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Abstract

This paper shows that private incentives influence the allocation of public guaranteed lending (PGL), resulting in weaker banks shifting riskier corporate loans' risk to taxpayers. We exploit data from the Banco de España's Central Credit Register during the COVID-19 shock in Spain, and a stylized model is used to structure the empirical results. Unlike non-PGL, banks provide more PGL to riskier firms accounting for a higher share of their total lending to firms before the crisis. Importantly, the effects are stronger for weaker banks. Results using firm (bank) fixed effects and loan volume/price information suggest a supply-driven mechanism. Exploiting exogenous variations across similar firms with different access to PGL, we show that PGL increases banks' lending to riskier firms, both overall and as a share of their total lending, especially for weaker banks.

Keywords: banking, private incentives, COVID-19, public guarantees, risk-shifting.

JEL classification: G01, G21, G38, E62, H81.

Resumen

En este documento mostramos que los incentivos privados afectan a la asignación de préstamos con aval público (PGL), lo que da como resultado que los bancos más débiles hayan acabado transfiriendo el riesgo de los préstamos con empresas más arriesgadas a los contribuyentes. En cuanto a la base de datos empleada, explotamos los datos de la Central de Información de Riesgos del Banco de España (CIRBE) durante el *shock* del COVID-19, junto con un modelo estilizado que guía los resultados empíricos. A diferencia de los préstamos que no son PGL, los bancos proporcionan más PGL a las empresas más arriesgadas en las que los bancos tienen una cuota más alta de su crédito total antes de la crisis. Es importante destacar que los efectos son más fuertes para los bancos más débiles. Los resultados que utilizan efectos fijos de la empresa (banco) y la información sobre el volumen/precio de los préstamos sugieren un mecanismo impulsado por la oferta. Además, explotando la variación exógena entre empresas similares con diferente acceso a PGL, mostramos que las empresas que reciben un PGL de un banco aumentan el volumen total de sus préstamos —y su cuota— con ese banco, y que esto ocurre sobre todo entre las empresas con más riesgo y, especialmente, para los bancos más débiles.

Palabras clave: banca, incentivos privados, COVID-19, garantías públicas, toma de riesgo.

Códigos JEL: G01, G21, G38, E62, H81.

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 paycheck protection programs and loan guarantee schemes (Granja et al., 2020; Humphries et al., 2020; Chodorow-Reich et al., 2021; Baudino, 2020; Falagiarda et al., 2020). In most cases, these public guaranteed schemes were implemented through third parties, i.e., the granting of public guaranteed loan (PGL) decisions were delegated to banks. While the potential merits of such government interventions in terms of supporting the overall economy have been well documented in the literature (e.g., Mankiw, 1986; Philippon and Schnabl, 2013), there is a potential economic trade-off when such decisions are delegated to privately-owned (non-government) banks arising from the possible divergence between *private* (*bank)* incentives and social incentives.

We analyze the effects of public credit guarantee schemes on the allocation of bank credit when lending decisions on public guaranteed loans are delegated to banks, focusing on the role of private banks' incentives. Public guarantee schemes offer credit protection on part of the loan in exchange for a fee, which banks pay to an administering agency, and typically come with eligibility criteria and lending requirements. While the guarantees are usually administered by government agencies on behalf of the government, the lending decisions are delegated to the bank and, hence, their allocation may depend on *private banks' incentives*.

We show that private banks' incentives shape the allocation of public guaranteed loans, notably pre-existing bank-firm credit exposures resulting in worse/riskier (weaker) banks shifting riskier corporate loans to taxpayers, exploiting for identification the COVID-19 crisis shock in Spain. In contrast to non-PGL, we find that banks provide more PGL to firms in which banks have a higher pre-crisis share of the firm's total credit, especially to riskier and more

COVID-affected firms. Importantly, these effects are stronger for weaker banks. Results using firm (-bank) fixed effects as well as loan volume vs. loan pricing data suggest a credit supply-driven mechanism. Moreover, exploiting exogenous variation across firms' access to PGL among similar firms (with versus without PGL access, or with differential PGL access), we show that PGL increases banks' both overall lending to and credit exposure share to riskier firms, especially for worse/riskier banks.

We rationalize and guide the results using a stylized model in which (private) bank incentives from existing bank-firm credit exposures shape the granting of loans. In the model, an exogenous negative shock to firm profitability (such as from COVID-19) decreases firms' credit worthiness and reduces bank lending incentives. For a large enough shock, lending (non-PGL) can be impaired. We show that a subsidized PGL system can increase bank lending incentives, with banks having more incentives to use PGL the larger is the pre-existing credit exposure to the firm. This is because PGL increase the repayment probability of pre-existing loans. A key testable prediction generated by the model is, therefore, that the pre-existing bank's share in the total credit of the firm is a key determinant of PGL granting decisions. Moreover, the model helps to understand that these effects are stronger for riskier firms, as the value of the public guarantee is higher for such firms, while these risk-taking effects for weaker banks are less clear-cut.

We conduct our analysis using Spanish loan-level data at the firm-bank level over the period December 2019 to June 2021. Spain during COVID-19 offers an excellent setting for identification. First, in contrast to many other PGL schemes, the Spanish scheme provided only a partial guarantee of up to 80% of the value of the loan, with residual credit risk being absorbed by the granting bank. This gives rise to an important role for private banks' incentives in lending decisions depending on firm and bank riskiness, as banks have some skin in the game despite a large part of the loan is publicly guaranteed. This contrasts with many other guarantee schemes, including the US Paycheck Protection Program (PPP) that much of the existing literature has focused on, which provided full guarantees resulting in banks not taking any residual credit risk. In such other schemes there is a much more limited role for differential bank's incentives, including the decision between granting PGL vs. non-PGL. Second, the Spanish credit register has rich data at the loan-level for the universe of borrowing firms with detailed data on bank-borrower credit exposures (different from the US credit register which covers only large banks and loans above 1 million dollars in size). Importantly, the Spanish dataset allows us to uniquely identify loans with COVID-19 related public guarantees, rather than generic public loan guarantees, which is a key difference with the European Anacredit database. Third, the Spanish PGL setting offered differential PGL access, even to firms which are otherwise similar, allowing for identification of the overall lending effects of PGL. Specifically, we exploit the fact that firms with defaulted loans as of December 2019 were not eligible for PGL, while firms with defaults only as of January or February 2020 were eligible for PGL. The COVID shock in Spain, including lockdowns, occurred in mid-March 2020 and the lending decisions of PGL under the new PGL scheme took place only afterwards (starting in April 2020), with firms being eligible for PGL only when they had no prior loan defaults as of the end of 2019. This implies a completely differential PGL eligibility between firms with defaulted loans as of December 2019 and firms with defaulted loans in January/February 2020, even if other firm characteristics are otherwise similar across these two groups of firms. In addition, for firms with access to PGL, we can analyze similar bank loans to firms with public guarantees with a coverage of 80% of the loan vs. lower public coverage amounts. Finally, compared to other schemes, the Spanish scheme was one of the largest PGL programs in terms of take-up amounts relative to GDP (Falagiarda et al., 2020), but nevertheless there also was substantial non-PGL being granted.

We find that during the COVID crisis, which negatively affected the real economy, ex-ante riskier firms participate more in PGL, a plausibly intended consequence of the PGL scheme. PGL are more likely to be granted to firms which are ex-ante riskier (i.e., worse credit score), smaller, and in sectors that are more negatively affected by COVID-19 (e.g., tourism, transport, and hospitality). In terms of bank characteristics, PGL are more likely to be granted by weaker (riskier) banks, in terms of higher NPL ratios. For non-PGL, just the opposite happens in terms of firm and bank risk characteristics, i.e., non-PGL are more likely provided to safer firms and granted by stronger banks during the COVID crisis.

The first set of main results of this paper are as follows. We find that firms are more likely to obtain PGL from those banks with whom they have larger pre-crisis credit exposures, measured as the share of the firm's total credit outstanding with the bank before the COVID-19. This finding is consistent with the role of private banks' incentives in exploiting the public guaranteed scheme to address possible defaults on pre-crisis debt. Interestingly, differently from pre-COVID bank-firm exposure, we do not find that banks are more prone to grant PGL to firms with which they have a longer relationship. These results are consistent with private banks' incentives arising from credit exposures (as the model suggests) as opposed to pure informational advantages linked to the duration of lending relationships. Further, non-PGL are also associated positively with banks to whom firms have larger pre-existing credit exposures, but the economic effects are substantially much lower than for PGL. Furthermore, if the pre-existing firm exposure is quantitatively large for the bank (a significant granular exposure for the bank), the bank grants both type of loans but with very similar economic effects.

Importantly, not only do we find that PGL are more likely to be granted to riskier firms and to firms that are in sectors more negatively affected by the COVID crisis, but these effects are increasing in the credit exposure between the firm and the bank prior to the shock, consistent with the relevance of bank's incentives in granting PGL. Moreover, this effect is stronger for worse/riskier banks, in terms of higher ex-ante NPLs. That is, worse/riskier banks provide more credit via PGL to riskier firms in which banks have a higher pre-crisis share of the firm's total credit.[1] We obtain the opposite effects for non-PGL: for higher firm-bank pre-COVID exposures, stronger banks provide more non-PGL to ex-ante riskier firms during the COVID period. All these results are consistent with worse/riskier banks shifting lending to riskier firms from private banks to taxpayers.

To disentangle the relevance of credit supply vs. demand factors driving our results, we analyze the intensive margin decisions of both PGL and non-PGL credit. We find that PGL have larger credit volumes and lower loan interest rates than non-PGL. Moreover, the higher the pre-COVID bank share of the firm total credit, the stronger the effects of PGL on increasing credit volumes and decreasing loan interest rates. These differential effects on higher loan volume and lower loan interest rates are enhanced for riskier firms, and especially for worse/riskier banks. These volume and pricing results are therefore not consistent with a borrower (demand)-driven channel, but instead are consistent with a credit supply(lender)-driven channel. Moreover, these results control for firm fixed effects, or firm-bank fixed effects, and thus for unobserved borrower (and borrower-lender) fundamentals. Altogether, all these results suggest that a credit supply mechanism is at play.

The economic effects are large. An interquartile range increase in the firm's prior share of total credit with the bank increases the probability of obtaining a PGL by that bank by 24.4%, while this increase is only 4% for non-PGL. Further, for PGL this increases to 32.5% for riskier firms (interquartile range increase), and to 27.4% for firms in adversely pandemic-affected sectors. If the bank has a high fraction of pre-crisis nonperforming loans, effects to riskier firms in pandemic-affected sectors increase to 43.6%. The granted loan amount is 46.0% larger for PGL than for non-PGL, increasing to 57.2% larger if the firm's ex-ante credit share with the bank is high (interquartile range increase) and to 72.7% for riskier firms working with weaker banks (interquartile range increase). Further, PGL have a 2.3 percentage points (pp) lower

[1] Results moreover stem from higher bank share of the firm total credit, not necessarily from being the main bank of the firm.

interest rate than non-PGL, which increases to 2.9 pp if the firm's ex-ante credit share with the bank is high and to 3.4 pp for riskier firms linked to weaker banks (interquartile range increase).

Second, we analyze the implications of PGL existence for credit. We find that banks that grant a PGL to a firm increase their overall credit exposure to the firm by 116.8 pp, resulting in a higher total credit share of the bank with that firm by 16.9 pp, and in overall higher firm credit. By contrast, there is a reduction by 15.4 pp in non-PGL, suggesting a substitution between PGL and non-PGL credit. These results may be contaminated by endogeneity of the decision to grant a PGL. To address this concern, we exploit two sources of exogenous variation across firms: (i) firms with versus without access to PGL; and (ii) firms with differential access to PGL.

