Public-Guaranteed Loans, Bank Risk-Taking and Regulatory Capital Windfall*

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Abstract

We study the effect of public-guaranteed loans (PGLs) on bank risk-taking during the Covid-19 pandemic in France. The presence of guarantee schemes may foster riskier lending, pushing banks to lend to riskier borrowers or worsening incentives to prevent write-offs of loan applicants. Yet, we find that the partial government guarantee (between 70% and 90% of the loan) encouraged banks to lend according to their usual risk criteria so that the safest companies have obtained higher amounts of PGL. In addition, banks that were lowly capitalized and more exposed to non-performing loans (NPLs) before the pandemic granted higher amounts of PGLs, thereby using the guaranteed loan program to improve their financial position and reduce their risk-weighted assets (RWA) through a regulatory capital windfall effect. Finally, at the aggregate bank level, we find that PGLs had no impact on the overall credit risk of banks portfolio.

Keywords: Loan guarantees, bank lending, COVID-19 pandemic, credit risk

JEL codes: G18, G21, E63, H12, H81.

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1 Introduction

To cope with the economic crisis that followed the Covid-19 pandemic, many countries introduced public guarantees to loans granted to firms by the banking system (OECD, 2020). The idea behind these measures, which were not taken in isolation but were part of broader interventions, was to support economic activity, and especially businesses operating in sectors particularly hit by the crisis. Figure 1 shows that the French PGL scheme has been effective in supporting sectors particularly affected by the crisis. The contraction in demand for goods and services due to the virus containment measures could have had severe consequences both on the short-term health of businesses and on the supply of credit to firms suddenly perceived as vulnerable by the banking system because of the crisis (Acharya & Steffen, 2020; Eichenbaum et al., 2021). The failure of the latter, given the size of their sectors, could have weakened the entire banking sector and created a risk of financial instability. By transferring part of the risk of loss given default to the government, public-guaranteed loans (PGLs) can not only encourage banks to sustain lending but also prevent illiquid but solvent firms from going bankrupt, thereby reducing problems in the real and financial sectors.

However, PGLs could also have negative consequences for financial stability. Indeed, the presence of guarantee schemes may encourage riskier lending (De Blasio et al., 2018; Wilcox & Yasuda, 2019; Bachas et al., 2021) by pushing banks to lend to riskier borrowers (adverse selection) or by worsening incentives to prevent loan delinquency (moral hazard). This mechanism is likely to be more pronounced for banks with more skin in the game, i.e., those that had a riskier credit portfolio prior to the Covid-19 crisis and did not have enough capital to absorb these losses (Holmstrom & Tirole, 1997).

Banks had two main economic reasons for participating in the PGL program: on the one hand, banks can use PGLs to support their risky borrowers that are likely to default during the pandemic in order to avoid weakening their capital base (i.e. the so called "the risk-taking channel"). On the other hand, banks benefit from a reduction in their capital requirements as PGLs carry lower credit risk weights (e.g. zero in the case of the fully guaranteed loans). Hereafter, we will call this incentive "the risk-weighted asset channel". In both cases, PGLs act as a capital top-up that allows banks to either continue lending or to invest excess capital in other activities that are more profitable.

This paper investigates these two non-exclusive channels stemming from PGLs by studying the case of France between spring 2020 and spring 2022. The French case is particularly interesting because in the space of a few months, between March 2020 and the beginning of 2021, more than 100 billion euros of PGLs were issued (Figures 2 and 4). Using granular data on loans and their characteristics, combined with data on bank and firms balance sheets, we find that the French loan guarantee scheme did not favor bank risk-taking but instead reinforced banks' financial soundness thanks to its beneficial effect on regulatory capital. Indeed, the partial public guarantee encouraged banks to lend according to their usual risk criteria while improving their financial position by reducing their risk-weighted assets (RWA) through a regulatory windfall effect. Finding, isolating and quantifying this effect is one of the major contributions of this paper.

More specifically, we test three hypotheses to assess which channel is at work. Our first two hypotheses relate to the risk-taking channel: the first is whether PGLs were associated with higher credit risk, and the second is whether more fragile banks (less capitalized and/or with higher NPL ratios) took even more risk with PGLs. The last hypothesis we test is related to the risk-weighted asset (RWA) channel and aims to determine whether weaker banks provided higher amounts of PGLs, regardless of the firms' risk profile.

The empirical strategies we use and results we find are as follows. First, we run a probit regression on granular firm-bank level data to find out, at the extensive margin, which firm and bank characteristics are associated with a higher probability of obtaining a PGL. We find that banks with a higher probability of granting PGLs were larger and more profitable but also less capitalized, less liquid and had higher non-performing loans (NPLs) before the onset of the crisis. On the other hand, firms with a higher probability of obtaining a PGL were smaller and more financially fragile - in a word, riskier. This potentially problematic result in terms of bank risk-taking raises the question of whether banks maintained their standards for screening new loans (especially those to riskier firms), or whether they were more lax, encouraged by the public guarantee.

We deal with this issue by running a set of panel regressions in which we focus on the intensive margin, i.e. on bank, firm and loan characteristics that are correlated with higher PGL amounts. In this context, our identification is at the new loan level where the dependent variable is the amount of new credit granted. This allows us to isolate the effect of credit demand from that of credit supply. Using this set of regressions, we first find that PGLs amounts, were almost more than two and a half times higher than non-guaranteed loans. Second, the best capitalized and most profitable firms had higher amounts of PGLs which goes against the risk-taking channel hypothesis. Third, banks with lower capitalization and higher NPL ratios were the ones that granted higher amount of PGLs. Consistent with the risk-weighted asset channel, these results may suggest that banks with lower regulatory capital ratios prior to the crisis provided higher amounts of PGLs to reduce the risk weights on their assets. This intuition is confirmed by adding the common Equity Tier one ratio (CET1) in the regression. The CET1 turns out to have the same sign and significance as the bank capital ratio.

Yet, this result could raise concerns about banks' risk-taking: did the riskiest banks use PGLs to support firms already weakened in their credit portfolio in order to avoid defaults in their existing loan portfolios during the crisis? Using triple interactions between our

PGL dummy and our measures of firm and bank financial strength, we find that banks that were more exposed to non-performing loans before the crisis made smaller PGLs to risky firms, thus rejecting the risk-taking channel.

As a final step we assess the overall impact of PGLs on the riskiness of credit portfolio at the bank-level. Hinging on a dynamic panel model that enables us to control for bank-specific variables as well as past values of banks' risk measures (the default rate, the non-performing loan ratio and the share of firms whose survival is threatened in the bank's credit portfolio according to the Banque de France rating), we find that granting more PGLs did not have any impact on banks' risk-taking. In addition, banks that took more risk associated with PGLs were those that started with stronger financial statements before the crisis. These result are robust to all bank risk measures that we employ and are consistent with previous analyses conducted at the firm-bank level which contradict the risk-taking channel.

The rest of the paper is organized as follows: the next section discusses related literature in detail; section three presents the institutional setting and pattern of PGLs in France between 2020 and 2022; section four presents the mechanism we identify; in section five we present our datasets, and especially the European credit registry Anacredit; in section six we outline our three different empirical strategies; section seven presents our results; in the Conclusion, we outline some policy insights.

2 Related literature

Our work contributes to two distinct but related literature: first the effect of public guarantees on bank risk-taking, and second the role of public intervention in mitigating credit market frictions.

First, we add to the growing body of research on the effect of public guarantees on bank risk-taking. Prior studies have focused on public deposit guarantees and their potential reduction of market discipline, as creditors anticipate a bank's bailout and, therefore, have less incentive to monitor the bank's risk-taking (Merton, 1977; Flannery, 1998). For example, the small business loan guarantee program carried out in Japan in the late 1990s increased risk-taking and lowered the monitoring effort by banks and showed windfall gains for equity weak banks (Uesugi et al., 2010; Saito & Tsuruta, 2018; Yoshino & Taghizadeh-Hesary, 2019; Wilcox & Yasuda, 2019). In our different institutional setting where the French guarantee program did not ensure repayment of 100 percent of the loan balance contrary to the Japanes case, we do not find this pathological effect where least capitalized banks lend to safer counter-parties. Moreover, the granularity of our databases also enables us to study bank risk-taking from both the banks' perspective and at the new loan level between a firm and its bank.

Second, our paper diverges from recent empirical literature in its conclusions drawn from firm-level data. Studies like Gazaniol & Lê (2021) and Lelarge et al. (2010) have found that public guarantee schemes can increase access to external finance but also result in higher bankruptcy rates due to increased financial debt. Our research, however, demonstrates that French public-guaranteed loans (PGLs) do not lead to a significant increase in risk-taking. This contrast could be attributed to the differences in the guarantee schemes, methodologies, and economic contexts analyzed in these studies. For example, De Blasio et al. (2018) showed that guarantees provided by the Italian "Fondo di Garanzia" scheme between 2005 and 2012, increased the likelihood of firms defaulting on their loans. Similarly, Bachas et al. (2021) found that lenders in the United States shifted riskier loans to notches in the Small Business Administration (SBA) lending program, where the guarantee rate was higher. Our findings contribute to this literature by offering a different perspective on the relationship between PGLs and risk-taking behavior in the context of the Covid-19 pandemic.

Third, our paper contributes to the literature on how public intervention can efficiently alleviate credit market frictions and generate positive macroeconomic effects. PGLs have been employed as a tool to mitigate credit constraints since the 2007-08 financial crisis (Beck et al., 2010). When information asymmetries exist between borrowers and lenders, government intervention can result in a more efficient allocation of resources, even if the government possesses no informational advantage over the lenders (Mankiw, 1986; Philippon & Schnabl, 2013; Philippon, 2021). The rationale behind this is that without government intervention, credit rationing can occur, and government interventions could correct this market failure. Numerous empirical studies provide evidence of the beneficial effect of PGLs on credit supply (Zecchini & Ventura, 2009; Lelarge et al., 2010; Boschi et al., 2014; De Blasio et al., 2018; Bachas et al., 2021; Gazaniol & Lê, 2021). We expand on this literature by examining the profiles of firms and banks most involved in PGL programs and analyzing their impact on risk-taking behavior.

Lastly, our research contributes to the burgeoning literature on the effects of PGLs during the Covid-19 crisis (Core & De Marco, 2021; Cororaton & Rosen, 2021; Corredera-Catalán et al., 2021; Chodorow-Reich et al., 2022; Autor et al., 2022; Granja et al., 2022; Cascarino et al., 2022). The study most closely related to ours is by Altavilla et al. (2021), which uses the same database (AnaCredit) to investigate the substitution effect between publicly guaranteed and non-guaranteed loans during the pandemic across four European countries. They find that banks extending guaranteed loans reduced non-guaranteed credit by about 40% more than other banks lending to the same firm. We differ from them in two ways: first, we focus on bank risk-taking and the allocation of new credit rather than substitution, and second, we analyze the PGL scheme over two years, while their study covers only the initial months of the crisis.

Another related study is by Jiménez et al. (2022), which emphasizes the importance of relationship lending in the effectiveness of PGLs during the Covid-19 crisis, using granular loan-level information in Spain. They find that Spanish firms were more likely to obtain a PGL from banks with which they had larger pre-Covid credit exposures. In line with risk-taking behaviors, this effect is more pronounced for riskier firms and weaker banks - those having lower capital and higher nonperforming loans ex ante. We complement their analyses by investigating the risk-taking effect of PGLs at both the firm-bank and bank level in-depth . Consistent with Baena et al. (2022) and Cros et al. (2021), we find that French banks, encouraged by the partial public guarantee, did not relax the terms of their loans, indicating a more cautious approach to risk-taking during the pandemic.

