. In terms of the contribution to the change in total lending to firms, it can be derived from Table 11 that pre-existing borrowers contribute, on average, at least twice that of new borrowers.

Figure 4 presents the time-varying coefficients of column (1) (Panel A), column (2) (Panel B) and columns (3) and (5) (Panel B) of Table 13. All of the figures indicate that there is no significant effect before the pandemic (February and March 2020), which validates the parallel trend assumption.

We conclude that the implementation of the public guarantee scheme resulted in an increase in market of those banks that participated more in the public scheme, and that these banks achieved this increase in their market shares by increasing their lending both to old and to new and less risky borrowers.

5. Conclusions

We have analyzed the impact of the Spanish public guarantee scheme on the composition of credit during the pandemic, using a unique dataset of loan-level data that allows to identify those loans that enjoy the protection from the public guarantee scheme and that can be matched with bank and firm characteristics. Compared to a rapidly emerging literature on the topic, our focus is on the role of bank-firm relationships in shaping the effects of the guarantee scheme on the provision of credit and on its effects on aspects such as credit reallocation, loan repayment, loan impairment recognition or market shares. Our analysis is therefore mostly conducted at the firm-bank level, allowing for the absorption of demand and supply effects through the inclusion of firm and bank fixed effects. We contribute to the literature by showing that borrower-lender relationships are a key determinant of the distribution of government credit guarantees when these are intermediated through financial intermediaries. We also contribute by showing how the distribution of such guarantees has important effects on loan repayments, loan impairment recognition and banks' market shares.

We find that firms are more likely to obtain a public guaranteed loan from banks to which they have larger pre-existing credit exposures, measured as the share of the firm's total credit outstanding with the bank as of December 2019. This effect is more pronounced for risky firms and for firms in more pandemic-affected sectors. These effects do not only operate at the intensive margin in terms of loan amounts but also on the extensive margin of lending as captured by new loans.

We also analyze the economic effects of the guarantee scheme and show how it results in credit substitution at the firm-bank level, with the share of nonguaranteed credit declining for firms that obtain guaranteed loans, in part reflecting early prepayment of outstanding credit. Moreover, banks that grant guaranteed loans are less prone to recognize loan impairment, in line with the guarantee acting as a protection against credit risk. Finally, we find that banks that participate more in the scheme gain market share by increasing their portfolio of loans to both old and (less risky) new borrowers.

These results indicate that banks use the credit guarantee scheme to actively engage in credit management by substituting guaranteed loans for nonguaranteed loans, by increasing the prepayment of nonguaranteed loans, and by reducing the classification of loans into the category of impaired loans, especially when the firm has stronger pre-existing lending relationships with the bank. These results are more pronounced for risky firms and firms in affected sectors, and for banks with weaker balance sheets (less capital and more NPLs), suggesting that the scheme can be encouraging risk shifting of credit risk by banks onto the state, and that pre-existing lending relationships promote this risk shifting. While such risk shifting may be individually optimal from the perspective of the bank and its main borrowers, it may be socially suboptimal. We leave a full-fledged welfare analysis for future research.

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FIGURE 1

FINANCIAL FLOWS OF SPANISH LOAN GUARANTEE SCHEME

This figure shows the financial obligations and flows of a loan disbursed on the Spanish loan guarantee scheme.

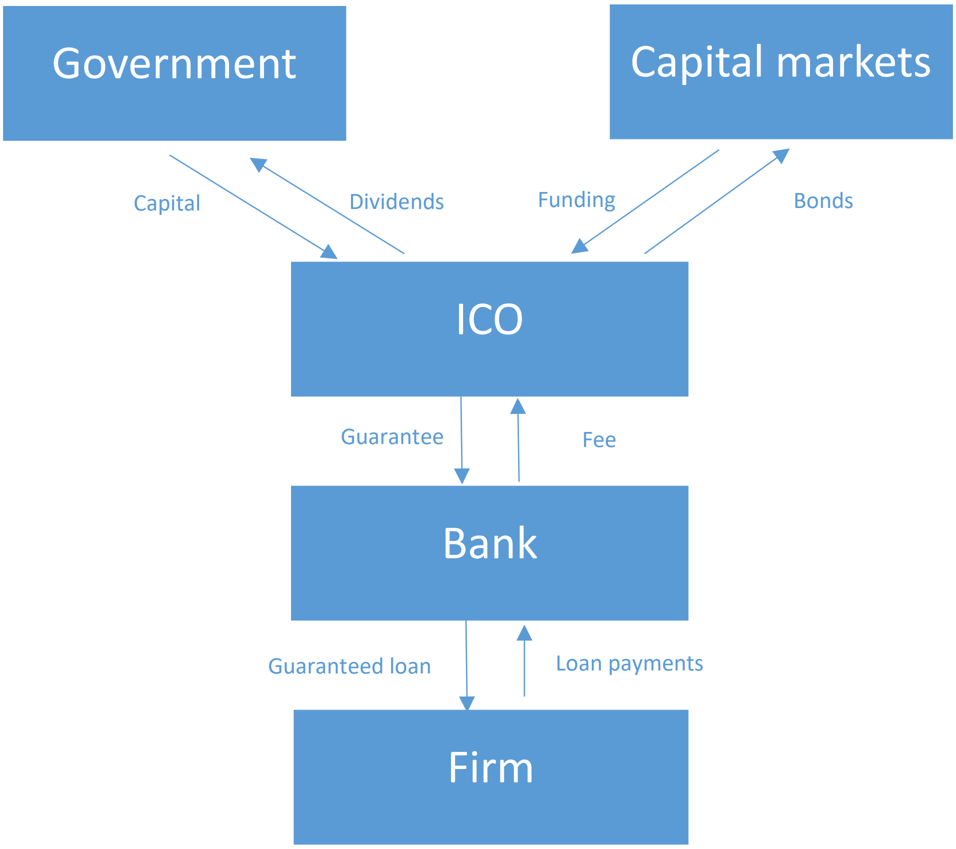
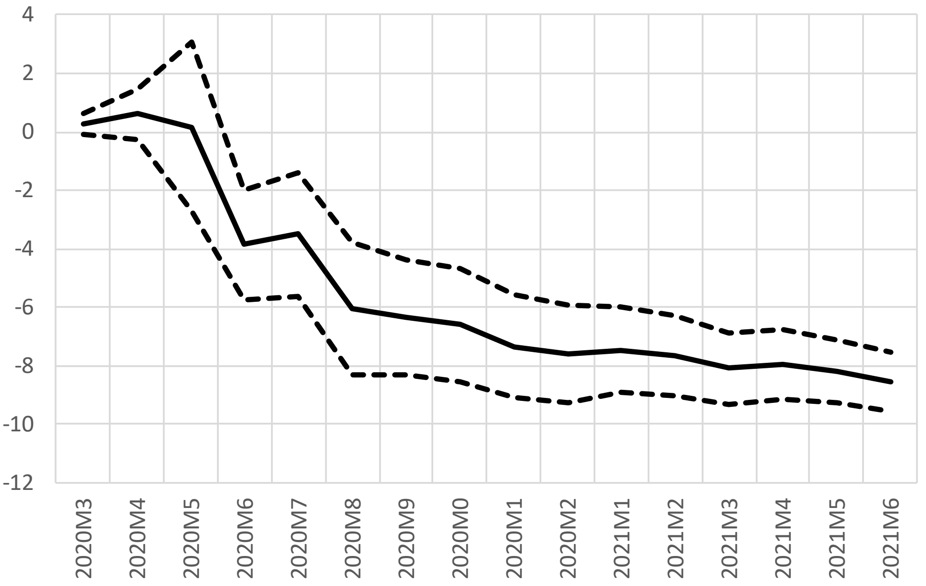


FIGURE 2

EFFECT OF THE PUBLIC GUARANTEED LOANS ON THE SHARE OF THE FIRM WITH A BANK: TIME VARYING COEFFICIENTS

This figure shows the analogous estimated coefficient on PGL of column 5, Tables 7 and 8, for different end periods. Confidence bands at 95%.