The first variation that we exploit is the exclusion criteria in the PGL program of firms having loans defaulted as of December 2019 not being eligible for the PGL. While firms could access the PGL if they had delinquent loans as of January or February 2020 (before the COVID outbreak in Spain), they could not access the program if they had delinquent loans in December 2019. Reducing the sample to only firms with loans defaulted between December 2019 and February 2020, we find that firms in these two groups (excluded vs. not excluded for the PGL scheme) are very similar in observables, but crucially one group of firms cannot access the PGL (excluded) while the other group can access PGL (eligible). Moreover, results using this much smaller sample of firms confirm our previous findings on PGL granting. In particular, different from non-PGL, banks with a higher pre-crisis credit share in a firm's total credit provide more PGL to the firm if the firm has defaulted loans only as of January or February 2020 (as compared to excluded firms with loans defaulted as of December 2019), and these effects are stronger for worse/riskier banks. Furthermore, firms with defaulted loans in January or February 2020 only (i.e., prior to the COVID outbreak and eligible) experience a relative increase in overall lending during the COVID crisis (of 6.7 pp) compared to firms with defaults as of December 2019 (i.e., excluded from the scheme). These lending effects are stronger for worse/riskier banks (6.0 pp higher) and are associated with an increase in the share of bank credit exposure to these risky firms (0.7 pp higher).

As a second source of variation, we exploit firms with differential access to PGL arising from different coverage levels of the public guarantee. For the group of firms without defaulted loans as of December 2019 (i.e., eligible for PGL), firms have differential access to PGL because the guaranteed amount varies by firm size: the coverage level is 80% of the loan amount for small and medium sized firms versus 70-60% for larger firms. In this case, different from the previous source of exogenous firm variation, firm observables are different across the two groups of firms, and hence, we use a matching estimator when we analyze the implications of PGL. Before using the matching estimator, we find that, different from non-PGL, firms with access to PGL with an 80% guarantee coverage level indeed obtain more PGL than those with a lower coverage level, and banks with a higher pre-crisis credit share in a firm with a possible 80%-coverage PGL provide more PGL to the firm, especially to riskier and more COVID-affected firms. These effects are stronger for worse/riskier banks. Importantly, exploiting variation across similar firms with differential PGL access using the matching estimator, we find that PGL increases overall lending (by 28.8 pp), especially to riskier firms (by 53.3 pp, for an interquartile change) by worse/riskier banks (by 84.3 pp). At the same time, PGL also increases the share of bank credit exposure to riskier firms (by 5.9 pp).

Contribution to the literature. Our paper contributes to an emerging literature on the effects and implications of government 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. For the United States, several papers have studied the U.S. pay protection program (PPP), 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. Several other papers have studied credit guarantee schemes in Europe. Altavilla et al. (2022) using the European Anacredit dataset find that public loan guarantees were predominantly extended to smaller firms and led to a substitution of guaranteed for non-guaranteed loans. Core and De Marco (2021) using Italian loan level data find that public guaranteed loans were disproportionately disbursed by larger and more technologically advanced banks.

What sets our paper apart is that we analyze the role of private banks' incentives in the decision to lend via public guaranteed as opposed to non-guaranteed loans. We can do this because, unlike the U.S. PPP and many of the credit schemes in Europe, the Spanish credit guarantee scheme offered only a partial government guarantee, thus leaving skin in the game for the lender. Additionally, the Spanish credit register covers all the business loans in the system, covering both PGL and non-PGL. In terms of bank incentives, we both focus on the role of the ex-ante credit exposure between the bank and each firm and the balance sheet strength of the bank. Moreover, different from the above papers, we exploit exogenous variation in differential PGL access (guarantee coverage as well as eligibility criteria) to identify the effects of PGL on bank lending.

We provide several novel results. We show that banks' private incentives shape the allocation of public guaranteed loans, resulting in worse/riskier banks shifting riskier corporate loans to taxpayers – with banks' incentives depending on the ex-ante share of the bank in each firm and the balance sheet strength of the bank. Moreover, exploiting exogenous variation across similar firms with different degrees of access to PGL coverage, we find that PGL increases overall lending to riskier firms especially by worse/riskier banks, thereby also increasing the share of the bank's credit exposure to the firm.

More generally, our paper contributes to the literature on the role of government interventions in credit markets. In the presence of frictions 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.[3] We contribute to this literature by focusing on the role of banks' private incentives in granting publicly guaranteed loans and showing that PGL disproportionately accrue to more vulnerable firms after a negative exogenous unexpected temporary shock, thus providing implicit evidence of these government interventions supporting credit availability for firms. Importantly, we also contribute by showing that the allocation of partial loan guarantees depends on pre-existing credit exposures

[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).

[3] 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.

at the firm-bank level (especially to riskier, more negatively affected firms), consistent with the notion that government support measures interact with private bank incentives.

The literature on government interventions in credit markets 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 the negative consequences of declines in output (Merton, 1977), can increase the risk-taking incentives of banks (Holmström and Tirole, 1997; Hellman et al., 2000; Freixas and Rochet, 2008).[4] We contribute to this literature by showing that the allocation of government guaranteed credit is shaped by banks' private incentives, notably pre-existing bank-firm credit exposures and riskier/worse banks shifting riskier credit to taxpayers, consistent with the view that these riskier (weaker) banks are more subject to moral hazard issues.

Our paper also relates to the literature on the value of lending relationships. The theoretical models in Sharpe (1990) and Rajan (1992) imply that lending relationships emerge to overcome informational asymmetries, bringing 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. 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

[4] Gropp et al. (2014) show evidence of this effect analyzing the removal of public insurance guarantees for a subset of banks in Germany and how such banks differentially change 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. Carletti et al. (2023) show that, in the presence of endogenous deposit runs, public loan guarantees can improve the underwriting standards for well capitalized banks but worsen them for weakly capitalized banks.

episodes of financial distress.[5] We contribute to this literature by showing that lending relationships are valuable in securing public loan guarantees during an exogenous economic downturn, especially for riskier and more negatively impacted firms. This effect derives completely from the credit exposure (share) of the firm to the bank, not from the duration of the lending relationship nor from granular exposure for the bank. Further, results stem from a higher bank share of the firm total credit, not necessarily from being the main bank of the firm.

The paper continues as follows. Section 2 provides institutional details on the Spanish loan guarantee scheme. Section 3 presents a simple model to develop our testable hypotheses. Section 4 describes the data. Section 5 describes the empirical strategy. Section 6 presents the empirical results. Section 7 concludes.

2. The Spanish Loan Guarantee Scheme

The Spanish loan public guarantee scheme was announced and implemented in mid-March 2020, immediately 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.[6] The public guarantee was intended to support the provision of public guaranteed credit up to 100 billion euros. Both companies and self-employed workers could access these guarantees through their banks, either by taking out new loans or by renewing existing ones. The public guarantee covered up

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[5] 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.

[6] 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.

to 80% of the amount lent for SMEs and self-employed; and for the rest of the companies, 70%, in the case of new loans, and 60% of the amount lent for the renewal of existing loans.

The PGL 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 PGL was high from inception of the program, with 70 percent of all PGL granted between April and June 2020. The guarantees are provided by the ICO (Institute of Official Credit) to the banks that grant the funding.[7] In exchange for issuing the government guarantee, the bank pays ICO a fee. Figure 1 offers an 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.[8] Loans intended for the restructuring of existing loans, as well 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, are excluded from these loans. Regarding the loan terms, the maximum eligible amount is 1.5 million euros, 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 grace period is up to 12 months (subsequently extended to 24 months).

The cost of the guarantee amounts to between 20 and 120 basis points of the loan volume and is paid by the lending bank through the payment of a fee to ICO. Moreover, banks commit to maintaining the conditions of the new loans and renewals under the public guarantee scheme at the same level as applied before the COVID-19 crisis. With respect to loan interest rates, banks have an obligation to ensure that the costs of new loans benefiting from these public

[7] ICO is a state-owned bank, with an independent legal status, linked to Spain's Ministry of Economy. It finances itself on the capital markets. The debt commitments and financial obligations it enters with third parties benefit from the explicit, irrevocable, unconditional and direct guarantee of the Spanish state.

[8] 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.

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.

3. Hypotheses and Stylized Model

We provide a stylized theoretical model to explain under which circumstances the introduction of public loan guarantees affects the equilibrium of the loan market and how it does so. We focus on identifying how both bank and firm characteristics, such as the exposure of a bank to a firm, the riskiness of the firm and of the bank affect the granting of PGL. The model generates the empirical prediction that banks prefer to grant guaranteed credit to existing clients to prevent defaults in their existing loan portfolios, as in Bolton et al. (2016). The main effect of public loan guarantees is that they act as a credit enhancement, thus providing an incentive for banks, particularly weaker ones with less skin in the game, to lend to riskier firms (that experienced a larger capital tightening). We use this simple model to develop testable hypotheses to guide our empirical analysis.

Consider a one period risk neutral economy populated by a firm and two lenders, which we refer to as banks from now on. At date 0, the firm has pre-existing senior zero-coupon debt of face value D. This debt is held by two different banks where $0<x_i<1$ is the proportion held by bank i. At date 1, if the firm succeeds, which happens with probability p, it produces $R>D$. When the firm fails it produces 0 and, given limited liability, does not repay its debt.

At an interim date, the firm receives an unexpected liquidity shock due to the pandemic. To continue operations, the firm needs an indivisible junior loan of quantity L. If such loan is not granted, we assume that the firm fails with probability 1.[9]

[9] While the assumption of the loan being indivisible is made for simplicity, this assumption could be micro founded by assuming that the loan has some costs of observing the liquidity need that each bank must bear.

3.1 Private market: Existence

We first analyze under which conditions a private market for such liquidity (pandemic) loan would exist. The maximum payment that the bank that grants the loan can receive from the liquidity-pandemic loan is given by the pledgeable income of the firm $Y=R-D$.[10] This allows us to determine that a bank will have incentives to grant the loan as long as the expected income that the bank receives from the firm, which includes the expected repayment of previous debt as well as the expected repayment of the liquidity loan, is larger than the loan disbursement.[11]

Bank i has incentives to grant a (private) loan as long as

$$-L + p\,[Dx_i + Y] \geq 0,$$

which can be rewritten as $Dx_i \geq \frac{L}{p} - Y$.

This condition states that a non-PGL (private loan) is more probable to exist the higher the exposure of bank i to the firm, x_i. Such condition is more probable to hold when p is larger (safer firms) and Y is larger. This states that the private market is more prone to exist for safer firms and those that have higher expected returns. On the other hand, when the firm is riskier and has lower expected returns (for instance, because it is more negatively affected by the pandemic), it is more probable that the bank does not have an incentive to extend the loan. In such case the private market would not exist, resulting in the failure of the firm.

3.2 Public guaranteed loans: Existence

We now turn to analyze how loan granting decisions are affected by the introduction of a public guarantee loan scheme, which is a key aspect of our paper. We assume that the

[10] Y could be lower if we assume that the firm has some moral hazard problem at the firm level that limits full pledgeability of returns as in Holmström and Tirole (1997).

[11] The exact pricing of the loan is going to depend on whether both banks have incentives to grant a loan or not and the bargaining power between the loan and firm. For now, we assume that the bank can extract all of the pledgeable income of the firm Y. Moreover, in this formulation, we implicitly assume that the bank assumes that if it does not grant the loan the other bank would not grant it either, i.e. that the firm can only approach one bank. In Appendix B, we extend this basic setup to incorporate the strategic decision of banks, i.e., that firms can approach all banks, and show that the main conclusions do not vary.

government introduces the possibility of banks granting PGL. In a PGL, by paying a fee F to the government the government repays a fraction $0<g<1$ of the granted amount L to the bank if the loan defaults.