3 The French loan guarantee scheme

As in many European countries, the design of the loan guarantee scheme in France followed the common features defined by the EU Commission Regulation No. 651/2014, although some details were determined by national rules. The EU Communication explicitly requested that banks use PGL to take risks: "The financial intermediary shall be able to demonstrate that it operates a mechanism that ensures that the advantages [of a public guarantee] are passed on to the largest extent possible to the final beneficiaries in the form of higher volumes of financing, riskier portfolios, lower collateral requirements, lower guarantee premiums or lower interest rates". The French PGL scheme, *Prêts Garantis par l'Etat* (PGE), was announced on March 16, 2020 in order to mitigate the negative economic effects stemming from the restrictive measures (lockdowns and business closures) decided by the French government to contain the Covid-19 pandemic.

The program became effective on March 23, 2020 and was originally to last until June 2021, but was extended four times and runs until December 2023. It was designed to support mainly small and medium-sized enterprises (SMEs). Figure 7 indicates that approximately 65% of the total volume of authorized PGLs was granted to SMEs. The public guarantee covered different shares of the loan depending on the size of the enterprise (see Table 1): while for SMEs , the coverage could reach 90% of the loan, the guarantee was only 70% for large entreprises[1]. It also mandated limits to the overall size of guaranteed loans: these could not exceed twice the annual wage bill of the beneficiary for 2019, or 25 % of total turnover of the beneficiary in 2019. The initial PGL budget was set up to 300 billion euros, about 12% of French GDP in 2019, of which 143 billion were made available immediately.

Regarding the cost of the loan, the interest rate applied to guaranteed loans could not exceed 0.25% or 0.5% annually, depending on the size of the firm. This rate was solely to cover the banks' cost of creating the loan[2]. Figure 6 presents the average interest rate charged on new loans between March 2020 and February 2022. The average interest rate on PGLs fluctuated exactly between these two figures during this period and the spread between the average rates applied to PGLs and non PGLs ranged between 1 and 1.5 percentage points. Firms that benefited from PGLs could not be required to make any repayment in the first year after the loan was granted. In January 2021, this deadline was extended for an additional year. After these first two potential years, the term of the PGLs could be extended to a maximum of six years in total, with rates ranging from 1% to 2.5% depending on the term, which was a one-sided decision from the firm. Each PGL request was checked, given a unique token and was recorded by the French public investment bank Bpifrance[3]. In practice, almost all applications were validated by Bpifrance[4]. The estimated

[1] Note that given the high turnover threshold associated with the 90% guarantee, almost all French firms were able to benefit from this guarantee.

[2] Each firm also had to pay a commission between .25 and 2% to the French government.

[3] Bpifrance is jointly owned by two public entities: the Caisse des dépôts et consignations and EPIC BPI-Groupe, both wholly owned by the French State. Bpifrance finances and promotes the development of companies operating in France.

[4] The purpose of the validation was to ensure that no company would obtain multiple PGLs and exceed its maximum threshold.

PGL rejection rate by banks was 2.9%, a percentage in line with that of pre-crisis rejection rates[5].

4 Conceptual framework

In this section, we distinguish the two possible economic incentives that may have led French banks to participate in the PGL program. We refer to the first as the "risk-taking channel" and the second as the "risk-weighted asset channel". In the first case, weaker banks (less capitalized or/and with higher NPLs) provide more PGLs to their riskier counterparties that are likely to default in order to avoid weakening their capital base. In the second case, as with non-guaranteed loans, banks provide more PGLs to healthy firms so as to reduce their risk-weighted assets to release some regulatory capital, which might be crucial in times of uncertainty.

4 .1 Public-guaranteed loans and regulatory capital windfall

Under Basel III requirements, banks must meet various capital requirements (Tier 1, CET1, etc.). Equity capital must represent a predetermined fraction of risk-weighted assets (RWA), which varies according to the type of capital. For example, the ratio of Common Equity Tier 1 (CET1) must be at least 4.5%. Common Equity Tier 1 represent the highest quality of regulatory capital, as it absorbs losses immediately when they occur. This minimum percentage can also be increased depending on the bank's risk profile. The bank's asset items enter the denominator of this ratio with different weights reflecting each item riskiness. For example, currency and reserves held at the central bank have a weight of 0%. Other assets have weights above 0% (10%, 15%, 50%, 65%, etc., depending on the type

[5] For more details: https://www.ccomptes.fr/system/files/2022-07/20220725-rapport-prets-garantis-par-Etat.pdf

and risk of the asset). Loans or investments considered particularly risky have a weight of 100% or more.

During the PGL negotiations, the French banks obtained that the part of the loan guaranteed by the government (90, 80 or 70% depending on the firm's turnover, as mentioned above) benefits from a credit risk weight of zero. Therefore, only the remaining non-guaranteed portion of these loans contributes to the denominator of the CET1/RWA ratio. Figure 10 explains the mechanism involved.

By making public-guaranteed loans instead of non-guaranteed loans, for a given level of CET1 ratio, banks can lend a higher nominal volume of loans. A second-round capital windfall effect that some bank supervisor mentioned was that granting PGLs to a given counter-party would mechanically reduce its perceived riskiness as most internal risk models would not be sensitive to the limited macroeconomic shock experienced during the COVID-19 in France. This would significantly reduce the RWA even for existing non-guaranteed loan volumes in the banks portfolios. As the first and second-round effects cannot be distinguished in our supervisory data, for lack of granular information on internal risk weighing, we consider both as our main regulatory capital windfall effect, and we can identify this effect when banks with lower CET1 ratios would grant proportionally more PGLs to improve the risk-weighted density of their assets. Two additional windfall effects are worth mentioning for future studies. First, in case of substitution of maturing non-guaranteed loans by PGLs, part of the bank's regulatory capital has been freed up. This additional capital can either be used to take on more risk or to strengthen its financial soundness. Lastly, if the interest rates were end up higher than the cost of risk, the PGLs can have been used to improve bank asset profitability.

4 .2 Testable predictions

Two mechanisms may have led to this release of capital. The first mechanism is what we call the risk-taking channel. In this scenario, banks, especially the most fragile ones, used PGLs to support their low-quality creditors. The latter could have failed in times of crisis, causing problems for their banks. These failures could have led to negative medium-term consequences for financial stability, since PGLs are not fully guaranteed by the French government (i.e., the minimum 10 percent must be borne by the banks). On the other hand, since the French government has guaranteed between 70 and 90 percent of the loans made by the private banking sector, the presence of guarantee schemes may encourage riskier loans (De Blasio et al., 2018; Wilcox & Yasuda, 2019; Bachas et al., 2021) by pushing banks to lend to riskier borrowers (adverse selection) or by worsening incentives to prevent loan defaults (moral hazard). This effect is likely to be stronger for weaker banks, i.e., those that are less capitalized and have more NPL (Holmstrom & Tirole, 1997). Consequently, two hypotheses can be tested to see whether the risk-taking channel is at work:

(H1) *PGLs are associated with higher credit risks.*

(H2) *Banks that are less capitalized and/or have higher NPLs have taken on even more risk with PGLs.*

The last hypothesis refers to the risk-weighed assets channel. In this scenario, banks, particularly those with lower regulatory capital ratios prior to the pandemic (i.e., weakly capitalized or/and with higher NPLs), provided more PGLs through the regulatory windfall effect explained above. An extensive theoretical (Koehn & Santomero, 1980; Rochet, 1992; Furlong & Keeley, 1989; Jeitschko & Jeung, 2005) and empirical (Shrieves & Dahl, 1992; Berger, 1995; Fraisse et al., 2020; Juelsrud & Wold, 2020) literature has studied the impact of capital requirements on the behavior of banks, and in particular on the reallocation of their assets. This literature has mainly focused on the increase in capital requirements induced by the increase in the share of capital on risk-weighted assets (i.e. the numerator). In contrast, the risk-weighted asset channel leads to an increase in the regulatory capital ratio through a decrease in risk-weighted assets (i.e. the denominator). Against this background, the last hypothesis to be tested is the following:

(H3) *Banks that were less capitalized and/or had higher NPLs have granted higher PGLs amounts.*

The solid line in figure 11 shows the evolution of the CET1 capital ratio (CET1 capital / RWA) for French banks between the end of 2017 and March 2022. Since March 2020 (i.e. the introduction of the PGL program), this ratio has been steadily increasing. Over the same period, CET1 capital for the same banks did not increase but fluctuated around the pre-crisis level (dotted line). If capital has remained constant, it is the denominator of the ratio that has decreased. In other words, on average, the risky assets in the portfolios of French banks have decreased. This means that the released capital has not yet been reinvested, but served as an additional buffer in 2022. It is important to note that the increase in this ratio, at least in the initial phase (March 2020-September 2021), may also be due to the ban on dividend payments that has been imposed on banks by the European Central Bank (ECB). In Section 7 , we test our different hypotheses to understand which channel was at play during the COVID-19 crisis.

5 Data

We draw on five different databases provided by the Banque de France (BDF), the French banking supervisor (ACPR) and the European central bank (ECB). The definitions of the variables of interest are presented in Table 2.

5 .1 Loan-level variables

Core data come from the AnaCredit[6] database (*Analytical Credit Dataset*), a proprietary and confidential database of the ECB which begins in September 2018. AnaCredit is a database that reports loan-level attributes on a monthly frequency in a harmonised way across all euro area countries. Each loan is uniquely identified by instrument, contract, debtor and creditor identifiers, which allows us to detect new loans with all their characteristics (outstanding amount, maturity, type of instrument, interest rate, collateral). For each country participating in the construction of the database, the minimum reporting threshold is 25,000 euros, to be calculated at the bank-firm relationship level and not at the individual loan level. AnaCredit covers a comprehensive set of credit instruments: overdrafts, revolving credit, credit lines, reverse repurchase agreements and other loans, including term loans.[7]

This database improves the level of information stemming from national credit registers that were already collected at country-level by several euro area members. For instance, since 2006 the French credit register has gathered monthly data on credit exposures of all banks operating in France to all firms whose total credit exposure is higher than €25,000.[8] Yet, it is not a loan-level database and granular information on new loans is not available. Overall, around 25 million individual loans are reported monthly, granted by around 7,000 individual credit institutions to approximately 5 million of individual debtors. To ensure the representativeness of AnaCredit we perform a data quality check using bank balance sheet items (BSI) collected by the Banque de France. Figure 3, which provides a comparison of the outstanding amount of credit to non-financial corporations (NFC) between the Banque

[6] An extensive description of AnaCredit is available in the AnaCredit reporting manuals: `https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html`

[7] The complete list of instruments also includes credit card debt, trade receivables, financial leases as well as well as deposits other than reverse repurchase agreements.

[8] Note that before 2006, this threshold was €75,000.

de France (BSI) and Anacredit indicates that the latter represents on average 80% of total credit to NFC.