Panel A. Change in the share of non-public guaranteed loans



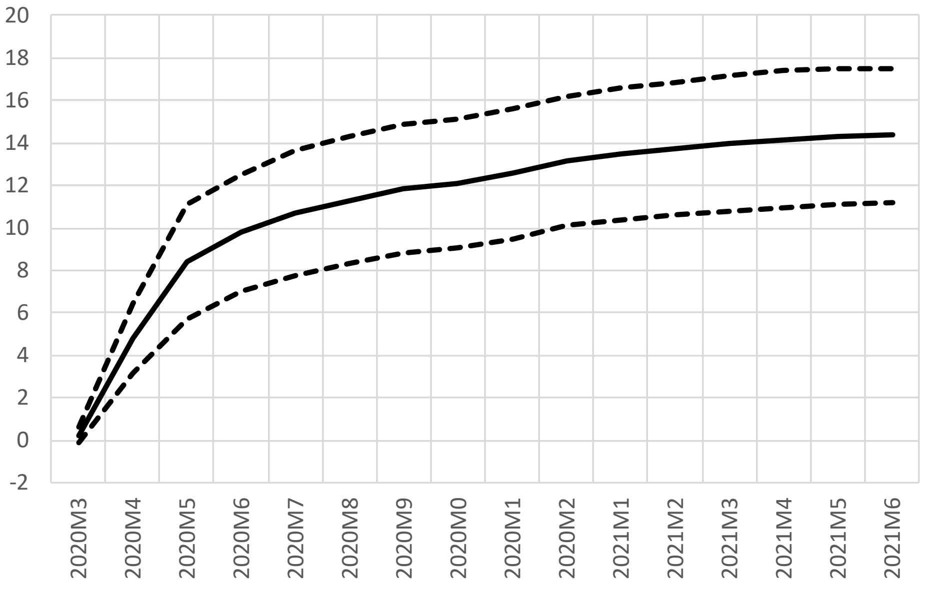
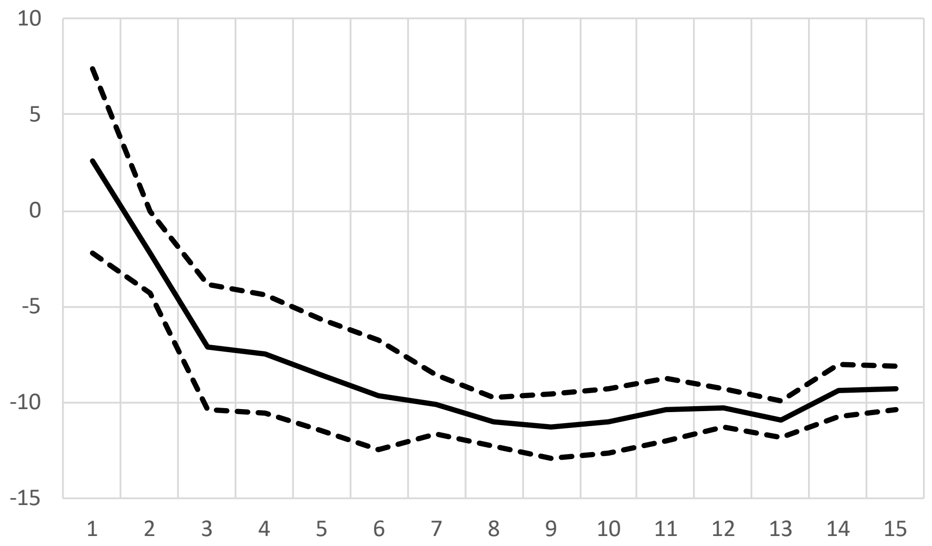


FIGURE 3

EFFECT OF THE PUBLIC GUARANTEED LOANS ON THE SHARE OF THE FIRM WITH A BANK: NUMBER OF MONTHS SINCE ORIGINATION

This figure shows the estimated coefficient on PGL of column 5, Tables 7 and 8, for different origination periods of the public guaranteed loan. Confidence bands at 95%.

PANEL A. Change in the share of non-public guaranteed loans



PANEL B. Change in the share of total loans

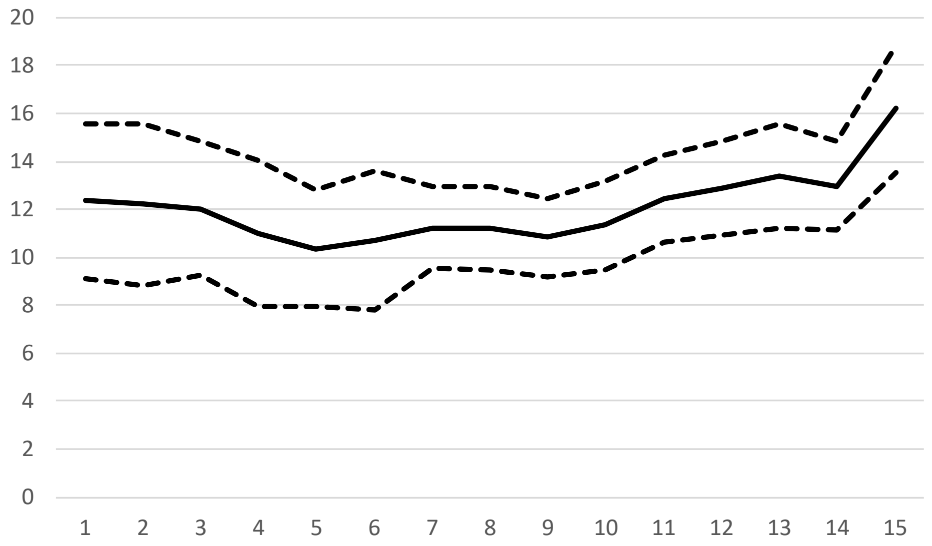
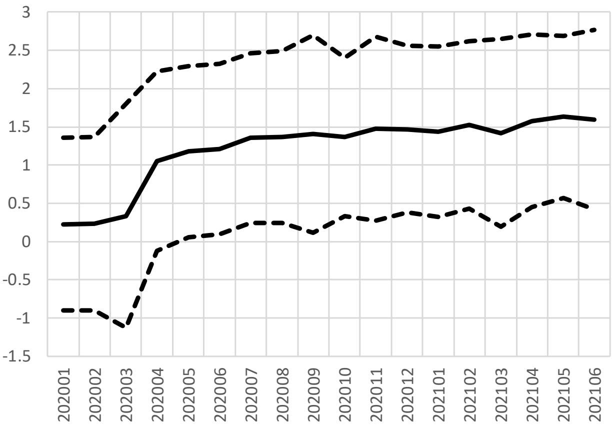


FIGURE 4

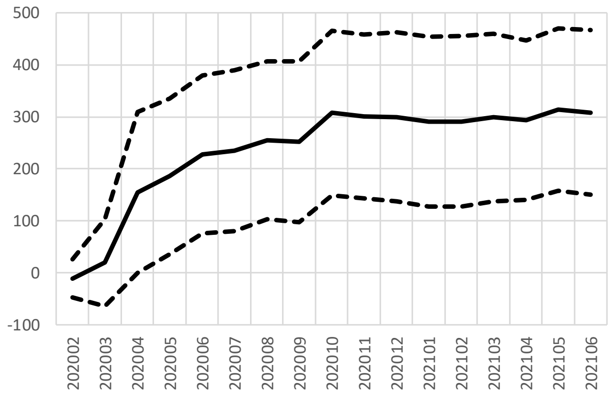
EFFECT OF THE PUBLIC GUARANTEED SCHEME ON THE BANK CREDIT PORTFOLIO: TIME VARYING COEFFICIENTS

This figure shows the analogous estimated coefficient on PGL of Table 13 (columns (1) , (3), (5) and (7)), for different end periods. Confidence bands at 95%.