A bank would grant a PGL when doing so results in higher profits than granting a non-PGL, and at the same time the PGL has a positive NPV for the bank. These two conditions can be expressed as

$$-L + p[Dx_i + Y] - F + (1-p)gL \quad \geq -L + p[Dx_i + Y] \text{ and}$$

$$-L + p[Dx_i + Y] - F + (1-p)gL \quad \geq 0$$

The first condition, which states that granting a PGL is preferred to granting a non-PGL, can be rewritten as:

$$-F + (1-p)gL \quad \geq 0.$$

Such condition states that the PGL would be granted instead of the non-PGL, whenever the value of the guarantee is positive. Rearranging, this occurs when

$$p \leq 1 - \frac{F}{gL}$$

which states that a PGL is only going to be granted for a sufficiently risky firm.[12] The main intuition is that the riskier the firm the larger the value of the guarantee the government provides making paying the fee more probable. This condition also suggests that banks more subject to moral hazard problems resulting in lower probability of loan success (for example because of lower incentives to monitor) are more prone to grant a PGL. We analyze this point in more detail is the next subsection.

[12] The second condition (the PGL has a positive NPV for the bank) imposes a limit to the riskiness of such firm, i.e., a firm with probability of success tending to 0 would never receive a PGL. That is, given F, PGL are valuable to recover the existing debt D.

At this point, it is relevant to note that there are two different cases in which the PGL is granted. The first one is a situation in which the non-PGL would also have existed, which is the case when the following condition holds

$$-L + p[Dx_i + Y] - F + (1-p)gL \;\; \geq \; -L + p[Dx_i + Y] \geq 0.$$

In such case, the PGL would only be substituting the private market of credit and the exposure bank i to the firm, x_i is not a main determinant for granting it. However, there is a second case in which the PGL has a positive NPV for the bank but the non-PGL does not. This occurs when the following condition holds

$$-L + p[Dx_i + Y] - F + (1-p)gL \;\; \geq 0 \geq \; -L + p[Dx_i + Y].$$

In such case, the inclusion of the PGL has the positive effect of allowing a loan to be granted when the private market was not operating. These are the circumstances in which PGL have a positive effect on overall amount of credit at the firm level. From now on we focus on this later case as the main objective of the PGL scheme in Spain was to support overall lending.

3.3 Public guaranteed loans: Comparative statics

We now turn to developing our main testable hypotheses by analyzing which bank and firm characteristics make a PGL more probable to be granted. We focus on understanding the effects of bank exposure, *x*, firm's riskiness, *p*, and, in the following subsection, the risk of the bank. Under the previous condition, i.e., that the PGL scheme expands credit, the relevant condition that determines if a PGL is granted is that it has a positive NPV for the bank

$$-L + p[Dx_i + Y] - F + (1-p)gL \geq 0,$$

which allows us to determine that a bank would have incentives to grant a PGL as long as

$$Dx_i \geq \frac{[1-(1-p)g]L + F}{p} - Y.$$

This expression highlights how granting a PGL is more probable the higher the exposure bank i to the firm, x_i.[13]

More specifically, we can define

$$D\bar{x} = \frac{[1-(1-p)g]L + F}{p} - Y$$

as the minimum exposure that a bank has to have with a firm in order to have incentives to grant a PGL. This determines that, only banks with high enough exposure to a firm have incentives to grant a PGL.[14] From this follows our first testable hypothesis:

Hypothesis 1: The probability of granting a guaranteed loan is increasing in the ex-ante loan exposure of the firm to the bank.

By analyzing how the exposure threshold, $\bar{x}$, varies with p, we can determine when the exposure of a bank is a key determinant in granting a PGL. Note that the larger the $\bar{x}$, the lower the range of x such that both banks have incentives to grant the loan, and also the lower the range of x such that the bank with the larger exposure has incentives to grant a loan. Specifically, we find that

$$\frac{d\bar{x}}{dp} = \frac{gLpD - D[1-(1-p)g]L - F}{p^2D^2} < 0.$$

Hence, the safer the firm the lower the necessary threshold for a bank to grant the PGL. In other words, the exposure of a given bank x is more determinant to grant a PGL the riskier the firm.

[13] As previously shown, when the PGL do not expand the loan market, then the only relevant determinant of granting a PGL versus a non-PGL is the value of the guarantee, which is independent of the exposure of the bank.

[14] Whenever $\bar{x}$=([1-(1-p)g]L+F)/pD-Y/D<0.5, there would be circumstances in which both banks have incentives to grant the PGL. Those circumstances are the ones in which the bank with the lowest exposure x_l has 0.5> x_l >$\bar{x}$. For those cases we could assume that bank grants the loan either in a purely random manner or in proportion to the ex-ante weights (as they might capture some hidden costs). Irrespective of the underlying assumption, in such cases the holding of a given bank x would not be as crucial a determinant in the granting the PGL, as both banks have incentives to grant a loan, as when only one of the banks has incentives to grant the loan x_l <$\bar{x}$< x_h =1- x_l.

Similarly, we can obtain how a decrease in the firm's pledgeable income Y, which can capture if the firm belongs to a sector that is more affected by the pandemic, makes the exposure threshold increase. Specifically, we can obtain that

$$\frac{d\bar{x}}{dY} = -\frac{1}{D} < 0.$$

Hence, the lower the pledgeable income of the firm, the higher the exposure needed to grant a PGL. This leads to the next hypothesis:

<u>Hypothesis 2</u>*: The positive effect of the ex-ante bank-firm loan exposure on the granting of guaranteed loans is stronger the riskier (or more affected by the pandemic) the firm is.*

One further aspect that we analyze in our empirical setup is the relevance of banks non-performing loan (NPL) ratio at the onset of the crisis. The final effect of this variable is not clear cut. On the one hand, banks with higher NPL ratios are more prone to end in failure giving them incentives to risk-shift. This would lead banks to have incentives to forgo paying of the fee and take a gambling for resurrection strategy by lending in the private market. On the other hand, banks with higher NPL ratios would have less incentives to properly monitor their loans making the value of the guarantee higher and inducing them to grant through the PGL system. Therefore, we conclude that the effect of NPL on the granting of PGL and non-PGL is not clear cut from a theoretical point of view, and hence empirics are crucial.

4. Data description

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 comes 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 their banks. This is particularly relevant as one of our main variables 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 as its identity, industry (at NACE 3 digits), location (at zip-code level) and size. In terms of the lender, the CIR has information on the bank identity. This firm and bank identification allows us to match each loan to firm and bank characteristics from the Spanish Mercantile Register and supervisory bank balance sheet information.

Important 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. For example, the European credit register Anacredit does not have this information.

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 use this information on loan applications, joint with granted loans, to capture firms that have actively sought funding during the pandemic.

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. We use the unique firm identifier (CIF) to merge this information with the credit registry. 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 merge this information using the bank identifier which is 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 (main) sample firms that are not eligible for participation in the ICO guarantee scheme, because they had loans in arrears as of December 31, 2019. We use the latter set of loans for identification purposes in a regression as explained in the Introduction and the following sections.

5. Empirical Strategy

We perform alternative empirical analyses to test the hypotheses developed in section 3 and provide answers to the following three sets of questions: (i) What firms/banks are more likely to participate in the public loan guarantee scheme as opposed to non-PGL? Does larger ex-ante loan bank-firm exposure affect differently PGL vs non-PGL, and do effects change for riskier firms and banks? Exploiting borrower (or borrower*lender) fixed effects and loan volume vs. interest rates, are results consistent with a borrower (credit demand) or with a lender (supply) channel? (ii) What are the implications of PGL for lending to firms? Importantly, in each of the analyses we study the relevance of pre-existing bank lending share 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.

To answer the first question, we construct a dataset at the firm-bank level to capture firms that have actively sought funding during this 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 bank-firm relationships as of December 2019, to account for the possibility that if a company seeks a loan, it will likely probe the banks with which it has a prior relationship. We pool the observations at the firm-bank level for the considered period. This allows us to include firm and bank fixed effects to account for unobservables in some specifications. This database includes 128 banks and around 200,000 firms, and results in 718,000 (firm-bank) observations. With this database we investigate what firm, bank and firm-bank characteristics make a company more likely to get a PGL from a bank between March and December 2020.

We first 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 total credit as of December 2019. This variable allows us to understand whether, in line with hypothesis 1, 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 also interested on whether firm and bank risk characteristics are associated to PGL. $Firm_i$ is a vector of firm variables that include firm ex-ante credit risk (captured by a scoring measure with higher values meaning more risk),[15] a dummy for more severely affected sectors by the pandemic (defined as those whose turnover decreased by more than 15% in 2020) and the size of the firm (proxied by a SMEs dummy).[16] $Bank_j$ refers to a set of bank variables that includes the NPL ratio (defined as the ratio of non-performing loans, doubtful and 90 days overdue, over total loans of the bank), bank 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), ROA and the size of the bank (defined as the log of total assets). We also include the average residual maturity of loans outstanding between the firm and the bank as an additional control in the $Firm\text{-}Bank_{ij}$ 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. Finally, ε_{ij} is the error term. All firm and bank explanatory variables are measured as of December 2019, before the unexpected COVID shock. 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-PGL, we run the same exercise but replacing the dependent variable by one capturing whether the firm only obtained a non-PGL 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 distinguish between three types of firm-bank pairs: those with a PGL, those with a non-PGL, or those without any credit during our COVID sample period. We can perform this analysis because our dataset is compiled by associating banks to firms with loan applications during the COVID period, with information on credit granted in the COVID period and on previous bank-firm lending

[15] 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.
[16] Based on the definition of the Commission Regulation (EU) No. 651/2014, of June 17, 2014.

exposures. Therefore, effectively we have the pool of potential lenders for each firm that have positive credit before COVID as of December 2019.

We are also interested in analyzing whether the effect of the loan share variable (proxying for bank incentives) on the likelihood to obtain a PGL is more pronounced for ex-ante riskier firms and/or banks as stated in our hypotheses 2. To capture this possibility, we estimate a model where we include double and triple interactions terms of the *Share* variable with the firm risk scoring variable and the severely affected sector dummy, from the firm side, and the NPL ratio (doubtful loans over total loans), from the bank side. The enriched regression specification is as follows:

$$PGL_{ij} = \beta_0 Share_{ij} + \beta_1 Share_{ij} * Risk_i + \beta_2 Share_{ij} * Affct.sector_i + \beta_3 Share_{ij} * Risk_i * Affct.sector_i + \beta_4 Share_{ij} * Risk_i * Affct.sector_i * Bank\ NPL_j + Controls_{ij} + \eta_i + \eta_j + \varepsilon_{ij} \quad (2)$$

where $Controls_{ij}$ is a vector of variables that contains the rest of the interactive terms of lower degree not showed and not absorbed by the fixed effects. Moreover, it also includes triple or quadruple interactions of the other bank controls (including always lower degree terms) to mitigate concerns about omitted variables. With this specification we can evaluate whether weaker banks lend more to riskier firms after the COVID shock using PGL. If this were the case, following hypotheses 1 and 2, we would expect the estimated betas to be all positive and statistically significant.[17]

[17] In the Appendix, we show some robustness exercises on the share and risk variables. First, in addition to including the share variable we use a dummy variable that captures whether the bank is the main lender of the firm as of December 2019 to show that the *Share* variable is not just capturing main bank. Second, we replace the risk variable with the bad credit history of the firm before December 2019 (note that mechanically a firm with defaults as of December 2019 cannot get PGL). We also study if the results are robust to focusing on high-risk firms, defined as those in the highest decile of the distribution of the risk variable. Finally, it is possible that the results were affected by some seasonal effects 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. In addition, not only do we analyze the exposure of a bank to a given firm just before the negative unexpected shock, but also from the (long) time since the bank started lending to the firm for the first time. Further, we also analyze the importance that firms that have significant (granular) lending exposures to a bank have in obtaining private non-public guaranteed loans as compared to PGL.

Table 1 presents summary statistics of the main regression variables. Just over a third of the observations (37.8%) have a PGL during the analyzed period, while 28.7% of all firm-bank pairs only have non-PGL, which highlights the relevance of both the guaranteed and nonguaranteed (private) credit market during this period. A total of 95% of all observations correspond 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%. Appendix Table A1 presents the definition of the main regression variables.