Importantly for our analysis, among the attributes collected for each loan, there is extensive information on the protection securing the bank's credit exposure. We take advantage on those provided by government entities to identify PGL. Indeed, in France special identifiers were introduced to mark guarantee schemes provided by the government during the pandemic[9] and the protection identifier includes "PGE" (Prêt garanti par l'Etat). Selecting loans related to public guarantees in AnaCredit, Figure 2 shows that we capture almost 90% of the outstanding credit as reported by the European Banking Authority (EBA).[10]

In our analysis, we restrict our sample to new loans granted to NFC[11] from March 27th 2020 (the starting date of PGL in France) until February 28th 2022. In this regard, we consider the total commitment of the bank to the debtor with respect to an instrument (i.e. the drawn and the undrawn part of credit) and we focus on investment credit and credit line[12] which represent 99% of observations related to PGL in AnaCredit. Over our observation period, half of enterprises ask for at least two loans (see Figure 9 for more details about the distribution of the number of new loans per firm).

9 More precisely, we consider loans to be PGL whether the protection provider identifier is "FR130019763" (Ministère de l'Action et des Comptes Publics) or "FR100000017" (République Française)

10 For more details on the EBA reporting: `https://www.eba.europa.eu/regulation-and-policy/supervisory-reporting/guidelines-covid-19-measures-reporting-and-disclosure`.

11 The associated institutional sectors is "S 11".

12 To be specific, we select the instruments type 1002 and 1004, which are described in the manual as credit line and "loans other than overdrafts, convenience credit, extended credit, credit card credit, revolving credit other than credit card credit, reverse repurchase agreements, trade receivables and financial leases".

5 .2 Firm-level variables

We first match the AnaCredit dataset with firms' balance sheet information coming from the FIBEN (Fichier bancaire des entreprises) database, which gathers balance sheet data on all companies with a turnover of over EUR 750,000 since 1990. Based on fiscal documents, firm's information is yearly collected by the Banque de France at the legal entity level (non-consolidated), through a unique national identifier called SIREN. Each year, this dataset contains individual company accounts for 250,000 firms. These firms represent a third of all companies taxed under the "bénéfice industriel et commercial" or "bénéfice réel normal" regimes (Kremp & Sevestre, 2013). The database thus covers a large share of the French economy.[13] Above all, a great advantage of FIBEN is that it enables us to focus on non-listed SMEs that are often neglected by American studies based on the Compustat database [14]In this regard, 95% of firms in the database can be considered as SMEs with respect to the European definition based on the number of employees (less than 250), the turnover (less than EUR 50 million) and total assets (less than EUR 43 million). Firms whose balance sheet and interest rate variables are incomplete are excluded from the original sample. To account for observable firm heterogeneities, we rely on a traditional set of financial indicators such as profitability (i.e. the ratio of cash flow over total assets of the firm), liquidity (i.e. the ratio of cash over total assets of the firm), solvency (i.e. the ratio of own funds over total assets of the firm) and variables that typically proxy for the presence of asymmetric information (i.e. the size and the age of the firm).[15]

The FIBEN database also includes the in-house credit assessments of individual firms computed by the Banque de France. These credit ratings are one of the four in-house credit assessment systems (ICAS) validated by the Eurosystem, which means that the

[13] Note that the dataset is composed of 18% of observations coming from industry, 12% from construction, 52% from trade, 13% from services and 5% from other sectors.

[14] .

[15] To minimize the effect of gross outliers, we winsorize variables at the first and 99th percentile.

Eurosystem can rely on them when assessing the credit quality of eligible credit claims within its collateral framework. The Banque de France assigns a full-scale rating to firms which are monitored in FIBEN on a yearly basis. The rating reflects the overall assessment of a firm's ability to meet its financial commitments at a 3-year horizon. The rating has two components: a turnover rating and a credit rating which ranks the company on a credit risk scale. Regarding the latter, there are 12 credit rating positions (3 ++, 3+, 3, 4+, 4, 5+, 5, 6, 7, 8, 9, and P), from the most favorable (3 ++) to the least favorable (P, which stands for a formal bankruptcy). According to the Banque de France [16], a firm with rating of 4 "has an acceptable capacity to fulfill its financial commitments, but shows some elements of weakness or uncertainty" (because, e.g., of business or capital links with weak firms, or a somewhat weakened solvency or liquidity position of its own). In our analysis, we then create a dummy variable *investment grade* that takes the value 1 whether the firm has a credit rating higher than 4 and 0 otherwise.

5 .3 Bank-level variables

Afterwards, we match the database with the French unified reporting system for financial institutions (SURFI) to assess how the strength of a bank's balance sheet is related to the amount of credit granted. The bank level database contains financial statements at the non-consolidated level on all commercial and cooperative banks in France. Our sample ends up containing 128 banks that belong to 21 different banking groups, representing 60% of corporate credit in Q1 2020. Following the bank balance sheet channel thesis, we control for the heterogeneous bank response to an unexpected adverse shock. We look at traditional indicators of bank financial strength, such as solvency (i.e. bank equity over total assets of the bank), liquidity (i.e. the sum of securities, balance with the central bank,

[16] Available (in French) at www.fiben.fr.

loans and advances to credit institutions and repurchase agreements over total assets of the bank), non-performing-loans and bank size (Kashyap & Stein, 2000; Jiménez et al., 2012). In addition, we also control for capital requirements at the banking group level using the CET1 ratio. This variable is calculated as the ratio of Common Equity Tier 1 over its risk-weighted assets (RWA). The source of this data is the COREP reporting (COmmon solvency ratio REPorting), which reports the solvency ratios of European banks to national and European supervisors.

5 .4 Relationship lending variables

To capture the different channels through which relationship lending affects the credit supply, two proxies are used. The first one comes from the French national credit register which gathers data on credit exposures of all banks operating in France to all firms whose total credit exposure is greater than €25,000. Our credit register starts in 1998. We compute the relationship length to capture the ability of lenders to accumulate soft information about their borrowers (Boot & Thakor, 2000). The longer the relationship, the more precise the lenders' knowledge of borrowers' credit risk. Throughout our analysis, the variable duration corresponds to the elapsed time between the first relationship established between a firm and a bank and the last one. The second variable corresponds to the structure of information available to lenders. Like the length of the relationship, single-banking has sometimes been used as a relationship lending measure in the seminal literature (Petersen & Rajan, 1994). Indeed, banks holding a larger share of credit have better access to information about the borrower (Elsas, 2005). Thus, we consider a firm to be a single-bank firm if it has had a relationship with only one bank since the starting date of the French Credit Register. Consequently, the dummy *single-bank* takes the value of 0 if a firm has had two different relationships in the past, and remains the same even if the firm temporarily borrows from only one bank thereafter.

5 .5 Bank market power variable

Finally, to gauge the effect of bank market power on loan granting, we follow Nicolas (2021) and compute a consolidated Herfindahl-Hirschman Index (HHI) on a quarterly basis using the *Centralisation Financière Territoriale* (CEFIT) dataset. This original dataset, which covers the 13 French regions, collects monthly information on loans and deposits for each individual bank at the regional level. Interestingly, CEFIT contains breakdowns by types of borrowers which enables us to collect data on corporate credit only. This HHI corresponds to the sum of the squared market shares of all banking groups at the regional level.

6 Empirical strategy

To assess the effects of PGL on bank risk-taking we take advantage of alternative empirical methodologies that are articulated among three main questions. The first part of our analysis seeks to know what kind of firms and banks benefited from the PGL mechanism. For instance, is access to PGL driven by riskier firms and financially weaker banks? The second part investigates which characteristics of banks and firms increase the amount of loan granted. In other words, do PGLs change the distribution of new credit to risky firms and, if so, do weaker banks contribute more? Finally, the third part departs from the previous granular analyses and focuses only on banks to answer the following question: do banks that grant more PGLs increase their overall credit risk?

6 .1 Access to PGL : a probit model

We first focus on the extensive margin of PGL by estimating the probability of firms to obtain at least one PGL between March 2020 and February 2022 as a function of their financial situation, the financial situation of their bank and the relationship they have with the latter. In particular, we consider solvency, liquidity, and profitability measures, and we control for other possible determinants like region and sector specific effects as well as the size and the age of the firm. These variables are traditionally used in the literature on determinants of financial constraints(Jiménez et al., 2012; Ferrando & Mulier, 2015; Nicolas, 2022). Importantly, in each of our empirical analyses, we take the value of our covariates in December 2019, before the outbreak of the COVID-19 crisis, in order to clearly distinguish the effect of these variables from the effect of PGL that may have artificially increased the financial strength of firms through, for example, greater liquidity. The specification that we estimate is at the firm-bank level:

$$APGL_{ib} = \beta_1 F_{Q4-2019} + \beta_2 B_{Q4-2019} + \beta_3 R_{Q4-2019} + \beta_4 HHI_{Q4-2019} + \eta_s + \eta_r + \epsilon_{ibr} \quad (1)$$

Where $APGL_{ib}$ is a dummy variable which takes the value 1 if firm i has obtained at least one PGL from the bank b over the period Q2/2020-Q2/2022; F and B are matrices of firm and bank characteristics, respectively, accounting for financial soundness; R is a matrix of relationship variables and *HHI* is the Herfindhal-Hirchmann index, a measure of bank market power that is computed at the banking group level. We finally introduce sector fixed effects η_s and region fixed effects η_r to control for time-invariant heterogeneity among regions and sectors and ϵ_{ibr} is the error term.

In this specification, we capture whether a firms have asked for a loan to a bank during this particular time period. We first identify all firm-bank pairs in the AnaCredit database in terms of new financing transactions granted between March 2020 and February 2022. This database includes 134 banks and around 99,916 firms representing 140,901 observations. Table 3 presents summary statistics of the main regression variables in the extensive margin analysis. Overall, almost 30% of firms have received a PGL during the analyzed period and 35% belong to sectors than can be considered as severely affected by the pandemic (i.e. sectors with a negative growth rate of turnover between December 2019 and December 2020).

6 .2 New credit allocation: a fixed effect model

Second, we look at the intensive margin, that is, whether higher amounts of guaranteed loans are related to higher risk-taking by banks. Following Beatriz et al. (2018), we use a panel data structure[17] on new loans using firm and bank fixed effects in our linear regressions to control for time-invariant unobserved heterogeneity[18]. As a result, the second specification that we estimate is at the new-loan-level:

$$LN(CREDIT)_{ibrt} = \beta_1 PGL_{ibt} + \beta_2 L_{ibt} + \beta_3 R_{Q4-2019} + \beta_4 HHI_{irt} + \eta_i + \eta_b + \epsilon_{ibrt} \quad (2)$$

where PGL_{ibt} is a dummy that takes value 1 if the loan that firm i obtained from bank b in month t is guaranteed by the government, 0 otherwise. $LN(CREDIT)_{ibt}$ is the log of the total new credit amount (drawn and undrawn) granted by bank b to firm i located in region r at time t. L and R are respectively matrices of loan and relationship lending controls while HHI is the Herfindhal-Hirchmann index a measure of bank market power

[17] Note that as there may be several credits from the same firm with the same bank each month, we randomly select one new loan from all these new credits. We challenge this selection process in the section 7 .4.

[18] Note that, contrary to the use of the within-firm estimator in the seminal work of Khwaja & Mian (2008), our fixed effects methodology does not control for all observed and unobserved time-varying firm heterogeneity.

that is computed at the banking group level. Finally, η_i, η_b are respectively firm, bank fixed effects and ϵ_{jbr} is the error term. Standard errors are clustered at the firm and bank level.