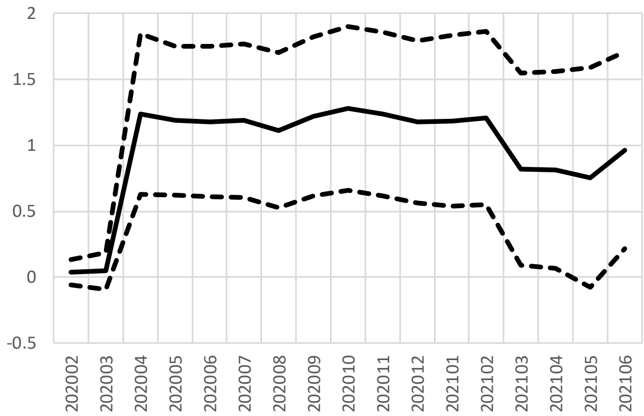
Panel A. Banks’ market share



Panel B. Change of credit of firms with a relatioship with the bank at December 2019



Panel C. Ratio of the number of new firms at *t* over total firms of a bank (left) and newly grated credit amount at *t* over total bank credit (right)



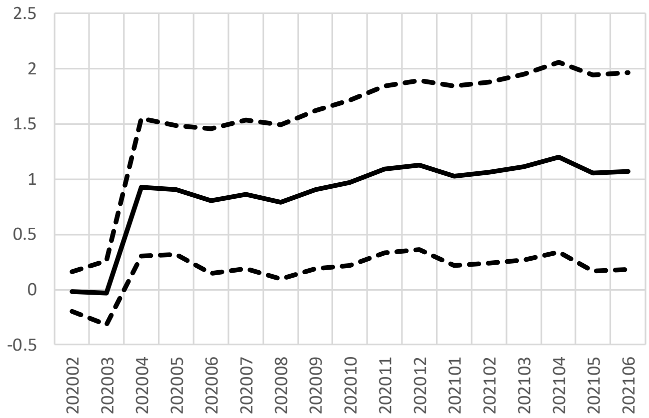


TABLE 1

SUMMARY STATISTICS

This table reports units, means, standard deviations and first/second/third quartiles of the variables used in our analysis. In Panel A we show the descriptive statistics at firm-bank level of the study of the extensive margin (receiving a public guaranteed loan), and of the intensive margin at firm-bank-type of loan (public guaranteed or not) level (credit amount, interest rate and maturity) in Spain between 2020:03 to 2020:12. In Panel B we report the statistics at firm-bank level of the study of credit substitution between public and non-public guaranteed loans, of the analysis at firm-bank-type of loan level of early repayment of pre-existing loans after the public guaranteed loan was granted, and of the study at firm-bank level of the future loan performance of firms in Spain between 2020:03 to 2021:06. All firm and bank characteristics are calculated as of December 2019. Public guaranteed loan (PGL) is a dummy equal to 1 if the firm received a loan guaranteed by the estate and 0 otherwise. Non-PGL is a dummy equal to 1 if the firm only received non-public guaranteed loans during the sample period. Stage 3 is a dummy equal to 1 if the bank classified the firm as stage 3 during the period analyzed and 0 otherwise. SME is a dummy that takes 1 if the firm is a small or medium-sized enterprise (based on Commission Regulation (EU) No. 651/2014) and 0 otherwise. Risk is a scoring variable which captures the credit risk of the firm (higher values implies higher risk). Liquidity is the ratio between cash and other liquid assets of the firm over total assets. Growth opportunities is the growth of rate of firm sales between 2019 and 2018. Affected sector is defined as sectors in which firm turnover on average decreased by more than 15% in 2020. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Ln(Average residual maturity) is the weighted average residual maturity of loans at the firm-bank pair level, weighted by loan size. *HHI* measures the weighted average of the exposure of a firm with all its banks as of December 2019. Ln(Assets) is the log of the bank's total assets (expressed in thousands of euros). The capital ratio of the bank is defined as own funds over total assets. ROA is the ratio of the bank's net profits to total assets. Liquidity ratio of the bank is the ratio of liquid assets over total assets. NPL ratio captures the non-performing loans (doubtful and 90 days overdue) over total loans of the bank. Stage 3 is a dummy equal to 1 if the bank classified any loan of the firm as stage 3 during the period analyzed, and 0 otherwise. Cumulative early repayment 6 months is the cumulative early repayment during the first 6 months following the inception of the credit guarantee scheme, divided by the firm's total assets, and computed based on all loans. For the analysis of banks 'market share, PGL is the ratio of government-guaranteed loan amount granted during the period over total assets of the bank as of December 2019; PGL dummy is a dichotomous variable equal to 1 if the usage of the public scheme by the bank is in the third quartile of the distribution, and 0 otherwise; bank's market share is the market share of the bank for non-financial firms; ΔOld firms (amount) is the change in credit with the bank of firms that had a previous relationship with the bank between December 2019 and time *t*; New firms (number/amount) is the ratio of new firms, computed either using the number of new firms or the amount granted to new firms at *t*, where a firm is classified as new for a bank if the firm has a relationship at *t* and not in December 2019.

PANEL A. Extensive and Intensive Margin

		Mean	S.D.	P25	Median	P75
Extensive Margin						
Public Guaranteed Loan (PGL)	0/1	0.378	0.485	0.000	0.000	1.000
Non-PGL	0/1	0.287	0.453	0.000	0.000	1.000
Intensive Margin						
Public Guaranteed Loans (PGL)	0/1	0.500	0.500	0.000	0.500	1.000
Committed amount	€	129,649	162,690	20,000	59,994	163,897
Interest rate	%	3.334	2.966	1.530	2.427	3.665
Maturiry	months	25.665	24.998	2.667	12.000	57.286
Firm Characteristics(i)						
SME	0/1	0.954	0.208	1.000	1.000	1.000
Risk	Standardized	0.000	1.000	-0.729	-0.105	0.614
Liquidity	0.0x%	0.112	0.154	0.012	0.050	0.149
Growth opportunities	0.0x%	0.126	0.349	-0.053	0.050	0.200
Affected Sector	0/1	0.623	0.485	0.000	1.000	1.000
Firm-Bank Characteristics(ij)						
Share	0.0%	0.266	0.312	0.003	0.136	0.429
Ln(Average residual maturity)	0.0%	1.859	1.612	0.000	1.946	3.258
Bank Characteristics(j)						
Ln(Assets)	Log(1000€)	18.212	1.894	17.405	18.991	19.810
Capital ratio	0.0x%	0.093	0.040	0.064	0.080	0.118
ROA	0.0x%	0.009	0.012	0.005	0.006	0.007
Liquidity ratio	0.0x%	0.074	0.039	0.069	0.074	0.095
NPL ratio	0.0x%	0.046	0.018	0.030	0.050	0.056

PANEL B. Substitution, Early Repayment, Future Loan Performance of Firms and Market Share

		Mean	S.D.	P25	Median	P75
Substitution						
ΔShare non-PGL$_{2021:06-2019:12}$	%	-4.163	23.971	-12.091	-1.956	3.621
ΔShare all loans$_{2021:06-2019:12}$	%	-3.42	21.37	-9.88	-1.72	3.51
ΔCredit non-PGL$_{2021:06-2019:12}$	%	-89.732	95.755	-200.000	-81.530	-15.916
ΔCredit all loans$_{2021:06-2019:12}$	%	-36.127	108.986	-129.901	-12.065	37.068
Stage 3	0/1	0.021	0.142	0.000	0.000	0.000
PGL	0/1	0.397	0.489	0.000	0.000	1.000
PGL amount/total assets	0.0x%	0.069	0.144	0.000	0.000	0.077
Early repayment						
Cumulative early repayment 6 months	0.0x%	0.004	0.036	0.000	0.000	0.000
PGL	0/1	0.054	0.227	0.000	0.000	0.000
Market share						
Bank's market share	%	0.659	2.669	0.004	0.026	0.125
ΔOld firms (amount)	%	-7.837	20.814	-14.870	-4.703	0.239
New firms (number)	%	13.371	13.162	5.386	10.470	16.667
New firms (amount)	%	10.799	13.321	2.523	7.040	13.393
PGL	0.0x%	0.021	0.024	0.000	0.014	0.037
PGL dummy	0/1	0.176	0.381	0.000	0.000	0.000
Firm Characteristics(i)						
Risk	Standardized	0.000	1.000	-0.728	-0.104	0.615
Affected Sector	0/1	0.621	0.485	0.000	1.000	1.000
HHI	%	0.028	0.988	0.000	0.001	0.003
Firm-Bank Characteristics(ij)						
Share	0.0x%	0.291	0.276	0.065	0.197	0.455
Ln(Average residual maturity)	0.0x%	2.270	1.495	1.099	2.398	3.478
Bank Characteristics(j)						
Capital ratio	0.0x%	0.086	0.033	0.063	0.080	0.093
NPL ratio	0.0x%	0.046	0.018	0.037	0.047	0.056

TABLE 2

EXTENSIVE MARGIN ANALYSIS: PUBLIC GUARANTEED LOANS

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan (PANEL A) or a non-stated-backed one (PANEL B) between 2020:03 to 2020:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL A. Public Guaranteed Loans