Turning to the analysis of the lending terms of granted loans, i.e., the amount granted or the loan interest rate applied, 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: PGL and non-PGL. As a result, we obtain a database at the firm-bank-type of loan level. This dataset has more than 620,000 observations and allows us to control for firm or firm*bank fixed effects. Using this data, we estimate the following equation:

$$Loan\ conditions_{ijk} = \beta_0 PGL_{ijk} + \beta_1 PGL_{ijk} * Share_{ij} * Risk_i * Affct.sector_i * Bank\ NPL_j + +Controls_{ijk} + \eta_{ij} + \varepsilon_{ijk} \quad (3)$$

where *k* refers to the loan type and PGL is a dummy that equals 1 for public guaranteed loans, and 0 for private (non-PGL) loans and $Controls_{ijk}$ is a vector of variables that contains the rest of the interactive terms of lower degree not showed and not absorbed by the fixed effects. 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 bank and firm fixed effects. In Eq. (3) the coefficient on PGL is capturing the differential effect on the committed amount or the interest rate charged of the granted loan being a PGL, while the interaction captures whether the effects depend on *Share, firm risk, and bank risk*. In this way we can analyze whether our results on equation (1) and (2) are more consistent with a credit supply (bank-driven) rather than demand (borrower-driven) channel. For the analysis of the loan amount granted, Eq. (3) is estimated using a Poisson model to reduce possible biases arising from a classical log linear estimation (see Santos Silva and Tenreyro, 2006). When the left-hand-side variable is the interest rate, Eq. (3) is estimated by OLS. As before standard errors are clustered at the firm and bank level. 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. The average new loan has an interest rate of 3.3%.

Second, we analyze whether banks that grant a PGL increase the overall credit to the firm while reducing their exposure to non-PGL. To estimate this substitution effect, we analyze the evolution of outstanding credit between two dates (2019:12 and 2021:06), an event (the COVID-19 pandemic that started in March 2020) and banks that grant a PGL to a firm versus those that do not. Using this approach, we measure the change in credit or the change in the share of the firm with a bank both for non-PGL and total loans stemming from the introduction of the loan guarantee program due to the pandemic. We do so by comparing the evolution of the *Credit* or *Share* (left-hand-side) variables in firm-bank pairs that have a PGL. 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 credit or share based either on total loans or on non-PGL only. 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 model:

$$\Delta \mathrm{y}_{ij} = \beta PGL_{ij} + \eta_i + \eta_j + \varepsilon_{ij} \qquad (4)$$

where y_{ij} refers to the change in credit or the change in the share between the firm and the bank for the periods 2019:12 and 2021:06. Our key right-hand-side variable (PGL dummy) captures if that bank-firm pair has a PGL. We start by estimating the model with only zip code fixed effects, to progressively saturate it with more fixed effects until we arrive at Eq. (4), which includes bank and firm fixed effects.[18]

[18] In the Appendix, we analyze whether there are differential early repayments and defaults of non-PGL credit.

While in our analysis saturating the model with firm and bank fixed effects is important to reduce endogeneity concerns, we also exploit two relevant characteristics of the program that allow to better identify our results as causal. The first, and cleanest, of them is the fact that some firms are excluded from the program and the second one is that some firms have differential access to the program.

First, we make use of the fact that firms with loans in arrears at the end of 2019 were excluded from the PGL program. We take advantage of this fact comparing these excluded companies with companies with defaulted loans between January and February 2020 and not before that were not excluded. Note that the pandemic shock came in mid-March 2020 and the PGL in April. Reducing the sample to only firms with loans defaulted between December 2019 and February 2020, we find that firms in these two groups (excluded vs. not excluded for the PGL scheme) are very similar in observables, but crucially one group of firms cannot access the PGL (excluded) while the other group can access PGL (eligible).

Second, we use the difference in the coverage degree of the program to compare similar firms on observables covered at 80% with those covered at a lower level (60 or 70%). For the group of firms without defaulted loans as of December 2019 (i.e., eligible for PGL), firms can have differential access to PGL because the guaranteed amount varies by firm size: the coverage level is 80% of the loan amount for small and medium sized firms versus 70-60% for larger firms. In this case, different from the previous firm source of exogenous variation, firm observables are different across the two groups of firms, and hence, we use a matching estimator when we analyze the implications of PGL. Before using the matching estimator, we analyze the determinants of PGL and non-PGL depending on 80% (vs. lower) guarantee coverage level.

6. Results

This section provides the results of our analysis. We first document in section 6.1 what are the key determinants driving the allocation of public guaranteed loans. We start by analyzing loan granting decisions at the firm-bank level and, then analyze for granted loans their amount and interest rates at the loan-firm-bank level. We then document in section 6.2 the effects of such allocation of public guaranteed loans in terms of total credit and credit substitution between publicly guaranteed and non-publicly guaranteed credit.

6.1 Allocation of credit: Loan granting decision

The results on the analysis of obtaining a PGL are presented in columns (1) to (5) of Table 2. The analysis is conducted at the firm-bank level. Regressions include an increasingly richer set of fixed effects as one moves across the table columns (keeping the sample fixed to avoid composition effects), with column (5) including firm and bank fixed effects.

We find that PGL are more likely to be granted to risky firms (based on ex-ante credit risk scoring), firms in more negatively affected sectors by the pandemic (e.g., tourism, transport, hospitality), SMEs and firms with less liquid assets. This indicates that, as suggested by our theoretical framework, there is an association between PGL extension and firms' risk, hypothesis 2. In terms of bank-firm characteristics, we find that PGL are more likely to be extended by banks to firms with a higher ex-ante loan share with the bank, in line with our hypothesis 1, and that have higher residual maturity on outstanding loans with the firm. Moreover, we find that PGL are more likely to be extended by banks with higher NPL ratios, banks with lower capital ratios and lower return on assets (ROA), and bigger banks. This indicating that, there is an association between PGL extension and bank risk/weakness.

The remainder of Table 2 presents results for non-PGL. Specifically, we find that the *Share* variable obtains a much smaller coefficient (0.03) when compared with the results for PGL (0.22). Quantitatively, an interquartile range increase in the firm's prior share of credit outstanding with the bank increases the probability of obtaining a PGL by 24.4% (0.216*(.429-.003)/0.378*100), comparing with the 4.0% for non-PGL (0.027*(.429-.003) /0.287*100). This highlights that while, as our model suggests, *Share* is a relevant determinant of granting non-PGL credit, it is much more so for public credit. Importantly for non-PGL, the firm and bank variables have the opposite sign (and statistically significant) than for PGL.

In sum, we find that, during the COVID crisis period, ex-ante riskier firms and weaker banks participate more on PGL. In particular, PGL are more likely to be granted to firms which are ex-ante riskier and in negatively affected sectors by the COVID. In terms of bank characteristics, we find that PGL are more likely to be extended by banks with higher NPL ratios. Just the opposite in terms of firm and bank risk characteristics happens for non-PGL – i.e., during the COVID crisis non-PGL are more likely associated to safer firms and by stronger banks. Moreover, we find that firms are much more likely to obtain PGL (also as compared to non-PGL) from those banks to whom they have larger pre-existing credit exposures, consistent with the role of banks' private incentives in exploiting the public guarantee scheme to address potential debt repayment problems at the firm level.[19]

In Table 3, we estimate heterogeneous effects of the *Share* variable depending on pre-determined bank and firm risk characteristics based on the more demanding specification with firm and bank fixed effects. The heterogeneous results for the granting of PGL 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 higher NPL ratios. The regressions for non-PGL presented in columns (6) to (10) of Table 3 obtain much smaller effects of the *Share* variable and the opposite sign for its interaction with risky firms and banks.

[19] Results presented thus far also include loan applications that did not result in the granting of loans. We obtain similar results when limiting the sample by conditioning only on granted loans, presented in Appendix Table A2, Panel A. These estimates show the differential effects between granted PGL and non-PGL and highlight the different loan granting strategies followed in PGL and non-PGL conditional on a loan being granted.

The economic effects of the results in Table 3 are substantial. The heterogeneous effects estimated in Table 3 imply that the probability of obtaining a PGL increases by 32.5% for risky firms (interquartile rage increase), by 27.4% for firms in adversely pandemic-affected sectors and by 40.0% for risky firms in pandemic-affected sectors. If the bank has a high fraction of nonperforming loans (those with a NPL ratio above the third quartile of the distribution), these effects on riskier firms in PGL increase by 43.6%. Instead, for non-PGL stronger banks grant more loans to riskier firms in negatively affected sectors by the COVID. Therefore, these results are consistent with weaker (riskier/worse) banks shifting risky credit to taxpayers.

In addition to fixed effects and controls shown in Table 3, results are robust to other permutations. For example, as before, the differential effects for granted loans are presented in Appendix Table A2, Panel B, with similar results. Results in Appendix Table A3 show that the results so far are robust to alternative measures of the exposure of a firm with a bank (the *Share* variable) and to how we measure firm risk. In Panel A, 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. Panel B horse races the *Share* variable and the main bank dummy showing that our results on Share are over and above the bank is the firm's primary lender (i.e., results are not purely driven by the main bank of the firm). Panel C 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 Appendix Table A4, we perform a falsification test to make sure that the effect of the *Share* variable is specific to PGL and derives from the pandemic period, and not to possible seasonal effects. 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 may be 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 periods before COVID-19 suggesting the inexistence of relevant seasonal effects.

Next, we consider two alternative dimensions of lending relationships: granularity and duration of lending relationships. A substantial amount of credit risk of banks tends to be concentrated among few firms, consistent with the notion of granularity developed by Gabaix (2011). Moreover, durable lending relationships may produce valuable informational advantages for banks, as in Bolton et al. (2016). We want to understand whether our main results on lending exposures, as captured by the *Share* variable, are robust to controlling for these alternative lending relationship considerations. To capture the granularity of the lending relationship between the bank and the firm, we use the ratio between the total amount of loans of the firm with the bank over the *total assets of the bank* as of 2009:12, and to capture the duration of the lending relationship between the bank and the firm, we use the log of one plus the number of months since the first lending relationship with the bank since 1999:12. The results are presented in Table 4. We find that our main results on the *Share* variable are robust to controlling for the concentration of the bank's credit risk in the firm (Panel A) and for the duration of lending relationships between the bank and the firm (Panel B). Moreover, we find that for important firms for the bank (the granularity measure), interestingly, the bank lends equally with PGL as compared to non-PGL.

In Table 5, we estimate the implications of the public guarantee scheme for the loan amount (Panel A) and the interest charged (Panel B) of granted loans. The analysis is conducted at the firm-type of loan-bank level, which allows us to include firm*bank fixed effects and effectively compare different type of loans granted to the same firm by the same bank (columns (3) to (6)), however we also show that results are also present when only firm and bank fixed effects are included which compares loans of the same firm with different banks (columns (1) and (2)). In Panel A we find that PGL are on average larger in magnitude, 46% higher than non-PGL (column (3)), and that the *Share* variable has a positive effect on the loan amount (column (1)). We also observe that the amount granted for PGL is even higher among firms with higher ex-ante credit dependency with the bank (i.e., with higher *Share*); the granted PGL amount for a given firm increases by 57.2% if the firm's credit share with the bank is high (interquartile range increase). This effect increases to 64.4% for firms in sectors more affected by the pandemic and when the bank has a higher NPL (72.7%).

We also estimate the effect on the loan interest rate in Panel B. We find that PGL also tend to have lower interest rates than non-PGL (2.3 pp on average). We also find that a higher *Share* reduces the loan interest rate and, interestingly, that the effect on *PGL* is amplified for higher levels of *Share*. Interest rates of PGL further decreases to 2.9 pp if the firm's credit share with the bank is high (an interquartile range increase) and for riskier firms working with riskier banks (3.4 pp from column (6) and using interquartile changes).

These differential volume and pricing results are therefore not consistent with a borrower (demand)-driven channel, but instead are consistent with a credit supply(lender)-driven channel. Moreover, these results control for firm fixed effects, or firm-bank fixed effects, and thus for unobserved borrower (and borrower-lender) fundamentals. Altogether, all these results suggest that a credit supply mechanism at play.