In this specification, as our firm- and bank-specific variables do not vary across time (we take their values at the end of 2019), they are collinear with our firm and bank fixed effects. Yet, we also investigate the heterogeneity of our results by taking into account the risk of the firm or the financial soundness of the bank. To test our different hypotheses related to the risk-taking and the risk-weighted assets channels, we estimate both two-way and three-way interactions between our PGL dummy and our measures of firm and bank financial soundness.

We construct a database based on the same previous sample period. For each amount of new loans granted, we distinguish whether the loan is a PGL or not. Merging this loan-level database with firm and bank characteristics as well as relationship lending variables, we end up with 182,757 observations, composed of 129 banks and 43,294 firms. Table 4 provides summary statistics of this new database. The new loan amount has an average value of 515,517 euros with a median of around 100,000 euros. Finally, the average maturity is 3.5 years and 15.2% of new loans are PGLs.

6 .3 A dynamic panel model of bank risk-taking

Aside of the granular analyses at the firm-bank level, one should wonder what is the overall impact of PGL on the riskiness of credit portfolio at the bank-level. To address this issue, we rely on a final panel of 96 banks representing 576 observations and 60% of corporate credit in March 2020. Since lagged values of risk measures are likely to determine, at least partially, the current level of risk taking of a given bank, we consider a dynamic panel model that can be represented by the following equation:

$$RISK_{bt} = \alpha_1 RISK_{bt-1} + \alpha_2 PGLR_{bt-1} + \alpha_3 CONTROLS_{bt-1} + \upsilon_b + \upsilon_t + \epsilon_{bt} \qquad (3)$$

Where $RISK_{bt}$ denotes our indicators of banks' risk and $RISK_{bt-1}$ their past values. Hinging on the AnaCredit database we use two different measures as indicators of a bank's risk. [19] For each bank and month, our first measure is the average default rate of the bank's credit portfolio,[20] while our second measure is the average non-performing loan ratio of the bank's credit portfolio.[21] We compute these two measures for each firm-bank pair and then weight them according to each firm's share in the total amount of credit granted by the bank. Considering that PGLs may have affected these measures through the increase of firm liquidity, we set the risk measures of each firm-bank pair in December 2019 and apply them over the whole sample period.

As for the other variables, $PGLR_{bt-1}$ is the ratio of public-guaranteed loans over total credit of the bank; $CONTROLS_{bt-1}$ is a matrix of bank controls that may affect banks' risk-taking such as the total assets of the bank, its capital ratio, its liquidity ratio, its non-performing loan ratio and its return on assets; υ_b is a bank-specific fixed effect; υ_t is a quarter-specific fixed effects and ϵ_{bt} is the idiosyncratic error term. The subscript b indexes banks while t indexes month, where t=2020:09-2022:03. Table 5 shows descriptive statistics of the above variables.

With such a model both the pooled and fixed effects estimators are likely to suffer from a dynamic panel bias (Nickell, 1981). We implement a dynamic panel methodology that

[19] Note that, for each firm, the granularity of AnaCredit enables us obtain the probability of default, the default rate and the amount of non-performing loans computed by its banks.

[20] Note that loans considered to be in default fall into one of the following three categories : i) default because unlikely to pay; ii) default because more than 90/180 days past due; iii) default because both unlikely to pay and more than 90/180 days past due (ECB (2019)).

[21] According to the European Central Bank, non-performing loans are those "instruments classified as non-performing in accordance with the definition of the amended ITS" (ECB (2019)).

relies on the Generalized-Method of Moments (GMM) following Arellano & Bover (1995) and Blundell & Bond (1998) and refined by (Roodman, 2009). This GMM estimator is called the system-GMM estimator since it combines the regression in differences with the regression in levels within a system.[22] The instruments for the equation in differences are the lagged exogenous variables (the environmental controls) and the lagged values of the potential endogenous variables. The instruments for the equation in levels are the lagged differences of the corresponding variables.[23] In this framework, exogenous time dummies are instrumented by themselves. These are appropriate instruments under the following additional assumption: although there may be correlation between the levels of the right-hand side variables, there is no correlation between the differences of these variables and the firm-specific effect.

The GMM panel estimator relies on first-differencing the estimating equation to eliminate the firm-specific fixed effect, and uses appropriate lags of the right-hand side variables as instruments. As can be seen from the following equation, first-differencing allows us to eliminate the firm-specific effect υ_i. More specifically, we can rewrite a more general version of Equation 3 as follows::

$$Y_{bt} - Y_{bt-1} = \alpha(Y_{bt-1} - Y_{bt-2}) + \beta'(X_{bt-1} - X_{bt-2}) \tag{4}$$

$$+(\upsilon_t - \upsilon_{t-1}) + (\epsilon_{bt} - \epsilon_{bt-1})$$

Where Y is one of our measures of bank risk, and X, our set of control variables and

[22] In dynamic panel data where the observations are highly autoregressive an the number of time series is small, the standard GMM estimator has been found to have large finite sample bias and poor precision in simulation studies. The weak performance of the standard GMM panel data estimator is also frequent in relatively short panels with highly persistent data where lagged endogenous variables are weak instruments. Hence, the system-GMM estimator improves the performances of the standard GMM (Blundell et al., 2001).

[23] Estimation is implemented in Stata using Roodman's xtabond2 package, see Roodman (2009) for more detail.

the ratio of public-guaranteed loans over total credit of the bank; υ_b denotes a bank specific component (encompassing the bank unobserved time-invariant heterogeneity); υ_t represents a time-specific component (that we account for by including time dummies in all my specifications); and ϵ_{bt} is an idiosyncratic component.

The use of appropriate instruments is necessary to deal with the likely endogeneity of the explanatory variables, and also to deal with the fact that the new error term $\epsilon_{bt} - \epsilon_{bt-1}$ is correlated with the lagged dependent variable. Consistency of the GMM estimates depends on the validity of the instruments. We test for the validity of our instruments by using two tests suggested by Arellano & Bond (1991): the J-test and the test for second-order serial correlation of the residuals (m2).[24] Table5 presents the summary statistics of this last database. Regarding our measures of bank risk, loans in default and non-performing loans represent respectively 2.1% and 2.6% of the credit portfolio of the banks in our sample.

7 Results

7 .1 Is access to PGLs driven by riskier firms and financially weaker banks?

In this section we report our results with respect to the extensive margin of PGLs. The purpose of this analysis is to find which bank and enterprise characteristics are associated with higher access to PGLs (APGLs). Our main findings are twofold. Firms with higher probability of obtaining a PGL were smaller and more financially fragile than average. For their part, banks with higher probability of granting PGLs were larger and more profitable but also less capitalized and had higher NPLs before the pandemic. Table 6 reports the

[24] The former is the Sargan test for overidentifying restrictions, asymptotically distributed as a χ^2 with degrees of freedom equal to the number of instruments less the number of parameters, under the null of instrument validity. The m2 test is asymptotically distributed as a standard normal under the null of no second-order serial correlation, and provides a further check on the specification of the model and on the legitimacy of variables dated t-2 as instruments.

coefficients obtained by running Equation 1 on our dataset. We present the marginal effects at the means, so as to facilitate interpretation of the results.

Firstly, firms that were part of an economic sector particularly affected by the pandemic (such as restaurants, construction and retail trade) had a higher probability of obtaining a loan than other businesses. We measure the sector sensitivity to the pandemic by its average value-added growth rate between December 2019 (before COVID and the PGL mechanism) and December 2020. The 1.6% value can be interpreted as follows: for firms in an industry whose value-added growth rate between 2019 and 2020 was 4.93% (one unit below the average for all industries of 5.93%), the probability of obtaining a PGL was 1.6% higher than average. The other quantitatively large effect affecting firms concerns their size. The smaller the enterprise, the greater the likelihood of obtaining a guaranteed loan. More specifically, a firm with total assets of 260 thousand euros lower than the average benefited from a 4% higher probability of obtaining a PGL.

Looking at the other statistically significant effects, firms benefiting from the PGL mechanism were less capitalized (if the capital ratio decreases by one percentage point, the probability of obtaining a PGL increases by 0.1%), less liquid (cash ratio lower by one point results in a 0.3% higher probability of obtaining a guaranteed loan), less profitable (a ROA higher by one point results in a 0.3% lower probability of obtaining a loan), and younger (marginal effect at the mean is 0.1%). These results show that PGLs actually benefited the firms that needed the loans the most, and would have had less access to credit in the absence of the program (Jiménez et al., 2012; Ferrando & Mulier, 2015).

Regarding the relationship lending and credit market controls, all coefficients are negative and statistically significant. The negative coefficient associated with the duration variable means that bank-firm pairs with a longer duration credit relationship have lower access to PGLs. One possible explanation is that banks prefer to be protected by the public guarantee for firms they know less about, in other words, with which they have a shorter credit relationship. The negative coefficient associated with the single-bank variable means that multiple-bank firms were 12% more likely to obtain a PGL. This shows that diversification of borrowing may mitigate the volatility of credit supply during a crisis (Detragiache et al., 2000). Finally, the negative coefficient of the Herfindahl index goes in the same direction. The higher at the regional level the market share of the banking group that provided the loan, the lesser the chance the firm has of obtaining a guaranteed loan from another bank or banking group.

Finally, let's look at the factors that increase the likelihood of a bank making a PGL. Lenders more likely to grant a PGL were on average larger (a bank with above-average total assets of 90 billion euros was 1.1 % more likely to grant a guaranteed loan) and more profitable. This result is in line with the findings of Altavilla et al. (2021), according to which in the major euro area countries, government-guaranteed loans were mainly offered by large banks. However, the other results point in the opposite direction. In particular, higher access to PGLs is associated with banks that are less capitalized, less liquid, and have higher NPLs.

These results could be a cause for concern, especially when compared to the results for firms. In fact, two possible interpretations can be used. On the one hand, firms that can be considered riskier prior to the pandemic were more likely to obtain a PGL, which is consistent with the effectiveness of the PGL program that was designed to prevent the failure of firms that needed financing the most. On the other hand, following the risk-taking channel, one might ask whether access to credit for riskier firms undermined the credit portfolio of banks with higher risk-taking. This would be especially true if banks who granted higher PGLs amounts to riskier firms were less capitalized and/or had a higher ratio of non-performing loans before the crisis. To address this issue, it is particularly important to be able to give an interpretation of the supply-side effects of PGLs. For this reason, we will focus on the intensive margin of PGLs in the next section.

7 .2 Do PGLs increase the amount of new lending to risky firms for the most financially fragile banks?

In this section we deal with the intensive margin, i.e. the different characteristics of firms, banks, loans, and firm-bank relationships, that explain a higher loan amount of new credit. Our main results can be summarized as follows. First, public-guaranteed loans were on average almost two and a half times higher than non-guaranteed loans. Second, while at the extensive margin the firms with the easiest access to PGLs were the most fragile ones, at the intensive margin, the opposite is true: bigger, older and more profitable firms have obtained higher PGL amounts. Third, banks that were less capitalized and had higher NPL ratios before the COVID-19 crisis have granted higher PGLs amounts. Yet, banks that were more exposed to non-performing loans before the crisis made smaller PGLs to risky firms, thus rejecting the risk-taking channel. Consistent with the risk-weighted asset channel, these results may suggest that banks with lower regulatory capital ratios prior to the crisis provided higher amounts of PGLs to reduce the risk weight on their assets.