Dependent variable: Public Guaranteed Loan (0/1)		(1)	(2)	(3)	(4)	(5)
Firm Characteristics(i)	SME	0.119***	0.112***	0.106***	0.108***	
		(0.020)	(0.018)	(0.016)	(0.016)	
	Risk	0.026***	0.029***	0.029***	0.029***	
		(0.006)	(0.006)	(0.007)	(0.007)	
	Liquidity	-0.242***	-0.253***	-0.262***	-0.244***	
		(0.043)	(0.042)	(0.044)	(0.045)	
	Growth opportunities	0.038***	0.039***	0.041***	0.039***	
		(0.005)	(0.005)	(0.005)	(0.006)	
	Affected Sector	0.037***				
		(0.004)				
Firm-Bank Characteristics(ij)	Share	0.116***	0.112***	0.142***	0.129***	0.216***
		(0.020)	(0.020)	(0.021)	(0.022)	(0.023)
	Ln(Average residual maturity)	0.017***	0.018***	0.013**	0.015***	-0.005
		(0.006)	(0.006)	(0.005)	(0.006)	(0.004)
Bank Characteristics(j)	Ln(Assets)	0.056***	0.056***	0.058***		
		(0.005)	(0.005)	(0.005)		
	Capital ratio	-0.641*	-0.639*	-0.604*		
		(0.367)	(0.363)	(0.352)		
	ROA	-1.998**	-2.074**	-2.114**		
		(0.908)	(0.917)	(0.904)		
	Liquidity ratio	0.349	0.352	0.344		
		(0.258)	(0.258)	(0.250)		
	NPL ratio	1.665**	1.636**	1.509**		
		(0.640)	(0.643)	(0.623)		
	Zip code Fixed Effects	Yes	Yes	-	-	-
	Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-
	Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-
	Bank Fixed Effects	No	No	No	Yes	Yes
	Firm Fixed Effects	No	No	No	No	Yes
	Observations	718,204	718,204	718,204	718,204	718,204
	R2	0.154	0.161	0.260	0.279	0.475

PANEL B. Non Public Guaranteed Loans

Dependent variable: Only Non-Public Guaranteed Loans (0/1)		(1)	(2)	(3)	(4)	(5)
Firm Characteristics(i)	SME	-0.151***	-0.143***	-0.138***	-0.129***	
		(0.019)	(0.018)	(0.018)	(0.019)	
	Risk	-0.014**	-0.013**	-0.013*	-0.014**	
		(0.006)	(0.006)	(0.006)	(0.007)	
	Liquidity	0.006	0.020	0.022	0.036	
		(0.041)	(0.040)	(0.041)	(0.040)	
	Growth opportunities	-0.022***	-0.020***	-0.022***	-0.021***	
		(0.004)	(0.004)	(0.005)	(0.005)	
	Affected Sector	-0.012***				
		(0.004)				
Firm-Bank Characteristics(ij)	Share	0.035**	0.041***	0.043**	0.033**	0.027*
		(0.015)	(0.015)	(0.017)	(0.016)	(0.015)
	Ln(Average residual maturity)	-0.055***	-0.055***	-0.056***	-0.041***	-0.039***
		(0.010)	(0.010)	(0.010)	(0.007)	(0.006)
Bank Characteristics(j)	Ln(Assets)	0.006	0.007	0.006		
		(0.010)	(0.010)	(0.010)		
	Capital ratio	1.966*	1.980*	1.995*		
		(1.082)	(1.086)	(1.057)		
	ROA	5.097	5.185	5.190		
		(3.547)	(3.541)	(3.478)		
	Liquidity ratio	0.976***	0.978***	0.988***		
		(0.360)	(0.361)	(0.359)		
	NPL ratio	-1.507	-1.519	-1.492		
		(1.526)	(1.531)	(1.495)		
	Zip code Fixed Effects	Yes	Yes	-	-	-
	Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-
	Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-
	Bank Fixed Effects	No	No	No	Yes	Yes
	Firm Fixed Effects	No	No	No	No	Yes
	Observations	718,204	718,204	718,204	718,204	718,204
	R2	0.122	0.126	0.214	0.266	0.437

TABLE 3

EXTENSIVE MARGIN ANALYSIS: PUBLIC GUARANTEED LOANS. HETEROGENEITY

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan (PANEL A) or a non-stated-backed one (PANEL B) between 2020:03 to 2020:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL A. Public Guaranteed Loans

Dependent variable: Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)
Share	0.221***	0.216***	0.222***	0.223***	0.200***
	(0.024)	(0.023)	(0.023)	(0.024)	(0.022)
Share*Risk	0.050***		0.054***	0.055***	0.044***
	(0.004)		(0.004)	(0.004)	(0.004)
Share*Affected sectors		0.022***	0.041***	0.040***	0.031***
		(0.006)	(0.006)	(0.006)	(0.006)
Share*Risk*Affected sectors				0.015***	0.013***
				(0.004)	(0.004)
Share*Risk*Affected sectors*Capital ratio					-0.434**
					(0.177)
Share*Risk*Affected sectors*NPL ratio					0.719**
					(0.303)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204
R2	0.476	0.475	0.476	0.476	0.478

PANEL B. Non Public Guaranteed Loans

Dependent variable: Non-Public Guarantee Loans (0/1)	(1)	(2)	(3)	(4)	(5)
Share	0.027*	0.027*	0.027*	0.028*	0.028*
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Share*Risk	0.000		-0.001	-0.000	0.000
	(0.005)		(0.005)	(0.005)	(0.003)
Share*Affected sectors		-0.011***	-0.011**	-0.011**	-0.011**
		(0.004)	(0.004)	(0.004)	(0.004)
Share*Risk*Affected sectors				0.011***	0.012**
				(0.004)	(0.005)
Share*Risk*Affected sectors*Capital ratio					0.395**
					(0.190)
Share*Risk*Affected sectors*NPL ratio					-0.697*
					(0.360)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204
R2	0.437	0.437	0.437	0.437	0.441

TABLE 4

INTENSIVE MARGIN ANALYSIS: LOAN AMOUNT

This table reports regressions results of a Poisson model at firm-bank-type of loan (public guaranteed loan or not) level of the new commitment amount granted between 2020:03 to 2020:12. PGL is a dummy equal to 1 if the firm received a public guaranteed loan and 0 otherwise. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Loan amount captures the total committed amount of new loans. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Loan committed amount	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
PGL						0.374***	0.393***	0.401***	0.392***	0.426***	0.460***
						(0.079)	(0.077)	(0.079)	(0.081)	(0.084)	(0.106)
Share	-0.491***	-0.403***	-0.138**	-0.162***	0.823***	-0.492***	-0.402***	-0.140**	-0.163***	0.827***	
	(0.049)	(0.052)	(0.063)	(0.059)	(0.048)	(0.047)	(0.051)	(0.063)	(0.058)	(0.043)	
Zip code Fixed Effects	Yes	Yes	-	-	-	Yes	Yes	-	-	-	-
Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-	No	Yes	-	-	-	-
Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-	No	No	Yes	Yes	-	-
Bank Fixed Effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes	-
Firm Fixed Effects	No	No	No	No	Yes	No	No	No	No	Yes	-
Firm*Bank Fixed Effetcs	No	No	No	No	No	No	No	No	No	No	Yes
Observations	620,451	620,451	620,451	620,451	620,451	620,451	620,451	620,451	620,451	620,451	345,416
R2	0.239	0.271	0.435	0.451	0.698	0.260	0.294	0.457	0.471	0.720	0.785

TABLE 5

INTENSIVE MARGIN ANALYSIS: HETEROGENEITY

This table reports regressions results of a Poisson model at firm-bank-type of loan (public guaranteed loan or not) level of the new commitment amount granted between 2020:03 to 2020:12. PGL is a dummy equal to 1 if the firm received a public guaranteed loan and 0 otherwise. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Loan amount captures the total committed amount of new loans. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Loan committed amount	(1)	(2)	(3)	(4)	(5)	(6)
PGL	0.476***	0.471***	0.477***	0.472***	0.473***	0.473***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.108)	(0.038)
PGL*Share	0.189***	0.177**	0.188***	0.176**	0.181**	0.181**
	(0.071)	(0.072)	(0.071)	(0.072)	(0.072)	(0.072)
PGL*Share*Risk		-0.013		-0.007	-0.004	-0.015
		(0.021)		(0.021)	(0.021)	(0.022)
PGL*Share*Affected sectors			0.123***	0.111***	0.113***	0.079***
			(0.027)	(0.028)	(0.028)	(0.023)
PGL*Share*Risk*Affected sectors					0.057**	0.031*
					(0.028)	(0.018)
PGL*Share*Risk*Affected sectors*Capital ratio						1.523
						(1.684)
PGL*Share*Risk*Affected sectors*NPL ratio						-0.009
						(2.659)
Firm*Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,416	345,416	345,416	345,416	345,416	345,416
R2	0.785	0.786	0.785	0.786	0.786	0.795