6.2 Overall credit and substitution of non-PGL credit

We turn to analyze whether the granting of PGL results in a change in overall credit exposures between bank-firm pairs and in a substitution of non-PGL credit by PGL credit (Table 6). We first find that firm-bank pairs with PGL tend to increase their total credit and share of total loans (Panel A of Table 6). We find that firm-bank pairs with PGL tend to strengthen their lending relationships, in the sense that they increase their total loans as well as the share of total loans between the firm and the bank. This suggests that the public guarantee scheme contributes to an increase in the concentration of credit among pre-existing lending relationships. Interestingly, such concentration is based on PGL, as non-PGL credit is reduced as we show in Panel B, and further strengthens the evidence that the public guarantee scheme resulted in a credit substitution between PGL and non-PGL credit. The economic effects of the results on total loans are substantial. Firm-bank pairs with PGL experience an increase of 116.8 pp in overall credit (column (5) of Panel A). Results are qualitatively unaltered when replacing the PGL dummy with PGL amount/Assets (column (6)) and when analyzing the change in the share over the period, where we find an increases by 16.9 pp (column (7) of Panel A).

Next, we analyze the impact of PGL on non-PGL exposures between bank and firm pairs (Panel B of Table 6). In contrast to the effects on total loans, we find that firm-bank pairs with PGL tend to reduce their total credit and share of non-PGL in the firm. This suggests that the public guarantee scheme contributed to a substitution of non-PGL for PGL credit.[20] The estimated effect is economically meaningful. Based on the estimates in column (5) of Panel B, firm-bank pairs with PGL experience a decrease of 15.4 pp in nonguaranteed loans over the analyzed period. Results hold when replacing *ΔCredit* with *ΔShare*, computed based on non-guaranteed loans only (column (7)). Specifically, in column (7) we find that the share of the firm with the bank in terms of non-public guaranteed loans declines by 7.8 pp for banks that grant PGL to the firm.

Panel A of Figure 2 presents time-varying coefficients of the effect of public guaranteed loans on the firm's total loans share in a bank, derived from the estimation of the regression specification in column (7) of Panel A of Table 6 using different end points of the sample period. Panel B of Figure 2 presents similar time-varying coefficients but estimated for non-

[20] We analyze the mechanisms by which credit substitution takes place. The results suggest that the proceeds from PGL are partly used for the early repayment of outstanding private loans and banks that provide PGL have less delinquencies in their non-PGL to firms. See Tables A6 and A7.

public guaranteed loans based on the specification in column (7) of Panel B in Table 6. 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 PGL were granted in the first quarter following the inception of the guarantee scheme (i.e., between April and June 2020, 70% of all PGL were granted, and only 0.5% of all PGL were granted in March). Figure 2 shows that there was no change in loan share for total loans (Panel A) and non-PGL (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 PGL and bank-firm pairs without PGL. It is only in the subsequent two months, until June 2020, when the majority of PGL were granted, that a substantial difference emerges between PGL and non-PGL. Specifically, there is a change in loan share for non-PGL in this subsequent period (Panel A), while the change in loan share of total loans increases sharply from zero.

6.2.1 Exclusion criteria of the public guarantee program as a source of exogeneity

To push on the causality front of PGL on lending and improve our identification, we analyze a feature of the regulation that introduced exogenous variation in whether the firm can obtain a PGL or not: the prerequisite for companies to be eligible for the program, already mentioned in section 2, which has to do with their loan performance. Specifically, a necessary condition for firms to be eligible to request a PGL (starting after mid-March 2020) is not to be registered as delinquent in the CIR (credit register) as of December 31, 2019.

Regarding the loan impairment status of the firm, we select those firms with loans in arrears between December 2019 and February 2020. We compare firms with defaulted loans only in January or February 2020 (eligible for PGL) versus firms with defaulted loans in December 2019 (excluded from PGL). With this we obtain two sets of firms in a similar financial situation just before the COVID pandemic, but with completely different access to PGL: firms with defaults in December 2019, which are excluded of the program as they are ineligible, and those with defaults between January and February 2020 and not in December 2019, which are eligible for the PGL program. We use this stark discontinuity to test whether the change in total bank credit between December 2019 and June 2021 is larger for the set of firms eligible for the program.

Table A5 Panel A in the Appendix illustrates the differences between the two set of firms for firm observable characteristics. For comparison among groups, we use the Imbens and Wooldridge (2009) statistic, which avoids the sample-size dependence on the mean test by computing the difference of the means of each variable for the two groups normalized by the square root of the sum of the variances of the variables. Its absolute value is compared with 0.25, a heuristic value proposed by Imbens and Rubin (2015) to test whether the differences should be considered significant or not. The table shows that the differences are not statistically significant, meaning that both set of firms are similar on observables, including the banks lending to the two groups of firms.

Table 7 Panel A analyzes the granting decision, in line with our analysis in Table 2. The first three columns show that having some defaulted loan in the first two months of 2020 and not in December 2019 is a relevant determinant of whether the firm gets a PGL. In line with our previous results, we find that this effect is stronger when the share with the bank is higher (column (4)) and more so for riskier banks (column (5)). Columns (7) to (11) show that there are no differences in the case of non-PGL. These results confirm the relevance of our previous estimations in Section 6.1.

Table 7 Panel B studies the credit substitution for this particular sample of firms at the bank-firm level. In columns (1) to (10) we analyze the change in total and non-PGL credit between December 2019 and June 2021, whereas in column (11) we focus on the change in the share with the bank. Our most saturated specification, in column (4), which includes bank fixed effects, industry*zip code fixed effects as well as firm and bank controls, shows that the change in total credit is 6.7 pp higher for firms with delinquencies between January and February 2020 and not before, compared with the firms that had arrears as of December 2019. Moreover, in column (5) we instrument the dummy of whether the firms has a PGL or not with the differential delinquent situation of the firm and we observe that the first stage has a F-test of 34.6, indicating that the instrument is relevant, and having a PGL increases the total credit with the bank by 49.4 pp. Columns (9) and (10) show that the difference is stronger for banks with higher NPL ratio (6.0 pp more for an interquartile change).[21] Finally, in column (11) we find similar effects for the change in the firm's credit share. We also analyze the change in non-PGL in columns (6) to (8) and find that, in line with Table 6 Panel B, non-PGL credit is reduced for these firms. Moreover, columns (12) and (13) show how our results are consistent at the firm level. Summing up, exploiting a design feature of the public guarantee program established before its entry into force, we can identify that PGL causes higher bank credit (for risky firms) and that this is more likely for weaker/riskier banks.

6.2.2 The degree of coverage of the public guarantee program as a source of exogeneity

In this section we study the differences in the coverage of PGL to analyze another source of exogeneity. In Panel A of Table 8 we perform a similar analysis to that shown in Table 2 but using the fact that under the program the guarantee for SME loans was 80% while it was lower (70 or 60%) for large firms. We find that, as previously reported in Table 2, firms with public guarantees of 80% are more prone to receive a PGL and that the effect of the credit share of the firm with the bank on the likelihood of getting a PGL is more pronounced for firms that enjoy a higher degree of coverage. Moreover, this effect is stronger for riskier firms and more so when the loan is granted by a weaker bank (i.e., with a higher NPL ratio). We do not observe these differential effects for non-PGL. In terms of the economic impact, going from the 25th to 75th percentile of the distribution of the credit share raises the average probability of

[21] In unreported regressions we do not find a statistically significant effect of share in these results, similarly for Table 8.

obtaining a PGL from 24.1% to 33.8% for firms with public guarantees of 80%. Moreover, for riskier firms (interquartile range increase) or when the firms belong to those sectors more affected by the pandemic, the economic effects increase to 44.9% and 44.4%, respectively, and if the bank has a high NPL ratio (interquartile range increase again), the increase is to 49.7%.

In Panel B of Table 8 we analyze the implications of the different coverage provided by the program on total credit and credit substitution. To do so we refine the analysis as there are relevant differences between the set of firms with different public guarantee coverage. We first select among the firms with a PGL those with a lower guarantee. Then, we perform a propensity score matching to match firms with a similar set of firms except that they have a PGL with a 80% guarantee. Once we perform the match, based on a set of firm characteristics (assets, sales, employees, share, sector) as well as the banks lending to those firms (bank controls: size, capital, liquidity and NPL ratios, ROA), we analyze the effects of having different guarantee coverage on the change in credit for this restricted group of companies. Panel B in Table A5 shows the differences between the selected firms after the matching. There are no systematic differences in any characteristic.

In Panel B Table 8 we report the results of estimating the change in total credit for similar firms in observables that differ in their degree of coverage. Columns (1) to (5) show that firms with public guarantees of 80% are more likely to increase credit (around a 28.8 pp higher) than those with a lower level of coverage. Columns (6) to (8) analyzes non-PGL credit and shows that credit does not increase for loans with greater degree of coverage. Columns (5) and (8) instrument the dummy that captures whether the firm has a PGL or not with the bank with the degree of coverage and the results obtained shows that to have a PGL increases the total credit and does not affect the non-PGL credit with the bank. Columns (12) and (13) show how these previous results are confirmed when analyzing our data at the firm level. Columns (9) and (10) show that these effects are more pronounced for risky firms (the increase is 53.3 pp for an interquartile change), and more so for the banks with the highest risk (in terms an interquartile range change of the NPL ratio), with a 84.3 pp increase (see column 10).

In sum, exploiting exogenous variation in Table 7 and 8 across similar firms with different PGL access, we show that PGL increases banks' overall lending —and credit share— to riskier firms, especially for weaker banks.

7. Conclusions

The COVID-19 pandemic prompted large-scale government interventions to keep firms afloat, including pay protection programs for employees and loan guarantee schemes. Crucially, some COVID-19 related policies were implemented through third parties, notably PGL, as PGL granting decisions were delegated to privately-owned banks. Hence, this delegation could lead to potential allocative problems in the presence of divergences between banks' private incentives and social incentives. In this paper, we analyze the effects of PGL on the allocation of bank credit focusing on the role of private banks' incentives when credit decisions on PGL are delegated to banks.

To guide the empirical analysis, we build a stylized model in which banks' private incentives shape the granting of guaranteed loans. A key testable prediction generated by the model is that pre-existing credit exposure is a key determinant of PGL granting decisions. Moreover, the model predicts that this effect will depend on firm risk, while the effects are not clear-cut for bank weakness. For empirical identification, we exploit the COVID-19 crisis and the Spanish credit register with unique information on COVID-related PGL, as well as a setting in which banks provide PGL and non-PGL to similar firms.

We find that during the COVID crisis: First, ex-ante riskier firms and weaker banks participate more on PGL, while the opposite happens for non-PGL. Second, firms are more likely to obtain a PGL 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 ex-ante risky firms and for firms in more pandemic-affected sectors, and this riskier lending is especially stronger for ex-ante weaker banks, with higher nonperforming loans. These results are the opposite for non-PGL. Moreover, results using firm(-bank) fixed effects and loan volume vs. price suggest a supply-driven mechanism. Third, the guarantee scheme results in higher credit to firms driven by PGL (substituting non-PGL credit). Exploiting exogenous variation across similar firms with different PGL access, we find that PGL increases both overall lending and the share of credit to riskier firms, especially for weaker banks. Overall, our results show that the allocation of government guaranteed credit is shaped by banks' private incentives, notably pre-existing bank-firm credit exposures resulting in weaker banks shifting riskier credit to taxpayers.

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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 guarantee loan was granted, and of the study at firm-bank level of the future private loan performance of firms in Spain between 2020:03 to 2021:06. All firm and bank characteristics are calculated as of December 2019. For a definition of the variables see the Appendix.