Column 1 of Table 7 reports estimates obtained by running Equation 2, a fixed-effects panel regression at the new-loan-level, on our dataset. In this regression we introduce firm fixed effects to control for time unvarying unobserved heterogeneity, bank fixed effects to take into account differences in the supply of credit that are bank-specific, as well as month fixed effects to account for month-specific variations in the distribution of new credit. The main result to note here is that the PGL dummy, which indicates whether the new loan is guaranteed by the government, has a magnitude of 1.373. This means that, *ceteris paribus*, PGLs are almost two and a half times higher than other loans.

As our firm- and bank-specific variables are collinear with our firm and bank fixed effects (i.e. they do not vary since we take their values at the end of 2019), in column (2) of Table 7 we remove bank and firm fixed effects in order to observe the relationships between our bank-specific and firm-specific variables and the loan amount received. While the coefficient of our PGL dummy remains significant and within the same range, we find than larger and more profitable firms obtained higher new loan amounts (PGL and non-PGL). Furthermore, banks that granted higher loan amounts were on average more capitalized, more profitable and had lower NPL ratios. These results are intuitive and confirm the existing literature on the determinants of firms' access to finance (Jiménez et al., 2012, 2014; Ferrando & Mulier, 2015).

Thereafter, we focus on the profile of firms that benefited more from PGLs. To address this issue, we run a panel regression equivalent to the previous one (Column (1) of Table 7) but this time we introduce firm-specific variables that capture firms' riskiness and make them interact with our PGL dummy to assess their differential impact according to public-guaranteed nature of the loan.[25] Importantly, the main results in Column (1) of Table 8 are opposite to those we found for the extensive margin: firms that were better capitalized, more liquid, more profitable, and older have obtained higher amounts of PGLs. Alternatively, in Column (2) of Table 8, we include a variable summarizing the Banque de France rating as regressor and we interact it with our PGL dummy. The variable *investment grade* described in section 5 , represents the evaluation of the quality of a firm calculated by the Banque de France on the basis of its balance sheet and income statement. In this regression, the variable *Investment grade* takes value 1 if the firm is considered as financially sound (i.e. the firm has an excellent ability to meet its three-year financial commitments) or 0 otherwise.

[25] As all our firm variables are from December 2019, it is important to consider that the main effects of our firm-specific variables are collinear with firm fixed effects and are therefore omitted from the regression results.

The coefficient of 0.288 presented in Column (2) is significant and goes in the same direction as the coefficients shown in Column (1). Being creditworthy from the point of view of the Banque de France increased the amount of PGLs granted by 29%. Taken together, these findings lead us to reject H1.

Turning to banks heterogeneity, we now look at the profile of banks that granted higher PGL amounts. To answer this question, we run a regression equivalent to that estimated through equation 2, in which we introduce bank-specific variables and make them interact with our PGL dummy to assess their differential impact on the amount of PGL granted.[26] Column (1) of Table 9 presents the results. Two coefficients are particularly interesting: the interaction coefficient between the PGL variable and the capital ratio, and the interaction coefficient between the PGL variable and the NPL ratio.

Let us first focus on the coefficient of the interaction between the PGL dummy and the capital ratio. This coefficient can be interpreted as follows: when considering two PGLs, on average, the amount of PGLs granted by banks with a capital ratio one percentage point higher is lower by 8.4%. Importantly, this result is confirmed when we change the specification slightly and add the CET1 ratio as a control, calculated as the ratio of Common Equity Tier 1 over risk-weighted assets of the bank, as of 31/12/2019. Since this ratio is calculated at the banking group level, and not at the individual institution level, we replace bank fixed effects with banking group fixed effects in this specification. Column (2) presents the results of this regression: the interaction coefficient between the PGL dummy and the CET1 ratio is negative and statistically significant. In other words, banks that had a lower CET1 ratio before the crisis granted higher PGLs amount, and vice versa. Both specifications therefore say that less capitalized banks are associated with higher amounts of guaranteed loans. Considering the interaction coefficient between the PGL dummy and the

[26] As above, note that the main effects of our bank-specific variables are collinear with bank fixed effects and are therefore omitted from the regression results.

ratio of non-performing loans, we find that PGLs granted by banks with a one percentage point higher NPL ratio are 51.8% higher than other PGLs.

These results may have two distinct meanings. Either the particularly risky banks took advantage of the PGLs to increase their lending to the riskiest firms, thereby increasing their risk-taking, or these banks lent more to less risky firms, as is the case for non-guaranteed loans, while using the PGLs to reduce the risk weight of their assets. To discriminate between these two possible channels and understand what mechanism is at work, we introduce triple interaction terms between our PGL dummy, the *investment grade* dummy and bank controls.

The results are presented in Table 10. Interestingly, we find no significant triple interaction term, with the exception of the triple interaction between PGL, Investment grade and NPLR which is positive. This coefficient should be interpreted in relation to the coefficient of the simple interaction between PGL and NPLR (0.662). Consider two PGLs to two different types of firms, one risky and one not risky, and made by two banks with an NPLR one percentage point higher than the average. The amount of a new loan made to a firm that is not considered as an *investment grade* by a bank with a one percentage point higher NPLR is 66.2% higher. However, as indicated by the coefficient 0.18 of the triple interaction, the amount obtained by the safer firm in the same situation will be 84% higher (66.2 + 18.1). This result rejects H2 and therefore validates H3: riskier banks provide higher PGL amounts but, as with non-guaranteed loans, they favored healthy firms and reduce at the same time the risk weight of their assets to obtain a capital buffer, which might be crucial in times of uncertainty.

Finally, we analyze the impact of relationship lending on the amount of PGLs granted. In column (1) of Table 11, we first interact our PGL dummy with two additional variables. The first variable *duration* corresponds to the elapsed time between the first relationship established between a firm and a bank and the last one, while the second variable *Single-bank* is a dummy that takes value 1 if the firm has only one bank and 0 otherwise. Consistent with Core & De Marco (2021) and Jiménez et al. (2022), we find that relationship lending increased the amount of PGLs granted. In column (2), we again introduce the *investment grade* variable and interact it with both relationship lending variables and our PGL dummy. Only the triple interaction term between *PGL*,*investment grade* and *Duration* appears significant and negative while the simple interaction term between our PGL dummy and *investment grade* remains positive and significant, thus indicating that relationship lending mitigates the effects of firm riskiness on the amount of PGL granted.

7 .3 Do banks that grant more PGLs increase their overall credit risk?

Using granular data at the firm-bank level, we have seen that the use of PGLs is not consistent with the risk-taking channel. Yet, we have not assessed the impact of PGLs on the overall level of banks' credit risk. Figure 8 shows that, on average, the banks' credit portfolio did not shift to the riskiest firms between Q4 2019 and Q1 2022.[27] Yet, assessing bank risk-taking associated with PGLs at the bank-level requires using a proper methodology. Building on a dynamic panel model that enables us to control for bank-specific variables as well as past values of banks' risk measures, we find that granting more PGLs did not have an impact on banks' risk-taking. In addition, banks that took more risk associated with PGLs are those that started with stronger financial statements before the crisis.

As outlined in section 6 , we use two different measures as indicators of a bank's credit risk: the default rate and the non-performing loan ratio. We want to know whether the lag of the ratio of PGLs over total credit of the bank (PGLR) has an effect on those measures.

[27] Note that the further to the right on the x-axis the more risky the firm is considered to be (according to the Banque de France rating).

For each specification, we include bank controls (defined in 2 and quarter fixed effects to capture movements common to all banks but specific to time. Finally, being in a dynamic panel model context, we add one lag of the dependent variable that captures banks' credit risk in the past.

The results we obtained by running equation 3 are presented in Table 12. The first row shows that having granted more PGLs did not have any impact on banks' risk-taking, as the two coefficients are not statistically significant. The lags of our dependent variables appear positive and significant, thereby highlighting the persistent effect of banks' risk-taking strategy. In addition, the size of the bank is the only control that turns out to be significant: the larger the bank, the less risky the credit portfolio. In contrast with Wilcox & Yasuda (2019) who found that loan guarantees increased banks' risk-taking in Japan,[28] our results are consistent with our previous analyses and suggest that PGLs did not encourage riskier banking behavior.

Finally, to test whether the amount of PGLs has a differential impact on banks' risk-taking according to bank heterogeneity, we interact the ratio of PGLs with our bank controls. Table 13 shows the results of these regressions for our two measures of bank risk-taking. While the ratio of PGLs remains not significant in both columns (1) and (2), the interaction coefficient between the PGL ratio and the liquidity ratio is statistically significant and positive. Furthermore, in column (2), the positive and significant coefficient associated with the interaction between ROA and the ratio of PGLs also indicates that banks that had a better profitability before the crisis were able to increase their NPL ratio through the distribution of PGLs. In other words, banks that took more risk associated with PGLS during the crisis are those that started with stronger financial statements. These

[28] It is worth noting that in the case of Japan, the totality of SME loans granted by banks could be covered by the government guarantee, whereas the French PGL program covers at best only 90% of loans.

results confirm what was found in the previous section and reject once again the risk-taking channel. Not only did banks not increase their credit risks during the pandemic but the weaker banks took less risk by using PGLs. Hence, H1 and H2 are once again rejected.

7 .4 Robustness checks and further developments

7 .4.1 Random draw of new loans

In Section 6 .2 we build a database at the new loan level to assess the impact of PGLs on banks' risk taking at the intensive margin. To perform a panel analysis, each month, we need to select only one new loan per firm. Yet, there may be multiple loans from the same firms to the same bank each month.[29] As a first set of robustness tests, we therefore ran other random selections, thus potentially obtaining loans with different characteristics for the same firm. We then ran all our regressions regarding the intensive margin (with simple and triple interactions) on these new databases. The results, which are available upon request, confirm precisely in terms of magnitude, sign and statistical significance those we presented in the Section 7 .2.

7 .4.2 Alternative measure of firm riskiness

One of our key findings concerns firms' credit risks and specifically the fact that banks did not lend more PGLs to riskier firms. In our paper, we hinge on two ways to measure firm riskiness. The first is to use balance sheet ratios and other measures of firm characteristics (age, size); the second is to use the rating developed by the Banque de France to measure credit risk. A third possible measure is to check whether the firm had non-performing loans before the COVID-19 crisis. We then create a dummy variable that takes the value 1 if the firm had a NPL with the lending bank in December 2019, and zero otherwise. Table

[29] Note that in our database, 25% of firms have at least two different new loans in the same month.

12A shows the results for this regression. The negative and significant coefficient of the interaction term between PGL and the NPL dummy means that firms that had NPLs at the end of 2019 obtained lower PGL amounts. This result corroborates those presented in Table 8: being a less risky firm significantly increases the amount of PGL obtained.

7 .4.3 Intensive margin: stability of coefficient

As an additional robustness test, we quantify the robustness of the coefficient associated with the PGL dummy variable to the presence of unobservable covariates in our intensive margin analysis. The objective is to understand whether the addition of various controls and fixed effects can have an impact on the stability of the coefficient associated with the PGL dummy. If it does, concerns may arise about omitted variable bias. This test, developed by Oster (2019), is based on the theoretical framework of Altonji et al. (2005) which evaluate the robustness of coefficient stemming from a linear regression in the presence of unobservable covariates. Table 17 presents these "Oster bounds". The results suggest that these sets of bounds never contain 0. Consequently, our findings on the impact of PGLs on the credit intensive margin (Section 7 .2) are robust to the presence of unobservable shocks. Please refer to the Appendice in Section A for more details on this methodology.