TABLE 6

INTENSIVE MARGIN ANALYSIS: OTHER LOAN TERMS

This table reports regressions results of a linear model (columns (3) and (4) of Panel A; and column (1) of Panel B), or a Poisson model (columns (1), (2), (5) and (6) of Panel A; and columns (2) of Panel B) at firm-bank-type of loan (public guaranteed loan or not) level of new loans granted between 2020:03 to 2020:12. Panel A shows the direct effects while Panel B shows the heterogeneous ones. PGL is a dummy equal to 1 if the firm received a public guaranteed loan and 0 otherwise. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Amount captures the total committed amount of new loans. Interest rate/maturity is the weighted average (using the loan amount) interest rate/maturity of new loans granted by type of loan. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Panel A. Loan terms

		(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Dependent variable:	Amount		Interest rate		Maturity	
Loan characteristics (ij)	PGL	0.419***	0.418***	-2.201***	-2.306***	1.474***	1.628***
		(0.041)	(0.054)	(0.199)	(0.237)	(0.072)	(0.102)
	Share	0.733***		-0.659***		-0.037**	
		(0.042)		(0.069)		(0.016)	
	Bank Fixed Effetcs	Yes	-	Yes	-	Yes	-
	Firm Fixed Effetcs	Yes	-	Yes	-	Yes	-
	Firm*Bank Fixed Effetcs	No	Yes	No	Yes	No	Yes
	Observations	470,263	289,358	470,263	289,358	470,263	289,358
	R2	0.705	0.765	0.546	0.695	0.558	0.651

Panel B. Loan terms, heterogeneity

	(1)	(2)
Dependent variable:	Interest rate	Maturity
PGL	-2.268***	1.638***
	(0.083)	(0.038)
PGL*Share	-0.801**	-0.333***
	(0.324)	(0.025)
PGL*Share*Risk	0.047	0.009
	(0.066)	(0.012)
PGL*Share*Affected sectors	-0.238***	0.014
	(0.073)	(0.031)
PGL*Share*Risk*Affected sectors	-0.145	0.067***
	(0.090)	(0.020)
PGL*Share*Affected sectors*Capital ratio	3.969	1.089
	(4.437)	(1.553)
PGL*Share*Affected sectors*NPL ratio	-13.654**	1.178
	(6.462)	(2.647)
PGL*Share*Risk*Affected sectors*Capital ratio	3.829	-1.327
	(3.506)	(1.536)
PGL*Share*Risk*Affected sectors*NPL ratio	-5.092	5.608**
	(6.148)	(2.794)
Firm*Bank Fixed Effects	Yes	Yes
Observations	289,358	289,358
R2	0.708	0.662

TABLE 7

SUBSTITUTION OF NON-PUBLIC GUARANTEED LOANS

This table reports regressions results of a difference-in-differences model estimated using OLS at the firm-bank level of the effect of public guaranteed loans on firm-bank relationships between December 2019 and June 2021. Panel A shows the impact on the change in share, ΔShare, which is the change in the firm's share of non-public guaranteed loans, based on loan amounts, over the period December 2019 to June 2021. Panel B shows the impact on the change in credit, ΔCredit, which is the log change in total non-public guaranteed loans between the firm and the bank, computed over the period December 2019 to June 2021. PGL is a dummy equal to 1 if the firm received a public guaranteed loan from the bank over the period December 2019 to June 2021, and 0 otherwise. PGL amount/Assets is the ratio of the total amount of public guaranteed loans that the firm received from the bank over the period December 2019 to June 2021, divided by the firm's total assets at year-end 2019. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Panel A. Change in firm share

Dependent variable:	$\Delta Share_{2021:06-2019:12}$					
	(1)	(2)	(3)	(4)	(5)	(6) Intensity
PGL	-3.095***	-3.129***	-4.010***	-5.118***	-7.781***	
	(0.850)	(0.837)	(0.763)	(0.411)	(0.340)	
PGL amount/Assets						-28.505***
						(2.843)
Zip code Fixed Effects	Yes	Yes	-	-	-	-
Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-	-
Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-	-
Bank Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.017	0.018	0.072	0.091	0.205	0.207

Panel B. Change in credit amount

Dependent variable:	$\Delta Credit_{2021:06-2019:12}$			
	(1)	(2)	(3)	(4)
PGL	-15.355***		-16.824***	-16.814***
	(2.454)		(2.675)	(2.729)
Share		6.172**	12.330***	12.343***
		(2.985)	(3.414)	(3.371)
PGL*Share				-0.556
				(3.755)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686
R2	0.458	0.455	0.459	0.459

TABLE 8

SUBSTITUTION OF TOTAL LOANS

This table reports regressions results of a difference-in-differences model estimated at the firm-bank level using OLS of the effect of public guaranteed loans on firm-bank relationships between December 2019 and June 2021. Panel A shows the impact on the change in share, ΔShare, which is the change in the firm's share of total loans, based on loan amounts, over the period December 2019 to June 2021. Panel B shows the impact on the change in credit, ΔCredit, which is the log change in total loans between the firm and the bank, computed over the period December 2019 to June 2021. PGL is a dummy equal to 1 if the firm received a public guaranteed loan from the bank over the period December 2019 to June 2021, and 0 otherwise. PGL amount/Assets is the ratio of the total amount of public guaranteed loans that the firm received from the bank over the period December 2019 to June 2021, divided by the firm's total assets at year-end 2019. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Panel A. Change in firm share

Dependent variable:	$\Delta Share_{2021:06\text{-}2019:12}$					
	(1)	(2)	(3)	(4)	(5)	(6) Intensity
PGL	13.565***	13.723***	14.786***	14.034***	16.894***	
	(1.242)	(1.229)	(1.264)	(1.338)	(1.522)	
PGL amount/Assets						59.997***
						(2.581)
Zip code Fixed Effects	Yes	Yes	-	-	-	-
Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-	-
Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-	-
Bank Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.104	0.105	0.161	0.176	0.299	0.305

Panel B. Change in credit amount

Dependent variable:	$\Delta Credit_{2021:06\text{-}2019:12}$			
	(1)	(2)	(3)	(4)
PGL	116.788***		119.002***	120.436***
	(3.930)		(4.415)	(4.846)
Share		24.977***	-18.582***	-16.721***
		(2.173)	(3.503)	(2.364)
PGL*Share				-78.904***
				(5.858)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	597686	597,686	597,686	597,686
R2	0.641	0.511	0.641	0.646

TABLE 9

SUBSTITUTION OF NON-PUBLIC GUARANTEED LOANS: HETEROGENEITY

This table reports regressions results of a difference-in-differences model estimated using OLS at the firm-bank level of the effect of public guaranteed loans on firm-bank relationships between December 2019 and June 2021. ΔShare, which is the change in the firm's share of non-public guaranteed loans, based on loan amounts, over the period December 2019 to June 2021. ΔCredit is the log change in total non-public guaranteed loans between the firm and the bank, computed over the period December 2019 to June 2021. PGL is a dummy equal to 1 if the firm received a public guaranteed loan from the bank over the period December 2019 to June 2021, and 0 otherwise. PGL amount/Assets is the ratio of the total amount of public guaranteed loans that the firm received from the bank over the period December 2019 to June 2021, divided by the firm's total assets at year-end 2019. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: $\Delta Share_{2021:06\text{-}20129:12}$	(1)	(2)	(3)	(4)	(5)	(6)
PGL	19.732***	19.898***	19.803***	20.776***	20.655***	20.277***
	(2.016)	(1.996)	(2.075)	(2.045)	(2.026)	(2.011)
PGL*Ln(residual maturity)	-1.240***	-1.280***	-1.416***	-1.636***	-1.616***	-1.616***
	(0.241)	(0.236)	(0.274)	(0.275)	(0.267)	(0.267)
PGL*Ln(residual maturity)*Risk		0.624***		0.670***	0.593***	0.631***
		(0.094)		(0.093)	(0.101)	(0.097)
PGL*Ln(residual maturity)*Affected sectors			0.308*	0.578***	0.566***	0.576***
			(0.165)	(0.158)	(0.159)	(0.158)
PGL*Ln(residual maturity)*Risk*Affected sectors					0.122	-0.880
					(0.118)	(1.742)
PGL*Ln(residual maturity)*Risk*Affected sectors*Capital ratio						3.983
						(5.783)
PGL*Ln(residual maturity)*Risk*Affected sectors*NPL ratio						13.249
						(9.244)
Zip code Fixed Effects						
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.302	0.303	0.302	0.304	0.304	0.309