PANEL A. Loan granting decision and loan terms of granted loans

		Mean	S.D.	P25	Median	P75
Loan Granting Decision						
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
Loan Terms						
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
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
Affected Sector	0/1	0.623	0.485	0.000	1.000	1.000
Firm-Bank Characteristics(ij)						
Share	0.0x%	0.266	0.312	0.003	0.136	0.429
Ln(Average residual maturity)	Log(months)	1.859	1.612	0.000	1.946	3.258
Granularity	%	0.001	0.034	0.000	0.000	0.000
Ln(1+length of the relationship)	Log(months)	3.969	2.122	3.091	4.159	5.198
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. Overall Credit and Credit Substitution

		Mean	S.D.	P25	Median	P75
Substitution						
ΔCredit non-PGL$_{2021:06\text{-}2019:12}$	%	-89.732	95.755	-200.000	-81.530	-15.916
ΔCredit Total loans$_{2021:06\text{-}2019:12}$	%	-36.127	108.986	-129.901	-12.065	37.068
ΔShare non-PGL$_{2021:06\text{-}2019:12}$	%	-4.163	23.971	-12.091	-1.956	3.621
ΔShare Total loans$_{2021:06\text{-}2019:12}$	%	-3.42	21.37	-9.88	-1.72	3.51
Firm defaulted in Jan. or Feb. 2020 and not in Dec. 2019	0/1	0.20	0.40	0.00	0.00	0.00
Firms with PGL covered at 80%	0/1	0.31	0.46	0.00	0.00	1.00
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
Delinquency						
Private Delinquency	0/1	0.021	0.142	0.000	0.000	0.000
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
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
Firm-Bank Characteristics(ij)						
Share	0.0x%	0.291	0.276	0.065	0.197	0.455
Ln(Average residual maturity)	Log(months)	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

LOAN GRANTING DECISION AT FIRM-BANK LEVEL

This table reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guarantee loan or a non-stated-backed one, 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%.

Dependent variable:		Public Guarantee Loan (0/1)					Non-Public Guarantee Loan (0/1)				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Firm Characteristics(i)	SME	0.119***	0.112***	0.106***	0.108***		-0.151***	-0.143***	-0.138***	-0.129***	
		(0.020)	(0.018)	(0.016)	(0.016)		(0.019)	(0.018)	(0.018)	(0.019)	
	Risk	0.026***	0.029***	0.029***	0.029***		-0.014**	-0.013**	-0.013*	-0.014**	
		(0.006)	(0.006)	(0.007)	(0.007)		(0.006)	(0.006)	(0.006)	(0.007)	
	Affected Sector	0.037***					-0.012***				
		(0.004)					(0.004)				
Firm-Bank Characteristics(ij)	Share	0.116***	0.112***	0.142***	0.129***	0.216***	0.035**	0.041***	0.043**	0.033**	0.027*
		(0.020)	(0.020)	(0.021)	(0.022)	(0.023)	(0.015)	(0.015)	(0.017)	(0.016)	(0.015)
	Ln(Average residual maturity)	0.017***	0.018***	0.013**	0.015***	-0.005	-0.055***	-0.055***	-0.056***	-0.041***	-0.039***
		(0.006)	(0.006)	(0.005)	(0.006)	(0.004)	(0.010)	(0.010)	(0.010)	(0.007)	(0.006)
Bank Characteristics(j)	Ln(Assets)	0.056***	0.056***	0.058***			0.006	0.007	0.006		
		(0.005)	(0.005)	(0.005)			(0.010)	(0.010)	(0.010)		
	Capital ratio	-0.641*	-0.639*	-0.604*			1.966*	1.980*	1.995*		
		(0.367)	(0.363)	(0.352)			(1.082)	(1.086)	(1.057)		
	ROA	-1.998**	-2.074**	-2.114**			5.097	5.185	5.190		
		(0.908)	(0.917)	(0.904)			(3.547)	(3.541)	(3.478)		
	Liquidity ratio	0.349	0.352	0.344			0.976***	0.978***	0.988***		
		(0.258)	(0.258)	(0.250)			(0.360)	(0.361)	(0.359)		
	NPL ratio	1.665**	1.636**	1.509**			-1.507	-1.519	-1.492		
		(0.640)	(0.643)	(0.623)			(1.526)	(1.531)	(1.495)		
	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
	Observations	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204
	R2	0.154	0.161	0.260	0.279	0.475	0.122	0.126	0.214	0.266	0.437

TABLE 3

LOAN GRANTING DECISION AT FIRM-BANK LEVEL: 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 or a non-stated-backed one 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%.

Dependent variable:	Public Guarantee Loan (0/1)					Non-Public Guarantee Loan (0/1)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share	0.221***	0.216***	0.222***	0.223***	0.200***	0.027*	0.027*	0.027*	0.028*	0.027*
	(0.024)	(0.023)	(0.023)	(0.024)	(0.022)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)
Share*Risk	0.050***		0.054***	0.055***	0.044***	0.000		-0.001	-0.000	0.000
	(0.004)		(0.004)	(0.004)	(0.004)	(0.005)		(0.005)	(0.005)	(0.003)
Share*Affected sectors		0.022***	0.041***	0.040***	0.031***		-0.011***	-0.011**	-0.011**	-0.011***
		(0.006)	(0.006)	(0.006)	(0.006)		(0.004)	(0.004)	(0.004)	(0.004)
Share*Risk*Affected sectors				0.015***	0.013***				0.011***	0.012**
				(0.004)	(0.004)				(0.004)	(0.005)
Share*Risk*Affected sectors*Bank NPL ratio					0.719**					-0.697*
					(0.303)					(0.360)
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	0.476	0.475	0.476	0.476	0.478	0.437	0.437	0.437	0.437	0.441

TABLE 4

LOAN GRANTING DECISION AT FIRM-BANK LEVEL: OTHER RELATIONSHIP 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 guarantee loan (columns (1) to (10)) or a non-stated-backed one (columns (11) and (12)) between 2020:03 to 2020:12. Granularity has been standardized to have 0 mean and the same variance that the share variable to make their effects comparable. 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. Lower degree terms of any interaction are included although not showed. "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. Granularity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Public Guarantee Loan (0/1)										Non-PGL (0/1)	
Share						0.216***	0.221***	0.216***	0.222***	0.223***		0.027*
						(0.023)	(0.024)	(0.023)	(0.024)	(0.024)		(0.015)
Share*Risk							0.050***		0.054***	0.055***		
							(0.004)		(0.004)	(0.004)		
Share*Affected sectors								0.022***	0.041***	0.040***		
								(0.006)	(0.006)	(0.006)		
Share*Risk*Affected sectors										0.015***		
										(0.004)		
Granularity	0.010***	0.010***	0.011***	0.012***	0.012***	0.007***	0.007***	0.007***	0.007***	0.007***	0.008**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Granularity*Risk		-0.001		-0.001	-0.001		-0.003**		-0.004**	-0.004**		
		(0.002)		(0.002)	(0.002)		(0.002)		(0.002)	(0.002)		
Granularity*Affected sectors			0.006	0.005	0.006*			0.002	0.001	0.001		
			(0.003)	(0.003)	(0.003)			(0.002)	(0.003)	(0.003)		
Granularity*Risk*Affected sectors					-0.005					-0.004		
					(0.004)					(0.003)		
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	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	718204	718204
R2	0.466	0.466	0.466	0.466	0.466	0.475	0.476	0.475	0.476	0.476	0.437	0.437

Panel B. Length of the relationship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	Public Guarantee Loan (0/1)										Non-PGL (0/1)	
Share						0.228***	0.233***	0.228***	0.233***	0.235***		0.036**
						(0.022)	(0.023)	(0.022)	(0.023)	(0.023)		(0.016)
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+lenght of the relationship)	-0.031***	-0.031***	-0.031***	-0.031***	-0.031***	-0.033***	-0.033***	-0.033***	-0.033***	-0.033***	-0.025***	-0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(1+lenght)*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+length)*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+length)*Risk*Affected sectors					-0.000					-0.000		
					(0.001)					(0.001)		
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	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	718204	718204
R2	0.475	0.475	0.475	0.475	0.475	0.485	0.486	0.485	0.486	0.486	0.444	0.444

TABLE 5

LOAN TERMS OF GRANTED LOANS AT FIRM-BANK-TYPE OF LOAN LEVEL

This table reports regressions results of a Poisson model (for the loan amount), or a linear model (for interest rate) at firm-bank-type of loan (public guarantee loan or not) level of the new commitment amount granted between 2020:03 to 2020:12. Panel A analyzes the effect on loan amount. Panel B analyzes the effect on interest rate. 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. Interest rate is the weighted average (using the loan amount) interest rate 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 amount

Dependent variable: Loan amount	(1)	(2)	(3)	(4)	(5)	(6)
PGL	0.442***	0.446***	0.460***	0.476***	0.472***	0.475***
	(0.089)	(0.088)	(0.106)	(0.107)	(0.107)	(0.049)
Share	0.768***	0.757***				
	(0.032)	(0.030)				
PGL*Share		0.141*		0.189***	0.176**	0.181**
		(0.085)		(0.071)	(0.072)	(0.072)
PGL*Share*Risk					-0.007	-0.024
					(0.021)	(0.016)
PGL*Share*Affected sectors					0.111***	0.080***
					(0.028)	(0.028)
PGL*Share*Risk*Affected sectors						0.031*
						(0.018)
PGL*Share*Risk*Affected sectors*Bank NPL ratio						4.000*
						(2.266)
Bank Fixed Effects	Yes	Yes	-	-	-	-
Firm Fixed Effects	Yes	Yes	-	-	-	-
Bank*Industry and Location Fixed Effects	Yes	Yes	-	-	-	-
Firm*Bank Fixed Effects	No	No	Yes	Yes	Yes	Yes
Observations	592,123	592,123	345,416	345,416	345416	345416
R2	0.760	0.760	0.785	0.785	0.786	0.793

Panel B. Loan interest rate

Dependent variable: Interest rate	(1)	(2)	(3)	(4)	(5)	(6)
PGL	-2.247***	-2.231***	-2.306***	-2.299***	-2.292***	-2.299***
	(0.200)	(0.188)	(0.237)	(0.224)	(0.222)	(0.209)
Share	-0.589***	-0.516***				
	(0.063)	(0.087)				
PGL*Share		-0.759***		-0.946***	-0.965***	-0.864**
		(0.282)		(0.348)	(0.367)	(0.377)
PGL*Share*Risk					0.050	0.032
					(0.071)	(0.073)
PGL*Share*Affected sectors					-0.318**	-0.278**
					(0.150)	(0.126)
PGL*Share*Risk*Affected sectors						-0.162
						(0.113)
PGL*Share*Risk*Affected sectors*Bank NPL ratio						-10.065*
						(5.921)
Bank Fixed Effects	Yes	Yes	-	-	-	-
Firm Fixed Effects	Yes	Yes	-	-	-	-
Bank*Industry and Location Fixed Effects	Yes	Yes	-	-	-	-
Firm*Bank Fixed Effects	No	No	Yes	Yes	Yes	Yes
Observations	450,453	450,453	289,358	289,358	289358	289358
R2	0.608	0.609	0.695	0.697	0.698	0.705

TABLE 6

OVERALL CREDIT AND CREDIT SUBSTITUTION

This table reports regressions results of a regression 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 analyzes total credit while Panel B analyzes non-PGL. ΔCredit the log change in total loans (Panel A) or non-public guaranteed loans (Panel B) between the firm and the bank, computed over the period December 2019 to June 2021. ΔShare is the change in the firm's share of total loans (Panel A) or non-public guaranteed loans (Panel B), based on loan amounts, 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%.