7 .4.4 PPML estimation

According to Silva & Tenreyro (2006), possible biases may arise from a classical log-linear estimation: under heteroskedasticity, the parameters of log-linearized models estimated by OLS lead to biased estimates of the true elasticities. As part of our analysis on the intensive margin (6 .2), we therefore re-run all our panel regressions with fixed effects using a Poisson model instead of a linear model. More precisely, we perform pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects. The results, which are available upon request, confirm those obtained with linear regressions (7 .2) in sign, magnitude, and statistical significance. This is true for all results (panel, simple interactions and triple interactions).

7 .4.5 Alternative measure of bank risk-taking

In Section 7 .3 we show the overall impact of PGLs on the riskiness of banks' credit portfolio according to two different measures of risk both computed using our loan-level database. In addition to these two measures, we add one calculated differently. Instead of starting from the AnaCredit database, we rely this time on the French credit register which provides the Banque de France rating that we use in our loan-level analysis. For each bank, we compute the share of firms whose survival is at risk in the credit portfolio, based on the Banque de France rating. Again, given that PGLs may have impacted these measures through an increase in firm liquidity, we define the risk measures for each firm-bank pair in December 2019 and apply it to the entire sample period. Table 15 presents the estimation of equation 3 where the dependent variable is the Banque de France measure of firm riskiness. As with other measures of risk, we find that granting more PGLs did not have any impact on banks' risk-taking.

7 .4.6 Deeper lags and additional instruments in the dynamic panel model

Concerning our dynamic panel analysis, one should also wonder whether deeper lags of our dependent variables have an impact on our various measures of bank risk-taking. In additional regressions, we therefore add three lags of our dependent variables and found no significance for the second and the third lags for all our measures of bank risk-taking. In addition, as additional instruments, we include in Equation 3 a loan to assets ratio (i.e. the ratio of credit over total assets of the bank) and a deposit ratio (i.e. the ratio of deposit to total assets of the bank) to account for the effect of bank business models on bank risk-taking (Pagano et al., 2014). To the extent that market-oriented banks have the opportunity to invest in assets that are more profitable than loans, they may be more inclined to lend to riskier firms associated with higher NPL ratios. Yet, these two variables turn out to have no effect on our measures of bank risk-taking. The results of these estimates, which are available upon request, validate our conclusions that larger volumes of PGLs did not impact bank risk-taking calculated at the bank level.

8 Conclusion

In this paper, we investigate the role of public-guaranteed loans (PGLs) in banks' risk-taking. To this end, we analyze the PGL program designed by the French government in response to the COVID-19 crisis over the period 2020Q2-2022Q2. Using three different empirical strategies based on granular data on new loans, we test two alternative hypotheses: the "risk-weighted asset (RWA) channel" and the "risk-taking channel". We find that PGLs did not encourage risk-taking by banks, but instead strengthened their financial soundness through their beneficial effect on regulatory capital. Indeed, the partial public guarantee encouraged banks to lend according to their usual risk criteria while improving their financial position by reducing their risk-weighted assets (RWA) through a regulatory windfall effect.

These results have policy implications. PGLs helped support credit to solvent but illiquid firms during the crisis and thus achieved the purpose for which they were created. However, these guarantees are not neutral on banks' balance sheets. In the case of post-COVID France, guaranteed loans have improved banks' balance sheets, especially for banks with higher non-performing loans and lower capital before 2020. The most likely explanation is the following: by making public-guaranteed loans instead of non-guaranteed loans, the percentage of risky assets in the bank's portfolio has been mechanically reduced and some regulatory capital was freed up. This additional capital could be used in two different ways: either to make new, more profitable investments or to act countercyclically.

It remains to be studied whether and to what extent this regulatory gain effect has led to a substitution of non-guaranteed credit for PGLs. Indeed, the question of how much of the change in the risk of bank assets is due to new loans and not simply to the renewal of old loans is of primary importance, both from an academic and a regulatory point of view. If PGLs have only helped to replace existing loans in order to lower regulatory capital requirements, one can wonder whether the transfer of risk from banks to the government is relevant. However, these issues are beyond the scope of this paper and should be addressed in future research.

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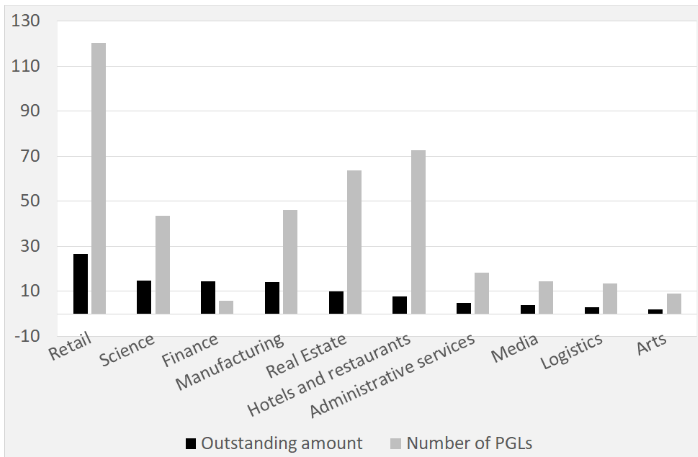
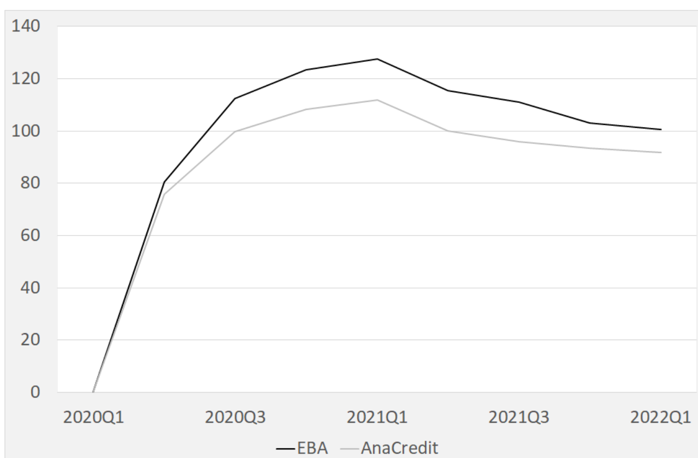
9 Figures and Tables

Figure 1: Outstanding amount of PGLs and number of PGLs per sector



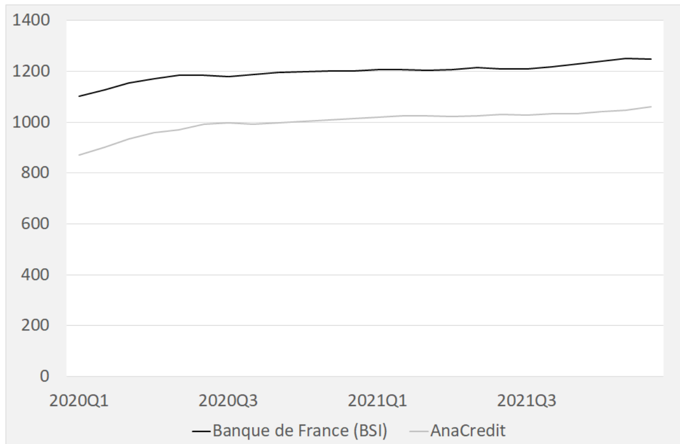
Notes: Outstanding amount of credit in billion euros; number of loans in thousands. The Figure shows only the top ten sectors in terms of outstanding amount of PGLs received. Source: Anacredit

Figure 2: Comparison of new public-guaranteed loans



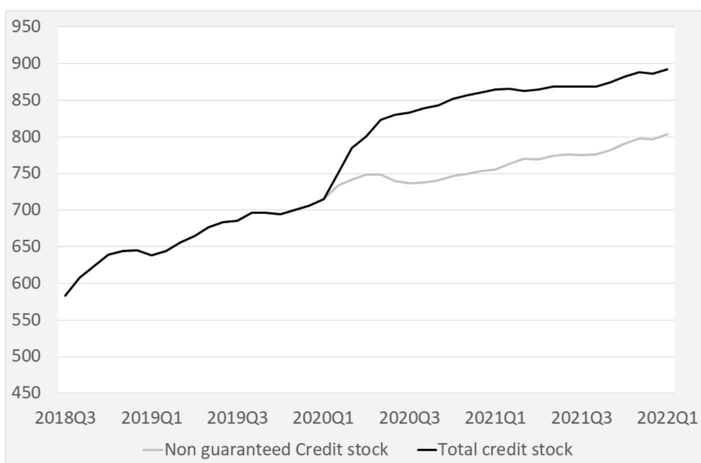
Sources: EBA from reporting and disclosure of exposures subject to measures applied in response to the COVID-19 crisis; Anacredit from AnaCredit database.

Figure 3: Outstanding credit to non-financial corporations: BDF vs. AnaCredit



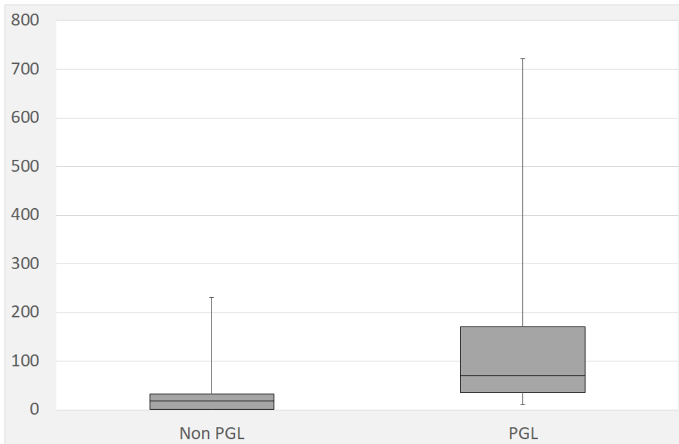
Note: The outstanding credit amounts are in billion euros. Sources: Anacredit and Webstat (Banque de France)

Figure 4: Outstanding amount of credit to non-financial corporations with and without PGLs



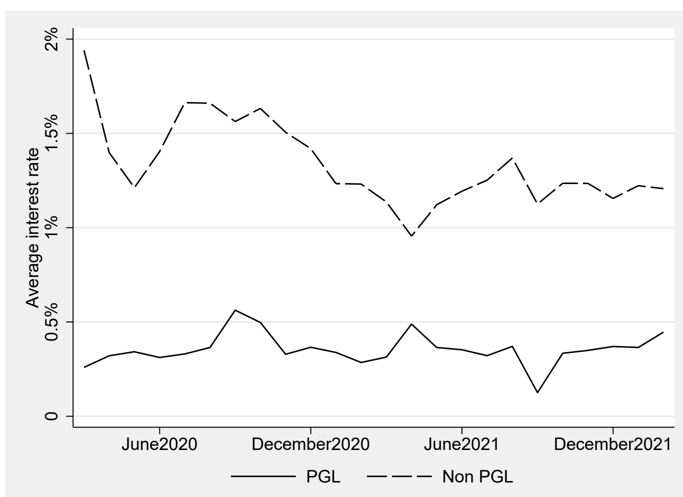
Note: The outstanding amount of credit is in billion euros. Source: Our own calculations from the AnaCredit database.