TABLE 10

SUBSTITUTION OF TOTAL LOANS: HETEROGENEITY

This table reports regressions results of a difference-in-differences model estimated at the firm-bank level using OLS of the effect of public guaranteed loans on firm-bank relationships between December 2019 and June 2021 ΔShare, which is the change in the firm's share of total loans, based on loan amounts, over the period December 2019 to June 2021. ΔCredit is the log change in total loans between the firm and the bank, computed over the period December 2019 to June 2021. PGL is a dummy equal to 1 if the firm received a public guaranteed loan from the bank over the period December 2019 to June 2021, and 0 otherwise. PGL amount/Assets is the ratio of the total amount of public guaranteed loans that the firm received from the bank over the period December 2019 to June 2021, divided by the firm's total assets at year-end 2019. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: $\Delta Share_{2021:06\text{-}20129:12}$	(1)	(2)	(3)	(4)	(5)	(6)
PGL	-15.506***	-15.302***	-15.870***	-15.595***	-15.671***	-15.671***
	(0.638)	(0.643)	(0.630)	(0.613)	(0.608)	(0.608)
PGL*Ln(residual maturity)	3.167***	3.074***	3.172***	3.043***	3.110***	3.077***
	(0.210)	(0.208)	(0.190)	(0.183)	(0.180)	(0.181)
PGL*Ln(residual maturity)*Risk		0.187*		0.187*	0.187*	0.187*
		(0.107)		(0.110)	(0.110)	(0.107)
PGL*Ln(residual maturity)*Affected sectors			0.003	0.048	-0.036	0.048
			(0.149)	(0.155)	(0.165)	(0.155)
PGL*Ln(residual maturity)*Risk*Affected sectors					0.278*	0.278*
					(0.148)	(0.148)
PGL*Ln(residual maturity)*Risk*Affected sectors*Capital ratio						-13.237**
						(6.252)
PGL*Ln(residual maturity)*Risk*Affected sectors*NPL ratio						14.142
						(11.088)
Zip code Fixed Effects						
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.210	0.211	0.210	0.211	0.211	0.211

TABLE 11

SUBSTITUTION OF TOTAL LOANS: EARLY REPAYMENTS

This table reports regressions results of a linear model estimated using OLS at firm-bank-month level of the effect of public guaranteed loans on early repayment between March 2020 and June 2021. The dependent variable is the cumulative early repayment amount divided by firm's total assets, computed based on all loans. PGL is a dummy equal to 1 if the firm received a public guaranteed loan by a bank in month 0, and 0 otherwise. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. We compare the early repayment amount of a firm to a bank in the subsequent months following the granting of a public guaranteed loan with respect to the rest of the loans. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL A. Direct effect

	Depnt. varib.: Cumulative early repayment amount/Total asset	(1)	(2)	(3)	(4)	(5)	(6)
		Compared to all outstanding loans					
		Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Loan characteristics (ij)	PGL	0.000	0.000	0.001*	0.001**	0.001**	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	Bank*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
	Firm*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
	Observations	5,934,971	5,934,971	5,934,971	5,934,971	5,934,971	5,934,971
	R2	0.403	0.405	0.407	0.410	0.413	0.415

PANEL B. Heterogeneous effects

Depnt. varib.: 6 month cumulative early repayment amount/Total assets	(1)	(2)	(3)	(4)	(5)
PGL	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PGL*Ln(residual maturity)	-0.000***	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PGL*Ln(residual maturity)*Share		-0.001***	-0.001***	-0.001**	-0.002***
		(0.000)	(0.000)	(0.000)	(0.001)
PGL*Ln(residual maturity)*Share*Risk			-0.001**	-0.001**	-0.002***
			(0.001)	(0.001)	(0.001)
PGL*Ln(residual maturity)*Share*Affected sectors			-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
PGL*Ln(residual maturity)*Share*Risk*Affected sectors				0.000	0.000
				(0.001)	(0.001)
PGL*Ln(residual maturity)*Share*Risk*Affected sectors*Capital ratio					0.087*
					(0.047)
PGL*Ln(residual maturity)*Share*Risk*Affected sectors*NPL ratio					-0.076
					(0.065)
Bank*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	478,160	478,160	478,160	478,160	478,160
R2	0.479	0.481	0.481	0.481	0.483

TABLE 12

BANK MANAGEMENT OF PUBLIC GUARANTEED LOANS

This table reports regressions results of linear probability model at firm-bank level of the effect of public guaranteed loans on credit management of banks between March 2020 and June 2021. In column (8), the sample is restricted to firms that as of June 2021 still have non-PG loans with the bank. Stage 3 is a dummy equal to 1 if the bank classified any loan of the firm as stage 3 during the period analyzed, and 0 otherwise. PGL is a dummy equal to 1 if the firm received a public guaranteed loan by a bank, and 0 otherwise. Share is the share of a firm's total credit obtained from the bank, computed at the firm-bank level using committed loan amounts as of 2019:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Stage 3	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PGL	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.014***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PGL*Share		-0.005**	-0.007***	-0.005**	-0.008***	-0.009***	-0.009***	-0.008***
		(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
PGL*Share*Risk			-0.012***		-0.013***	-0.013***	-0.016***	-0.011***
			(0.003)		(0.003)	(0.003)	(0.003)	(0.003)
PGL*Share*Affected sectors				-0.007*	-0.012***	-0.012***	-0.007*	-0.008**
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
PGL*Share*Risk*Affected sectors						-0.010***	-0.012**	-0.017***
						(0.003)	(0.006)	(0.006)
PGL*Share*Risk*Affected sectors*Capital ratio							0.177	0.095
							(0.198)	(0.266)
PGL*Share*Risk*Affected sectors*NPL ratio							-0.282	-0.240
							(0.323)	(0.426)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686	597,686	384,815
R2	0.500	0.500	0.501	0.500	0.501	0.501	0.501	0.597

TABLE 13

EFFECT OF THE PUBLIC GUARANTEED SCHEME ON THE BANK CREDIT PORTFOLIO

This table reports regressions results of linear probability model at bank level of the effect of public guaranteed loans on the bank portfolio between December 2019 and June 2021. PGL is the ratio of government-guaranteed loan amount granted during the period over total assets of the bank as of December 2019. PGL dummy is a dichotomous variable equal to 1 if the usage of the public scheme by the bank is in the third quartile of the distribution, and 0 otherwise. Bank's market share is the market share of the bank for non-financial firms (columns (1) to (3)). ΔOld firms amount is the change of credit of the firms a relationship with the bank at December 2019 between that date and *t* (columns (4) and (5)). New firms ratio is computed using the number of new firms (columns (6) and (7)) or the amount granted to new firms (columns (8) and (9)) at *t*, where a firm is classified as new for a bank if the firm has a relationship at *t* at not in December 2019. Coefficients are listed in the first row, robust standard errors are reported in the row below, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Bank's Market Share			ΔOld firms (amount)		New Firms (number)		New firms (amount)	
PGL	1.363***		1.014**	264.693***		104.100***		127.178***	
	(0.467)		(0.514)	(69.790)		(25.526)		(36.029)	
PGL dummy		0.057**			17.170***		6.878***		5.777*
		(0.024)			(3.493)		(2.321)		(2.994)
PGL*Log(Assets)			1.284***						
			(0.353)						
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,583	2,583	2,583	2,444	2,444	2,444	2,444	2,444	2,444
R2	0.999	0.999	0.999	0.839	0.839	0.908	0.909	0.885	0.884