Panel A. Total loans

	Total Loans						
Dependent variable:	ΔCredit (Total loans)$_{2021:06-2019:12}$						ΔShare (Total)$_{2021:06-2019:12}$
	(1)	(2)	(3)	(4)	(5)	(6) Intensity	(7)
PGL	124.380***	124.704***	126.784***	113.608***	116.789***		16.894***
	(8.451)	(8.323)	(8.230)	(4.453)	(3.930)		(1.522)
PGL amount/Assets						304.625***	
						(8.606)	
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	Yes
Firm Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.373	0.374	0.442	0.524	0.640	0.586	0.299

Panel B. Non-public guarantee loans

	Non-Public Guarantee Loans						
Dependent variable:	ΔCredit (non-PGL)$_{2021:06-2019:12}$						ΔShare (non-PGL)$_{2021:06-2019:12}$
	(1)	(2)	(3)	(4)	(5)	(6) Intensity	(7)
PGL	-14.487***	-13.940***	-11.431**	-20.707***	-15.355***		-7.781***
	(4.883)	(4.754)	(4.649)	(2.444)	(2.454)		(0.340)
PGL amount/Assets						-39.205***	
						(8.110)	
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	Yes
Firm Fixed Effects	No	No	No	No	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686	597,686
R2	0.101	0.104	0.202	0.276	0.458	0.457	0.205

TABLE 7

EXOGENOUS DIFFERENTIAL ACCESS TO PGL:

FIRMS WITH DEFAULTED LOANS IN JANUARY/FEBRUARY 2020 VERSUS IN DECEMBER 2019

This table shows the analysis of the exclusion criteria in the public guarantee program of having loans defaulted in December 2019 comparing firms with loans in arrears in that date (ineligible) with those firms without delinquent loans in December 2019 but with delinquent loans in January or February 2020 (eligible). 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 granting decision at firm-bank level restricted to firms with defaulted loans in Dec 2019 (ineligible) vs in Jan/Feb 2020 but not in Dec 2019 (eligible)

Dependent variable: Loan Granting Decision	Public Guarantee Loan (0/1)						Non-Public Guarantee Loan (0/1)					
	(1)	(2)	(3)	(4)	(5)	(5)	(7)	(8)	(9)	(10)	(10)	(11)
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019	0.132***	0.120***	0.119***				0.003	0.010	0.009			
	(0.015)	(0.023)	(0.023)				(0.016)	(0.024)	(0.023)			
Share	0.002	0.019**	0.018*	0.030***	0.021***	0.021***	-0.009	-0.006	-0.006	0.001	0.000	0.002
	(0.008)	(0.009)	(0.010)	(0.009)	(0.008)	(0.008)	(0.026)	(0.033)	(0.029)	(0.030)	(0.030)	(0.032)
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019*Share				0.231***		0.181***				-0.011		-0.022
				(0.040)		(0.042)				(0.041)		(0.047)
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019*Share*Bank NPL						5.779*						-1.317
						(3.046)						(2.414)
Bank & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry*Zip Code Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	25,308	25,308	25,308	25,308	25,308	25,308	25,308	25,308	25,308	25,308	25,308	25,308
R2	0.148	0.414	0.420	0.462	0.475	0.491	0.044	0.256	0.333	0.358	0.359	0.358

Panel B. Credit substitution at firm-bank level and overall firm-level credit restricted to firms with defaulted loans in Dec 2019 (ineligible) vs in Jan/Feb 2020 but not in Dec 2019 (eligible)

Dependent variable:	$\Delta Credit_{2021:06-2019:12}$										ΔShare (Total loans)	ΔCredit Firm Level	
	Total					Non-PGL			Total			Total	Non-PGL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019	5.949**	6.882***	4.643*	6.731*		-7.033***	-7.042*		6.285*			10.756*	-9.581*
	(2.782)	(2.324)	(2.357)	(3.901)		(2.460)	(3.630)		(3.666)			(6.265)	(4.982)
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019*Affected sectors									-0.6075				
									(4.890)				
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019*Bank NPL ratio									346.934***	372.533***	43.385**		
									(114.767)	(104.588)	(20.836)		
PGL					49.412*			-56.023*					
					(27.531)			(28.940)					
First Stage: PGL on Firm defaulted in Jan./Feb. 2020 vs Dec. 2019					0.126***			0.126***					
					(0.021)			(0.021)					
Bank & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry*Province Fixed Effects	No	No	Yes	-	-	Yes	-	-	-	-	-	-	-
Industry*Zip Code Fixed Effects	No	No	No	Yes	Yes	No	Yes	Yes	Yes	-	-	Yes	Yes
Firm Fixed Effects	No	No	No	No	No	No	No	No	No	Yes	Yes	No	No
F-test					34.57			34.57					
Observations	25,548	25,548	25,548	25,548	25,548	25,548	25,548	25,548	25,548	25,548	25,548	1,202	1,202
R2	0.061	0.204	0.270	0.412		0.272	0.418		0.416	0.441	0.164	0.500	0.506

TABLE 8

EXOGENOUS DIFFERENTIAL ACCESS TO PGL: THE DEGREE OF PGL COVERAGE

This table shows the analysis of the difference in the level of guarantees in the public guarantee program. The program states that SMEs has a guaranteed of 80% and large firms of 60% or 70%. Panel A reports regressions results of a linear probability model at firm-bank level of the probability of a firm to get a public guaranteed loan or a non-state-backed one, between 2020:03 to 2020:12. Panel A uses the 80% dummy as a proxy of the difference in guaranteed levels. Panel B analyses the evolution of total credit at bank-firm and firm-level level and makes a propensity score matching for firms with different PGL coverage. 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. Lower degree terms of any interaction are included although not showed. "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 granting decision at firm-bank level for firms with 80% coverage vs lower.

Dependent variable:	Public Guarantee Loan (0/1)				Non-Public Guarantee Loan (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firms with PGL covered at 80%	0.108***				-0.129***			
	(0.016)				(0.019)			
Share	0.129***	0.214***	0.244***	0.234***	0.033**	0.039**	0.038**	0.038**
	(0.022)	(0.023)	(0.021)	(0.019)	(0.016)	(0.018)	(0.018)	(0.018)
Firms with PGL covered at 80%*Share		0.086***	0.189***	0.140***		-0.069***	-0.070***	-0.047**
		(0.022)	(0.019)	(0.041)		(0.017)	(0.017)	(0.022)
Firms with PGL covered at 80%*Share*Risk			0.053***	0.070***			-0.009	-0.011
			(0.010)	(0.026)			(0.018)	(0.014)
Firms with PGL covered at 80%*Share*Affected sectors			0.073***	0.071***			-0.023	-0.033
			(0.022)	(0.023)			(0.031)	(0.031)
Firms with PGL covered at 80%*Share*Risk*Bank NPL ratio				1.208*				-2.014**
				(0.713)				(1.009)
Firms with PGL covered at 80%*Share*Affected sectors*Bank NPL ratio				1.045				-0.646
				(1.366)				(1.924)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Zip Code Fixed Effects	Yes	-	-	-	Yes	-	-	-
Firm Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	718,204	718,204	718,204	718,204	718,204	718,204	718,204	718,204
R2	0.279	0.475	0.477	0.478	0.266	0.438	0.438	0.441

Panel B. Credit substitution at firm-bank level and overall firm-level credit using matching estimator.

Dependent variable:	$\Delta Credit_{2021:06-2019:12}$										ΔShare (Total loans)	ΔCredit Firm Level	
	Total					Non-PGL			Total	Total		Total	Non-PGL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Firms with PGL covered at 80%	26.294***	28.578***	22.984***	28.747*		-0.039	-1.445		26.267*	28.113*	2.461	31.746***	7.923
	(6.463)	(5.055)	(6.832)	(16.049)		(6.138)	(8.875)		(15.606)	(16.284)	(1.572)	(4.969)	(5.432)
Firms with PGL covered at 80%*Risk									27.678***	28.385***	3.925**		
									(9.827)	(9.612)	(1.913)		
Firms with PGL covered at 80%*Affected Sector									8.220	5.816	-0.389		
									(27.076)	(26.090)	(3.417)		
Firms with PGL covered at 80%*Bank NPL									257.125	360.629	7.358		
									(327.896)	(305.487)	(53.382)		
Firms with PGL covered at 80%*Risk*Bank NPL										1340.475*	7.897		
										(760.667)	(121.309)		
PGL					116.914***			17.374					
					(35.087)			(38.257)					
First Stage: PGL on Firms with PGL covered at 80%					0.259***			0.259***					
					(0.074)			(0.074)					
Bank & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry*Province Fixed Effects	No	No	Yes	-	-	Yes	-	-	-	-	-	Yes	Yes
Industry*Zip Code Fixed Effects	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No
F-test					12.32			12.32					
Observations	3,858	3,858	3,858	2,948	2,948	2,948	3,858	2,948	3,858	3,858	3,858	418	418
R2	0.101	0.212	0.362	0.461		0.339	0.467		0.461	0.490	0.208	0.423	0.523

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.

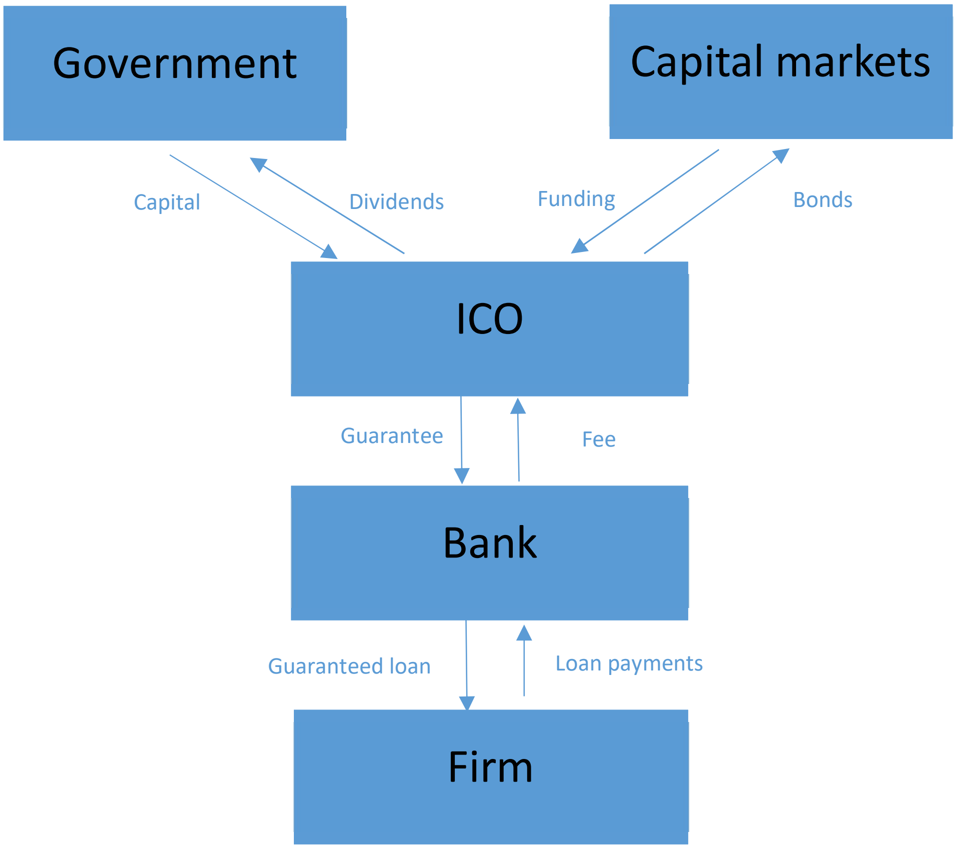
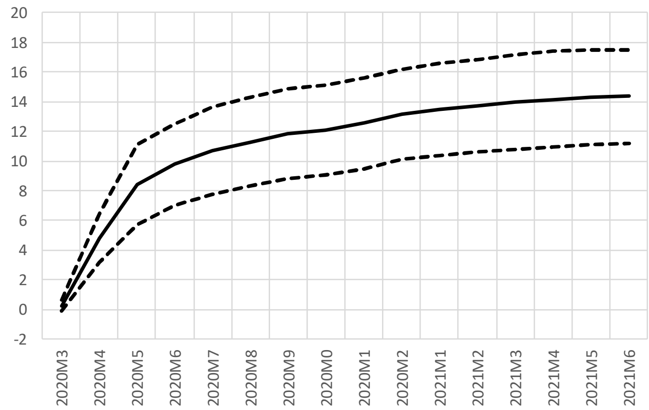


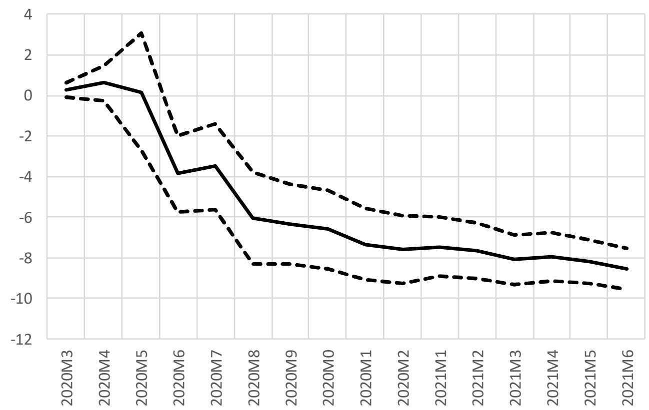
FIGURE 2
EFFECT OF GRANTING A PUBLIC GUARANTEE LOAN ON THE SHARE OF CREDIT OF THE FIRM WITH THE BANK

This figure shows the analogous estimated coefficient on PGL in Table 6 (column (7)) but referred to the first two months of 2020. Confidence bands at 95%.