Figure 5: Distribution of the amount of new credit granted



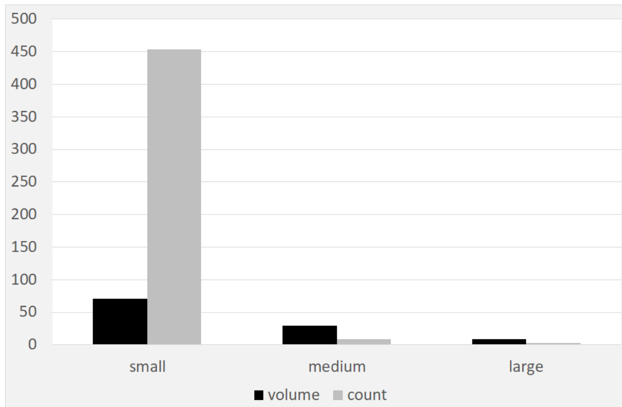
Note: The amounts of new loans are in thousand euros. Source: Our own calculations from the AnaCredit database.

Figure 6: Average interest rates on new loans, March 2020 - February 2022



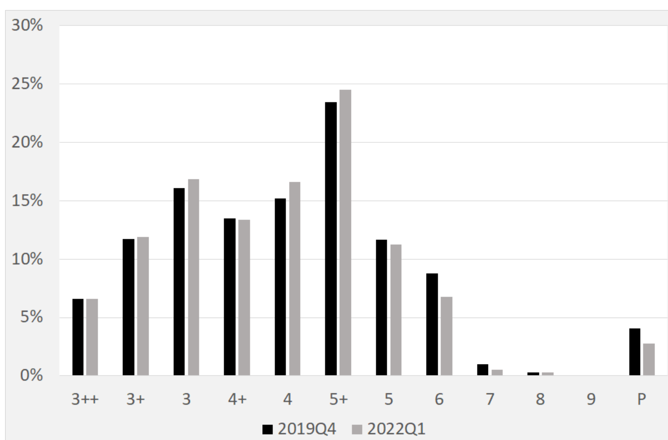
Source: Our own calculations from the AnaCredit database.

Figure 7: Outstanding amount of PGLs and number of PGLs by firm size



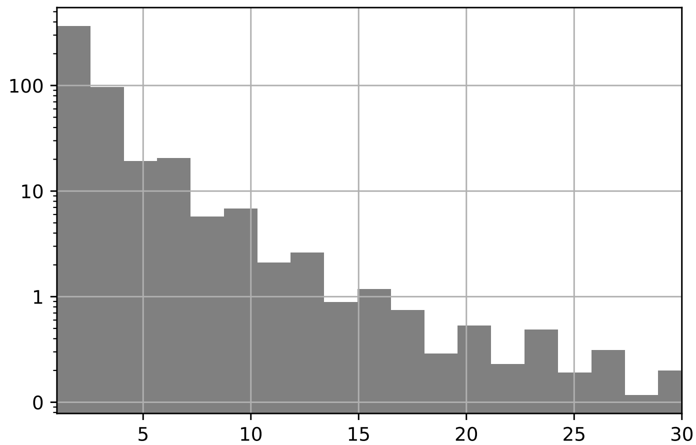
Notes: the outstanding amount of PGLs is in billion euros, while the number of loans is in thousand. Source: Our own calculations from the AnaCredit database.

Figure 8: Risk portfolio of French banks before and after the pandemic.



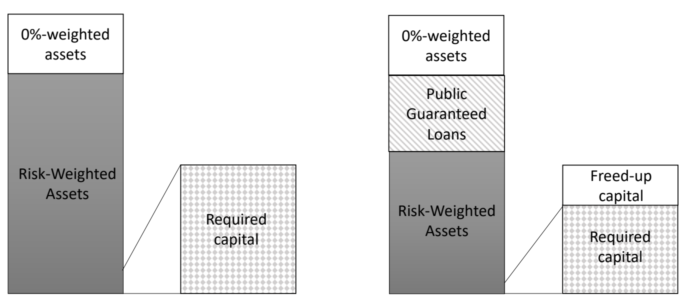
Note: Risk measures are those calculated according to the Banque de France rating (3++ is the best rating, 9 the worst. P indicates a firm in financial difficulty). Source: AnaCredit and the French credit register. Risk measures are those calculated according to the Banque de France rating (3++ is the best rating, 9 the worst. P indicates a firm in financial difficulty).

Figure 9: Number of new loans per firm



Note: The number of loans obtained is on the X-axis, while the number of firms (in thousand) that obtained that number of loans is on the Y-axis.
Source: Our own calculations from the AnaCredit database.

Figure 10: Liberation of regulatory capital through the issue of public-guaranteed loans



Note: The issuance of publicly guaranteed loans allows banks to free up regulatory capital. See section 4 .

Figure 11: Evolution of CET1 ratio and CET1 capital for French banking groups

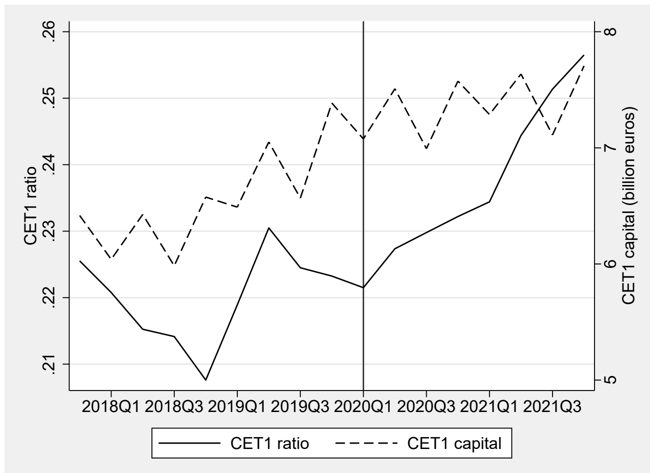


Table 1: Share of credit guaranteed by the French government according to firm size

N. employees	Turnover	Public guarantee
<5000	<1.5 billion €	90% of the loan
	Between 1.5 and 5 billion €	80% of the loan
Other firms		70% of the loan

Notes : This Table shows the share of credit guaranteed by the French government according to the turnover and the number of employees of the firms.

Notes: The figure presents the average of CET1 ratios (left-hand side) and CET1 capital (right-hand side) of all French banking groups. Source: our own calculations from COREP (ACPR-Banque de France) data.

Table 2: Variables definitions

	Definition
Loan variables	
Ln(total credit commitment)	The log of amount of euros granted for a new loan (drawn and undrawn).
Access to public-guaranteed loan (APGL)	A dummy that takes the value 1 whether the firm has obtained at least one public-guaranteed loan from a given bank between March 2020 and February 2022 and 0 otherwise
Public-guaranteed loan (PGL)	A dummy that takes the value 1 whether the loan is a public-guaranteed loan and 0 otherwise
Maturity	The number of month at which the final repayment of a loan is due.
Firm variables	
Capital ratio	The ratio of own funds over total assets of the firm.
Cash ratio	The ratio of cash holdings over total assets of the firm.
Cash flow ratio	The ratio of cash flow over total assets of the firm.
Age	The number of years since funding.
Industry VA growth	The percentage change in value added in the relevant industrial sector (NACE Rev.2) between December 2019 and December 2020.
Ln(total assets)	The log of the total assets of the firm.
Investment grade	A dummy that takes the value 1 whether the firm is considered as investment grade by the Banque de France.
Bank variables	
Capital ratio	The ratio of own funds over total assets of the bank.
Liquidity ratio	The ratio of securities over total assets of the bank.
ROA	The total net income over total assets of the bank.
NPL ratio	The non performing loan ratio of the bank.
Ln(total assets)	The log of the total assets of the bank.
PD	The average probability of default of the bank's credit portfolio.
Default rate	The average default rate of the bank's credit portfolio.
NPL rate	The average non-performing loan ratio of the bank's credit portfolio
BDF risk	The share of firms whose survival is threatened in the bank's credit portfolio according to the Banque de France rating.
Public-guaranteed loan ratio (PGLR)	The ratio of public-guaranteed loan over total credit of the bank.
Relationship lending variables	
Duration	The elapsed time between the first relationship established between a firm and a bank and the last one.
Single-bank	A dummy that takes the value 1 whether the firm is single-bank and 0 otherwise.
Credit market variable	
HHI	The consolidated Herfindahl-Hirschman Index on credit at the regional level.

Table 3: Summary statistics (extensive margin)

	Mean	Median	Sd	Min	Max
Dependent variable					
Access to public-guaranteed loan	0.30	1	0.49	0	1
Firm controls					
Age (*years*)	25.27	22	17.91	3	97
Total assets (*log*)	8.24	7.94	1.50	5.87	13.48
Total assets (*thousand euros*)	3,789	2,807	4,482	354	714,973
Capital ratio (*%*)	28.47	26.99	16.69	0	75.48
Cash flow ratio (%)	7.41	6.53	6.93	-12.64	31.80
Cash ratio (*%*)	10.16	6.11	11.28	0	51.83
Industry VA growth rate (*%*)	5.93	8.35	16.62	-45.69	33.35
Bank control					
Total assets (*log*)	17.76	17.17	1.68	14.46	20.96
Total assets (*billion euros*)	51.65	28.63	0.01	1.90	1,267
Capital ratio (*%*)	7.65	7.58	3.96	2.24	17.53
Liquidity ratio (*%*)	18.35	12.05	19.47	0.46	70.11
ROA (*%*)	0.41	0.41	0.20	-0.09	1.33
NPL ratio (*%*)	2.57	2.31	1.07	0	7.51
Relationship lending variables					
Duration (*year*)	9.71	8.66	6.77	0.16	22
Single-banked (*0/1*)	0.24	0	0.43	0	1
Credit market control					
Consolidated HHI (base 100)	24.12	25.27	6.30	14.89	28.98

Table 4: Summary statistics (intensive margin)

	Mean	Median	Sd	Min	Max
Dependent variable					
Total credit commitment	372.21	100	949.49	0.02	7,000
Ln(total credit commitment)	4.44	4.24	2.88	0.51	12.28
Credit controls					
Public-guaranteed loan (*0/1*)	0.22	0	0.41	0	1
Maturity (*months*)	43.12	11.96	106	1	680
Firm controls					
Age (*years*)	27.42	24	18.72	3	100
Total assets (*log*)	8.58	8.36	1.50	6.02	71.22
Total assets (*thousand euros*)	25,992	4,287	92,944	412	759,168
Capital ratio (*%*)	26.37	24.74	15.46	0	71.22
Cash flow ratio (%)	3.82	3.62	7.93	-24.62	26.93
Cash ratio (*%*)	8.40	4.71	9.87	0	46.83
Bank control					
Total assets (*log*)	17.39	17	1.64	14.34	20.96
Total assets (*billion euros*)	187.45	24.36	402	1.69	1,276
Capital ratio (*%*)	7.03	6.54	3.42	2.15	16.76
Liquidity ratio (*%*)	15.52	10.36	17.86	0.33	70.11
ROA (*%*)	0.28	0.34	0.58	-2.20	1.33
NPLR (*%*)	2.83	2.58	1.57	0	7.51
Relationship lending variables					
Duration (*month*)	121	108	81	3	264
Single-bank (*0/1*)	0.15	0	0.36	0	1
Credit market control					
Consolidated HHI (base 100)	20.92	24.37	8.11	5.83	30.32

Table 5: Summary statistics (Bank risk-taking)