APPENDIX

TABLE A1

EXTENSIVE MARGIN ANALYSIS CONDITIONAL ON HAVING A LOAN GRANTED

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan between 2020:03 to 2020:12 given that a loan was granted between the firm and the bank. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Public Guaranteed Loan (0/1)		(1)	(2)	(3)	(4)	(5)
Firm Characteristics(i)	SME	0.193***	0.185***	0.178***	0.177***	
		(0.023)	(0.022)	(0.021)	(0.023)	
	Risk	0.030***	0.031***	0.031***	0.032***	
		(0.007)	(0.008)	(0.009)	(0.009)	
	Liquidity	-0.181***	-0.197***	-0.212***	-0.195***	
		(0.055)	(0.053)	(0.054)	(0.054)	
	Growth opportunities	0.039***	0.037***	0.041***	0.040***	
		(0.006)	(0.005)	(0.005)	(0.006)	
	Affected Sector	0.024***				
		(0.005)				
Firm-Bank Characteristics(ij)	Share	0.048**	0.040*	0.068***	0.061**	0.127***
		(0.023)	(0.023)	(0.024)	(0.023)	(0.020)
	Ln(Average residual maturity)	0.043***	0.044***	0.039***	0.036***	0.019***
		(0.006)	(0.006)	(0.005)	(0.004)	(0.002)
Bank Characteristics(j)	Ln(Assets)	0.052***	0.051***	0.052***		
		(0.010)	(0.010)	(0.010)		
	Capital ratio	-1.710***	-1.720***	-1.653***		
		(0.528)	(0.533)	(0.519)		
	ROA	-3.535***	-3.657***	-3.733***		
		(1.258)	(1.278)	(1.260)		
	Liquidity ratio	-0.030	-0.038	-0.038		
		(0.409)	(0.408)	(0.399)		
	NPL ratio	1.796*	1.802*	1.725*		
		(1.007)	(1.015)	(1.012)		
	Zip code Fixed Effects	Yes	Yes	-	-	-
	Industry Fixed Effects (NACE 2 digits)	No	Yes	-	-	-
	Industry*Zip Code Fixed Effects	No	No	Yes	Yes	-
	Bank Fixed Effects	No	No	No	Yes	Yes
	Firm Fixed Effects	No	No	No	No	Yes
	Observations	413,104	413,104	413,104	413,104	413,104
	R2	0.212	0.218	0.343	0.375	0.565

TABLE A2

EXTENSIVE MARGIN ANALYSIS CONDITIONAL ON HAVING A LOAN GRANTED: HETEROGENEITY

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan between 2020:03 to 2020:12 given that a loan was granted between the firm and the bank. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)
Share	0.130***	0.127***	0.130***	0.129***	0.111***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)
Share*Risk	0.031***		0.033***	0.033***	0.031***
	(0.006)		(0.006)	(0.006)	(0.006)
Share*Affected sectors		0.009	0.020***	0.021***	0.035***
		(0.006)	(0.007)	(0.007)	(0.008)
Share*Risk*Affected sectors				-0.007	-0.003
				(0.005)	(0.008)
Share*Risk*Affected sectors*Capital ratio					-0.713***
					(0.268)
Share*Risk*Affected sectors*NPL ratio					1.098**
					(0.546)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	413,104	413,104	413,104	413,104	413,104
R2	0.565	0.565	0.565	0.565	0.566

TABLE A3

EXTENSIVE MARGIN ANALYSIS: ROBUSTNESS OF SHARE AND RISK VARIABLES

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan between 2020:03 to 2020:12. Panel A reports results when the share of the firm with the bank at 2019:12 is replace with a long-term share computed since 1999. Panel B replaces the *Share* variable with a main bank dummy, which equals to 1 if the bank was the main lender of the firm in 2019:12 (in terms of credit) and 0 otherwise. Panel C stress the risk variable replacing it with Bad credit history, a dummy that takes 1 if the firm made some default in the past and 0 otherwise. Panel D replaces the risk variable by its highest decile (high risk). Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL A

Dependent variable: Public Guaranteed Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Long-term share	0.101***	0.101***	0.101***	0.102***	0.103***	0.093***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)
Long-term share*Risk		0.029***		0.033***	0.034***	0.027***
		(0.007)		(0.007)	(0.007)	(0.005)
Long-term share*Affected sectors			0.029***	0.040***	0.039***	0.030***
			(0.006)	(0.006)	(0.006)	(0.007)
Long-term share*Risk*Affected sectors					0.016***	0.018***
					(0.004)	(0.006)
Long-term share*Risk*Affected sectors*Capital ratio						-0.466**
						(0.227)
Long-term share*Risk*Affected sectors*NPL ratio						1.042***
						(0.333)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.468	0.468	0.468	0.468	0.468	0.469

PANEL B

Dependent variable: Public Guaranteed Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Main bank	0.118***	0.119***	0.118***	0.119***	0.119***	0.105***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Main bank*Risk		0.021***		0.022***	0.023***	0.018***
		(0.002)		(0.002)	(0.002)	(0.002)
Main bank*Affected sectors			0.011***	0.018***	0.018***	0.015***
			(0.003)	(0.003)	(0.003)	(0.003)
Main bank*Risk*Affected sectors					0.001	-0.000
					(0.002)	(0.003)
Main bank*Risk*Affected sectors*Capital ratio						-0.300*
						(0.154)
Main bank*Risk*Affected sectors*NPL ratio						0.495**
						(0.226)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.474	0.474	0.474	0.474	0.474	0.475

PANEL C

Dependent variable: Public Guaranteed Loan	(1)	(2)	(3)	(4)	(5)
Share	0.217***	0.216***	0.217***	0.217***	0.195***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)
Share*Bad credit history	0.038***		0.039***	0.041***	0.056***
	(0.014)		(0.014)	(0.014)	(0.010)
Share*Affected sectors		0.022***	0.022***	0.022***	0.019***
		(0.006)	(0.006)	(0.006)	(0.005)
Share*Bad credit history*Affected sectors				0.037**	0.048***
				(0.016)	(0.014)
Share*Bad credit history*Affected sectors*Capital ratio					-1.900***
					(0.637)
Share*Bad credit history*Affected sectors*NPL ratio					1.558
					(1.270)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204
R2	0.475	0.475	0.475	0.475	0.477

PANEL D

Dependent variable: Public Guaranteed Loan	(1)	(2)	(3)	(4)	(5)
Share	0.217***	0.216***	0.217***	0.217***	0.195***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)
Share*High risk	0.068***		0.073***	0.074***	0.066***
	(0.009)		(0.010)	(0.009)	(0.011)
Share*Affected sectors		0.022***	0.026***	0.026***	0.021***
		(0.006)	(0.006)	(0.006)	(0.005)
Share*High risk*Affected sectors				0.007	0.028*
				(0.014)	(0.014)
Share*High risk*Affected sectors*Capital ratio					-1.364**
					(0.576)
Share*High risk*Affected sectors*NPL ratio					2.241**
					(1.015)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204
R2	0.475	0.475	0.475	0.475	0.477

PANEL E

Dependent variable: Public Guaranteed Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share						0.228***	0.233***	0.228***	0.233***	0.235***
						(0.022)	(0.023)	(0.022)	(0.023)	(0.023)
Share*Risk							0.050***		0.053***	0.054***
							(0.004)		(0.004)	(0.004)
Share*Affected sectors								0.024***	0.043***	0.042***
								(0.005)	(0.006)	(0.006)
Share*Risk*Affected sectors										0.013***
										(0.004)
Ln(1+duration of the relationship)	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(1+duration of the relationship)*Risk		0.001		0.001	0.001		0.000		0.000	0.000
		(0.001)		(0.001)	(0.001)		(0.001)		(0.001)	(0.001)
Ln(1+duration of the relationship)*Affected sectors			-0.001**	-0.001*	-0.001			-0.002***	-0.002***	-0.002***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
Ln(1+duration of the relationship)*Risk*Affected sectors					-0.000					-0.000
					(0.001)					(0.001)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.475	0.475	0.475	0.475	0.475	0.485	0.486	0.485	0.486	0.486

TABLE A4

EXTENSIVE MARGIN ANALYSIS: FALSIFICATION TEST

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a loan. Different time periods are considered to address concerns that the effect of the *Share* variable analyzed in the period 2020:03-2020:12 is not affected by seasonal effects other than the COVID-19 pandemic. Post is a dummy that equals 1 for the months after the reference date until December of that year. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable: Some loan received (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
				2019		
Post≥	2020:03	2019:02	2019:03	2019:04	2019:05	2019:06
Share*Post	0.025	-0.025	-0.022	-0.037	-0.018	-0.032
	(0.022)	(0.051)	(0.041)	(0.037)	(0.024)	(0.019)
Bank*Post Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Post Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,192,327	972,897	1,037,420	1,073,568	1,114,195	1,133,724
R2	0.440	0.410	0.409	0.397	0.393	0.391

TABLE A5

EXTENSIVE MARGIN ANALYSIS NON-LINEARITY OF SHARE

This table reports regressions results of a linear probability model at firm-bank level of the probability of a get a public guaranteed loan (PANEL A) or a non-stated-backed one (PANEL B) between 2020:03 to 2020:12. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Panel A. Public Guaranteed Loans