Panel A. Change in the share of total loan: Time varying coefficients



Panel B. Change in the share of non-public guaranteed loans: Time varying coefficients



ONLINE APPENDIX A

TABLE A1

DEFINITION OF THE VARIABLES

Loan Granting Decision	
Public Guarantee Loan (PGL)	A dummy equal to 1 if the firm received a loan guaranteed by the estate and 0 otherwise.
Non-PGL	A dummy equal to 1 if the firm only received non-public guaranteed loans during the sample period.
Loan Terms	
Loan amount	Drawn plus undrawn amount of the loan.
Interest rate	Interest rate of the loan.
Firm Characteristics(i)	
SME	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	A scoring variable which captures the credit risk of the firm (higher values implies higher risk).
Affected Sector	A dummy defined as sectors in which firm turnover on average decreased by more than 15% in 2020 with resepct 2019.
Firm defaulted in Jan./Feb. 2020 vs Dec. 2019	A dummy that takes 1 if the firm defaulted in January or February 2020 and not if December 2019 and 0 otherwise.
Firms with PGL covered at 80%	A dummy that takes 1 for firms to which the program establishes a guarantee of 80% and 0 otherwise.
Firm-Bank Characteristics(ij)	
Share	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)	The log of the average residual maturity of outstanding loans as of 2019:12.
Granularity	The ratio between the total amount of loans of the firm with the bank over the total assets of the bank as of 2009:12.
Ln(1+length of the relationship)	The log of 1 plus the number of months since the first relationship with the bank (since 1999:12).
Bank Characteristics(j)	
Ln(Assets)	The log of the bank's total assets (expressed in thousands of euros).
Capital ratio	The ratio of own funds over total assets of the bank.
ROA	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.
Liquidity ratio	Bank's liquid assets over total assets.
NPL ratio	Non-performing loans (doubtful and 90 days overdue) over total loans of the bank.
Early repayment	
Cumulative early repayment 6 months	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.
Delinquency	
Private Delinquency	A dummy equal to 1 if the bank classified any private loan of the firm as stage 3 during the period analyzed, and 0 otherwise.

TABLE A2

LOAN GRANTING DECISION AT FIRM-BANK LEVEL 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. Panel A shows the direct effect and Panel B shows heterogeneous effects. 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. Lower degree terms of any interaction are included although not showed. "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

Dependent variable: Public Guarantee 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)	
	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

Panel B. Heterogeneity

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*Bank 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

LOAN GRANTING DECISION AT FIRM-BANK LEVEL:

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 guarantee loan between 2020:03 to 2020:12. Panel A 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 B includes share and main bank at the same time, each one interacted with firm variables and bank NPL. Panel C 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. Lower degree terms of any interaction are included although not showed. "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: Main bank

Dependent variable: Public Guarantee 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*Bank 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 B: Share interactions controlling by main bank in all interactions

Dependent variable: Public Guarantee Loan (0/1)	(1)	(2)	(3)	(4)	(5)	(6)
Share	0.155***	0.162***	0.155***	0.163***	0.166***	0.183***
	(0.027)	(0.028)	(0.027)	(0.028)	(0.029)	(0.027)
Share*Risk		0.072***		0.076***	0.077***	0.078***
		(0.007)		(0.007)	(0.007)	(0.006)
Share*Affected sectors			0.023**	0.050***	0.049***	0.063***
			(0.010)	(0.011)	(0.011)	(0.011)
Share*Risk*Affected sectors					0.031***	0.034***
					(0.007)	(0.009)
Share*Risk*Affected sectors*Bank NPL ratio						0.830*
						(0.471)
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	0.476	0.476	0.479

Panel C: High firm risk

Dependent variable: Public Guarantee Loan (0/1)	(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*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

TABLE A4

LOAN GRANTING DECISION AT FIRM-BANK LEVEL: FALSIFICATION TEST OF THE PERIOD

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. Share is computed and the end of 2018. 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)
Post≥	2019:02	2019:03	2019:04	2019:05	2019:06
Share*Post	-0.025	-0.022	-0.037	-0.018	-0.032
	(0.051)	(0.041)	(0.037)	(0.024)	(0.019)
Bank*Post Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm*Post Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	972,897	1,037,420	1,073,568	1,114,195	1,133,724
R2	0.410	0.409	0.397	0.393	0.391

TABLE A5

EXOGENOUS DIFFERENTIAL ACCESS TO PGL

MEAN TEST

This table shows the results of a mean test comparing firms with loans in arrears in December 2019 with those firms without delinquent loans in December 2019 but in January or February 2020 (Panel A) or firms with a different level of public coverage (Panel B). The table reports the normalized difference test proposed by Imbens and Wooldridge (2009), for which Imbens and Rubin (2015) suggested a heuristic threshold of 0.25 in absolute value. The normalized difference statistic tests the null of no differences in means between treated and control group through a scale-and-sample-size-free estimator

Panel A: Firms with defaulted loans in Jan/Feb 2020 (and not in Dec 2019) vs defaulted in December 2019

	Firm defaulted in Dec. 2019		Firm defaulted in Jan. or Feb. 2020 and not in Dec. 2019		Normalized Differences
	Mean	S.D.	Mean	S.D.	test
PGL	0.00	-	0.16	(0.37)	0.44
Non-PGL	0.45	(0.50)	0.49	(0.50)	0.05
Affected sector	0.60	(0.49)	0.66	(0.47)	0.09
Log(Assets)	7.42	(1.93)	7.22	(1.96)	-0.07
Own funds/Total assets	13.66	(33.68)	18.76	(27.11)	0.12
Liquidity assets/ Total assets	0.05	(0.11)	0.05	(0.11)	0.03
Share	0.19	(0.24)	0.18	(0.22)	-0.03
Ln(Average residual maturity)	1.73	(1.78)	1.97	(1.63)	0.10
Log(Bank total assets)	18.22	(1.84)	18.14	(1.89)	-0.03
Bank capital ratio	0.09	(0.04)	0.09	(0.04)	0.04
Bank ROA	0.01	(0.01)	0.01	(0.01)	0.08
Bank liquidity ratio	0.08	(0.04)	0.08	(0.04)	-0.05
Bank NPL ratio	0.05	(0.02)	0.05	(0.02)	-0.05
No. Observations	20,284		5,024		

Panel B: The degree of PGL coverage (not 80% vs 80%)

	not 80%		80%		Normalized Differences
	Mean	S.D.	Mean	S.D.	test
PGL	0.25	(0.43)	0.52	(0.50)	0.41
Affected sector	0.61	(0.49)	0.63	(0.48)	0.03
Log(Assets)	10.50	(2.10)	10.78	(2.53)	0.09
Own funds/Total assets	35.72	(23.21)	35.90	(22.10)	0.01
Liquidity assets/ Total assets	5.78	(7.45)	6.19	(8.46)	0.04
Share	0.17	(0.21)	0.17	(0.21)	0.02
Ln(Average residual maturity)	2.20	(1.38)	2.14	(1.45)	-0.03
Log(Bank total assets)	18.04	(1.96)	18.18	(1.82)	0.05
Bank capital ratio	0.08	(0.03)	0.08	(0.03)	0.00
Bank ROA	0.01	(0.01)	0.01	(0.00)	-0.02
Bank liquidity ratio	0.08	(0.03)	0.08	(0.03)	0.00
Bank NPL ratio	0.05	(0.02)	0.05	(0.02)	0.04
No. Observations	2,161		1,697		

TABLE A6

FIRM'S 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. Panel A compares 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. Panels B and C 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 (private) 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. Lower degree terms of any interaction are included although not showed. "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. Early repayment of new loan only

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

Panel C. Heterogeneous effects of new loan only

Depnt. varib.: 6 month cumulative early repayment amount/Total assets ns	(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***	-0.000***
	(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**	-0.001***
			(0.001)	(0.001)	(0.000)
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)
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	0.485

TABLE A7

FIRM'S DELINQUENCY ON NON-PGL

This table reports regressions results of linear probability model at firm-bank level of the effect of public guaranteed loans on firm delinquency on private loans between March 2020 and June 2021. In column (7), the sample is restricted to firms that as of June 2021 still have non-PGL with the bank. Delinquent is a dummy equal to 1 if the bank classified any private loan of the firm as delinquent 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. Lower degree terms of any interaction are included although not showed. "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: Delinquent	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PGL	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
PGL*Share		-0.005*	-0.007***	-0.005**	-0.007***	-0.008***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PGL*Share*Risk			-0.011***		-0.012***	-0.012***	-0.010***
			(0.003)		(0.003)	(0.003)	(0.003)
PGL*Share*Affected sectors				-0.007*	-0.011***	-0.011***	-0.007*
				(0.004)	(0.004)	(0.004)	(0.004)
PGL*Share*Risk*Affected sectors						-0.009**	-0.012**
						(0.004)	(0.005)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	597,686	597,686	597,686	597,686	597,686	597,686	384,815
R2	0.492	0.492	0.492	0.492	0.492	0.492	0.592

ONLINE APPENDIX B

STRATEGIC INTERACTION IN BANK LENDING DECISIONS

This section provides a micro foundation for the loan granting decision of banks when banks are strategic and take into account that the other bank can have incentives to grant the loan.

To determine which of the two banks grants the loan we assume that the decision to grant the loan is sequential. First one bank decides to grant the loan or not, and if such bank declines to grant the loan, then the other bank can decide to grant the loan or not. To simplify the analysis, we assume that decisions are final, and that which bank is the first one to take the decision is random. For simplicity we assume that banks have all the bargaining power and set the maximum loan rate possible, which in our case is the pledgeable income Y.

We solve the problem by backwards induction. The bank that decides in second place, which without loss of generality we denote by subindex 2, will grant the loan as long as

$$Dx_2 \geq \frac{(1-(1-p)g)L+F}{p} - Y = D\bar{x}$$

The bank that decides in first place takes into account that if it decides not to grant the loan, the second bank will grant the loan as long as $x_2 > \bar{x}$. When $x_2 > \bar{x}$ we can show that there are circumstances in which the first bank will not grant the loan, as it would profit from the second bank being the one that incurs in the costs of granting the loan. This happens when

$$-L + p(Dx_1 + Y) - F + (1-p)gL \; < \; p(Dx_1),$$

which can be rewritten as

$$-L + pY - F + (1-p)gL \; < \; 0,$$

This states that, in such circumstances, the PGL is valuable for the bank because it also allows the bank to obtain previous debt, and without such previous debt the PGL would not be granted. In such circumstances we know that the first bank will grant the loan as long as $x_2 < \bar{x}$ and $x_1 > \bar{x}$. If on the other hand

$$-L + pY - F + (1-p)gL \; > \; 0,$$

the first bank will grant the loan as long as $x_1 > \bar{x}$.

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