Dependent variable: Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Zero share	0.045*	0.042*	0.045*	0.042*	0.042*	0.066**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.025)
Share	0.234***	0.240***	0.234***	0.240***	0.241***	0.223***
	(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.017)
Share*Risk		0.026***		0.029***	0.030***	0.023***
		(0.004)		(0.004)	(0.004)	(0.004)
Share*Affected sectors			0.025***	0.037***	0.037***	0.031***
			(0.005)	(0.006)	(0.006)	(0.005)
Share*Risk*Affected sectors					0.011**	0.010**
					(0.005)	(0.004)
Share*Risk*Affected sectors*Capital ratio						-0.603**
						(0.242)
Share*Risk*Affected sectors*NPL ratio						1.012**
						(0.429)
Zero share*Risk		-0.030***		-0.031***	-0.031***	-0.030***
		(0.006)		(0.006)	(0.006)	(0.005)
Zero share*Affected sectors			0.003	-0.006	-0.006	-0.003
			(0.005)	(0.005)	(0.005)	(0.006)
Zero share*Risk*Affected sectors					-0.003	-0.004
					(0.003)	(0.005)
Zero Share*Risk*Affected sectors*Capital ratio						-0.144
						(0.094)
Zero share*Risk*Affected sectors*NPL ratio						0.360
						(0.297)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.475	0.476	0.475	0.477	0.477	0.480

Panel B. Non-Public Guaranteed Loans

Dependent variable: Only Non-Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Zero share	0.075***	0.075***	0.075***	0.075***	0.074***	0.104***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.020)
Share	0.057***	0.056***	0.056***	0.056***	0.056***	0.025**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.010)
Share*Risk		0.001		-0.001	-0.001	-0.002
		(0.003)		(0.003)	(0.003)	(0.004)
Share*Affected sectors			-0.026***	-0.027***	-0.025***	-0.014**
			(0.005)	(0.005)	(0.005)	(0.007)
Share*Risk*Affected sectors					-0.002	0.005
					(0.004)	(0.005)
Share*Risk*Affected sectors*Capital ratio						0.296
						(0.258)
Share*Risk*Affected sectors*NPL ratio						-0.551
						(0.479)
Zero share*Risk		0.005		0.003	0.003	-0.002
		(0.005)		(0.005)	(0.005)	(0.005)
Zero share*Affected sectors			-0.023***	-0.022***	-0.020***	-0.023***
			(0.004)	(0.005)	(0.005)	(0.005)
Zero share*Risk*Affected sectors					-0.017***	-0.018***
					(0.004)	(0.004)
Zero Share*Risk*Affected sectors*Capital ratio						0.063
						(0.111)
Zero share*Risk*Affected sectors*NPL ratio						-0.263
						(0.312)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.439	0.439	0.439	0.439	0.439	0.456

TABLE A6

EXTENSIVE AND INTENSIVE MARGIN ANALYSIS: DIVIDEND RESTRICTIONS

This table reports regressions results of a linear probability model at firm-bank level (Panel A) of at firm-bank-type of loan (public guaranteed loan or not) level (Panels B and C) of the role of dividend restriction on the probability of granting loans with public guarantee as well as on the amount granted between 2020:03 to 2020:12. PGL is a dummy equal to 1 if the firm received a public guaranteed loan and 0 otherwise. Amount captures the total committed amount of new loans. Dividend restricted is a dummy equal to 1 if the bank restricted dividends following the European Central Bank recommendation and 0 otherwise. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

PANEL A. Extensive margin analysis. Public guaranteed loans

Dependent variable: Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Share	0.232***	0.232***	0.233***	0.203***	0.203***	0.203***
	(0.022)	(0.022)	(0.022)	(0.020)	(0.019)	(0.022)
Dividend restricted	0.002			0.000		
	(0.017)			(0.000)		
Amount restricted/Profits		-0.008			0.000	
		(0.065)			(0.000)	
Share*Risk				0.043***	0.043***	0.041***
				(0.004)	(0.004)	(0.004)
Share*Affected sectors				0.029***	0.029***	0.029***
				(0.006)	(0.006)	(0.006)
Share*Risk*Affected sectors				0.012***	0.012***	0.012***
				(0.004)	(0.004)	(0.004)
Share*Risk*Affected sectors*Capital ratio				-0.607**	-0.602**	-0.617**
				(0.235)	(0.232)	(0.246)
Share*Risk*Affected sectors*NPL ratio				0.780***	0.772***	0.699**
				(0.295)	(0.292)	(0.296)
Share*Risk*Affected sectors*Dividend restricted				0.010		
				(0.009)		
Share*Risk*Affected sectors*Amount restricted/Profits					0.035	
					(0.032)	
Bank Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.459	0.459	0.459	0.479	0.479	0.479

PANEL B. Intensive margin analysis. Loan amount

Dependent variable: Loan committed amount	(1)	(2)	(3)	(4)	(5)
PGL	0.460***	0.460***	0.460***	0.490***	0.490***
	(0.106)	(0.106)	(0.106)	(0.042)	(0.042)
Dividend restricted	0.079**				
	(0.036)				
Amount restricted/Profits		0.272**			
		(0.137)			
PGL*Dividend restricted				-0.029	
				(0.116)	
PGL*Amount restricted/Profits					-0.142
					(0.385)
Firm Fixed Effects	Yes	Yes	Yes	-	-
Firm*Bank Fixed Effects	No	No	No	Yes	Yes
Observations	345,416	345,416	345,416	345,416	345,416
R2	0.718	0.718	0.718	0.794	0.794

TABLE A7

SUBSTITUTION OF TOTAL LOANS: EARLY REPAYMENTS OF NEW LOANS ONLY

This table reports regressions results of a linear model estimated using OLS at firm-bank-month level of the effect of public guaranteed loans on early repayment between 2020:03 to 2021:06. The dependent variable is the cumulative early repayment amount divided by the firm's total assets, computed based on new loans only. PGL is a dummy equal to 1 if the firm received a public guaranteed loan by a bank in month 0, and 0 otherwise. We compare the early repayment amount of a firm to a bank in the subsequent months to the granting of a public guaranteed loan with respect to other newly granted loans. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Depnt. varib.: Cumulative early repayment amount/Total assets	(1)	(2)	(3)	(4)	(5)	(6)
	Compared to other new loans					
	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
PGL	-0.000	0.000	0.000	0.000	0.000**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year:month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	478,160	478,160	478,160	478,160	478,160	478,160
R2	0.471	0.475	0.480	0.474	0.476	0.481

TABLE A8

FIRM LEVEL ANALYISIS OF BANK CREDIT

This table reports regressions results of a linear model estimated using OLS at firm level of the effect of firm concentration on the change of credit between 2019:12 and 2021:06. The dependent variable is the change of commitment credit of a firm with a bank in the analyzed period. *HHI* measures the weighted average of the exposure of a firm with all its banks as of December 2019. Coefficients are listed in the first row, robust standard errors are reported in the row below which are corrected for multi-clustering at the firm and bank level, and the corresponding significance levels are in the adjacent column. "Yes" indicates that the set of characteristics or fixed effects is included, "No" that is not included and "-" that is comprised by the included set of fixed effects. *** Significant at 1%, ** significant at 5%, * significant at 10%.

Dependent variable:			$\Delta Credit_{2021:06-2019:12}$		
	(1)	(2)	(3)	(4)	(5)
HHI	-0.783***	-0.787***	-0.784***	-0.788***	-0.792***
	(0.062)	(0.063)	(0.061)	(0.062)	(0.063)
Risk	-8.620***	-8.162***	-8.606***	-8.094***	-8.180***
	(1.067)	(1.223)	(1.065)	(1.224)	(1.131)
Affected sectors	2.207	2.369*	1.998	2.142	2.077
	(1.429)	(1.418)	(1.395)	(1.388)	(1.400)
HHI*Risk		0.050**		0.056**	0.053**
		(0.021)		(0.022)	(0.021)
HHI*Affected sectors			0.087**	0.102**	0.090**
			(0.039)	(0.040)	(0.039)
HHI*Risk*Affected sectors					-0.046**
					(0.018)
Industry (3-NACE digits)*Zip-code Fixed Effects	Yes	Yes	Yes	Yes	Yes
Main Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Observations	274,054	274,054	274,054	274,054	274,054
R2	0.314	0.314	0.314	0.314	0.314