	Mean	Median	Sd	Min	Max
Dependent variable					
Default rate(*%*)	2.13	2	1.21	0	6.21
NPL rate(*%*)	2.56	2.41	1.16	0	6.95
BDF risk(*%*)	2.87	2.62	1.17	1.16	6.92
Bank controls					
Total assets (*log*)	16.82	16.84	1.28	13.70	21.08
Total assets (*billion euros*)	64.98	20.72	201	0.89	1,429
Capital ratio (*%*)	8.68	8.36	4.14	1.62	17.69
Liquidity ratio (*%*)	11.45	9.68	12.62	0.49	66
ROA (*%*)	0.14	0.1	0.18	-1.05	0.89
PGLR (*%*)	10.77	9.29	5.62	0.20	27.47

Table 6: Access to public-guaranteed loans (APGL): Marginal effects at the means

	Dependent variable = APGL
	(1)
Firm controls	
Industry VA growth rate	-0.016***
	(0.002)
Firm total assets	-0.040***
	(0.001)
Firm capital ratio	-0.001***
	(0.000)
Firm cash ratio	-0.003***
	(0.000)
Firm ROA	-0.003***
	(0.000)
Firm age	-0.001***
	(0.000)
Bank controls	
Bank total assets	0.071***
	(0.001)
Bank capital ratio	-0.035***
	(0.000)
Bank liquidity	-0.003***
	(0.000)
Bank ROA	0.242***
	(0.006)
NPL ratio	0.010***
	(0.001)
Relationship lending controls	
Duration	-0.009***
	(0.001)
Single-bank	-0.043***
	(0.003)
Credit market control	
HHI	-0.318***
	(0.105)
Industry FE	YES
Region FE	YES
Observations	150,067
Number of firms	105,104
Pseudo-R2	0.151

Notes : This table shows the marginal effects at the means of the Probit estimation of equation 1. The regression includes industry and region fixed-effects (coefficients are not reported but available upon request). Standard errors (in brackets) are robust. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 7: PGLs and Allocation of new credit

	Dependent variable = Credit amount (log)	
	(1)	(2)
Credit variables		
PGL	1.373***	1.429***
	(0.193)	(0.001)
Maturity	0.002*	0.002***
	(0.001)	(0.001)
Firm controls		
Firm total assets		0.618***
		(0.032)
Firm capital Ratio		-0.000
		(0.002)
Firm cash ratio		-0.004
		(0.003)
Firm ROA		0.003*
		(0.002)
Firm age		0.000
		(0.001)
Bank controls		
Bank total assets		0.009
		(0.136)
Bank capital ratio		0.113***
		(0.029)
Bank liquidity ratio		0.012
		(0.010)
Bank ROA		1.029***
		(0.102)
NPL ratio		-0.322**
		(0.114)
Relationship lending variables		
Duration	-0.006**	-0.031***
	(0.002)	(0.006)
Single-bank		-0.001
		(0.047)
Credit market control		
HHI	-0.005	0.008
	(0.007)	(0.010)
Firm F.E.	YES	NO
Bank F.E.	YES	NO
Time F.E.	YES	YES
Observations	182 757	182 757
Number of firms	43,294	43,294
Adjusted R2	0.669	0.342
Within R2	0.064	0.323

Notes : This table shows the regression results of a within estimation of equation 2 in column (1) and a cross section estimation of the same equation (i.e. without fixed-effects) in column (2). All regressions include firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 8: PGLs and Allocation of new credit: firm heterogeneity

	Dependent variable = Credit amount (log)	
	(1)	(2)
PGL	1.388***	1.585***
	(0.202)	(0.203)
Interactions with firm controls		
PGL x Firm total assets	0.028	
	(0.0027)	
PGL x Firm capital ratio	0.005**	
	(0.001)	
PGL x Firm cash ratio	0.016***	
	(0.003)	
PGL x Firm ROA	0.011***	
	(0.003)	
PGL x Firm age	0.004***	
	(0.001)	
PGL x Investment grade		0.288***
		(0.032)
Loan, relationship lending, and credit market controls		
Maturity	0.002*	0.002*
	(0.001)	(0.001)
Duration	-0.006***	-0.006***
	(0.002)	(0.002)
HHI	-0.004	-0.005
	(0.007)	(0.007)
Firm F.E.	YES	YES
Bank F.E.	YES	YES
Time F.E.	YES	YES
Observations	182,757	182,757
Number of firms	43,294	43,294
Adjusted R2	0.669	0.669
Within R2	0.066	0.065

Notes : This table shows the regression results of a within estimation based on equation 2. Column (1) interacts the dummy *PGL* with firm controls, while column (2) interacts the same dummy with a variable summarizing the Banque de France rating. The variable *Investment grade* described in section 5 , represents the evaluation of the quality of a firm calculated by the Banque de France on the basis of its balance sheet and income statement. All regressions include firm, bank, market and loan controls as well as firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 9: PGLs and Allocation of new credit: bank heterogeneity

	Dependent variable = Credit amount (log)	
	(1)	(2)
PGL	1.529***	1.789***
	(0.193)	(0.294)
Interactions with bank variables		
PGL x Bank total assets	0.157	0.129
	(0.149)	(0.094)
PGL x Bank capital ratio	-0.084*	-0.069**
	(0.039)	(0.055)
PGL x Bank liquidity ratio	-0.019	-0.044**
	(0.010)	(0.012)
PGL x Bank ROA	-0.586	0.432
	(0.479)	(0.377)
PGL x NPL ratio	0.518**	0.080*
	(0.185)	(0.086)
PGL x CET1 ratio		-0.370**
		(0.109)
Loan, relationship lending, and credit market controls		
Maturity	0.002*	0.001
	(0.001)	(0.001)
Duration	-0.006**	-0.007*
	(0.002)	(0.003)
HHI	-0.007	-0.008*
	(0.008)	(0.003)
Firm F.E.	YES	YES
Bank F.E.	YES	NO
Banking group F.E.	NO	YES
Time F.E.	YES	YES
Observations	182,757	182,757
Number of firms	43,294	43,294
Adjusted R2	0.674	0.668
Within R2	0.079	0.106

Notes : This table shows the regression results of a within estimation based on equation 2. Column (1) interacts the dummy *PGL* with unconsolidated bank controls without the consolidated CET1 ratio, while column (2) includes this ratio. All regressions include firm, bank, market and loan controls as well as firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 10: PGLs and Allocation of new credit: bank-firm interactions

	Dependent variable = Credit Amount (log)
	(1)
PGL	1.795***
	(0.215)
Interactions with firm and bank variables	
PGL x Bank total assets	0.146
	(0.155)
PGL x Investment grade	0.347***
	(0.057)
PGL x Investment grade x Bank total assets	-0.014
	(0.045)
PGL x Bank capital ratio	-0.070
	(0.042)
PGL x Investment grade x Bank capital ratio	0.017
	(0.014)
PGL x Bank liquidity ratio	-0.017
	(0.011)
PGL x Investment grade x Bank liquidity ratio	0.002
	(0.004)
PGL x Bank ROA	-0.594
	(0.478)
PGL x Investment grade x Bank ROA	0.024
	(0.177)
PGL x NPL ratio	0.662**
	(0.199)
PGL x Investment grade x NPL ratio	0.181**
	(0.057)
Loan, relationship lending, and credit market controls	
Maturity	0.002*
	(0.001)
Duration	-0.006**
	(0.002)
HHI	-0.007
	(0.008)
Firm F.E.	YES
Bank F.E.	YES
Time F.E.	YES
Observations	182,757
Number of firms	43,294
Adjusted R2	0.674
Within R2	0.080

Notes : This table shows the regression results of a within estimation based on equation 2. Column (1) presents triple interactions between the dummy *PGL*, bank controls and a variable summarizing the Banque de France rating. The variable *Investment grade* described in section 5 , represents the evaluation of the quality of a firm calculated by the Banque de France on the basis of its balance sheet and income statement. The regression includes firm, bank, market and loan controls as well as firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 11: PGLs and Allocation of new credit: relationship lending

	Dependent variable = Credit Amount (log)	
	(1)	(2)
PGL	1.142***	1.401***
	(0.172)	(0.184)
Interaction terms		
PGL x Duration	0.023***	0.015**
	(0.004)	(0.005)
PGL x Single-bank	0.071	0.099*
	(0.051)	(0.049)
PGL x Investment grade		0.315***
		(0.053)
PGL x Investment grade x Duration		-0.008*
		(0.004)
PGL x Investment grade x single-bank		0.062
		(0.074)
Loan and credit market controls		
Maturity	0.002*	0.002*
	(0.001)	(0.001)
HHI	-0.005	-0.005
	(0.007)	(0.007)
Firm F.E.	YES	YES
Bank F.E.	YES	YES
Time F.E.	YES	YES
Observations	182,757	182,757
Number of firms	43,294	43,294
Adjusted R2	0.669	0.669
Within R2	0.065	0.066

Notes : This table shows the regression results of a within estimation based on equation 2. Column (1) presents simple interactions between the dummy *PGL* and relationship lending controls, while column (2) presents triple interactions between the dummy *PGL*, relationship lending controls and a variable summarizing the Banque de France rating. The variable *Investment grade* described in section 5 , represents the evaluation of the quality of a firm calculated by the Banque de France on the basis of its balance sheet and income statement. All regressions include firm, bank, market and loan controls as well as firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 12: Dynamic panel regression : main results

Dependent variable$_t$ =	Default rate (1)	NPL rate (2)
PGLR$_{t-1}$	-0.003	-0.001
	(0.012)	(0.013)
Controls		
Total assets$_{t-1}$	-0.001**	-0.001*
	(0.001)	(0.001)
Capital ratio$_{t-1}$	0.012	-0.001
	(0.034)	(0.027)
Liquidity ratio$_{t-1}$	0.003	0.001
	(0.015)	(0.011)
ROA$_{t-1}$	-0.256	-0.201
	(0.122)	(0.175)
Lags of the dependent variable		
Default rate$_{t-1}$	0.832***	
	(0.064)	
NPL$_{t-1}$		0.811***
		(0.066)
Time F.E.	YES	YES
Number of instruments	35	35
H-test(p-value)	0.49	0.38
AR(2)(p-value)	0.83	0.91
Observations	576	576
Number of banks	96	96

Notes : The Table shows the regression results for the system-GMM estimation of specification 3. The estimates use three lags of instruments and are robust to heteroscedastic standard errors. Column (1) presents the results for the *default rate*, while column (2) presents the results for the *NPL rate*. All specifications were estimated with a constant and with quarter fixed-effects. AR(2) shows the p-value of the test of serial correlation in the error terms, under the null hypothesis of no serial correlation. Values presented for the Hansen test are p-values of the test of overidentifying restrictions of the instruments, under the null hypothesis of instrument validity. See section 3 for exact definitions and data sources. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 13: Dynamic panel regression : bank heterogeneity

Dependent variable$_t$ =	Default rate (1)	NPL rate (2)
PGLR$_{t-1}$	-0.001	-0.004
	(0.012)	(0.005)
Controls		
PGLR$_{t-1}$ x Total assets$_{t-1}$	-0.001	-0.007
	(0.008)	(0.007)
PGLR$_{t-1}$ x Capital ratio$_{t-1}$	0.310	0.195
	(0.192)	(0.151)
PGLR$_{t-1}$ x Liquidity ratio$_{t-1}$	0.065*	0.091**
	(0.035)	(0.045)
PGLR$_{t-1}$ x ROA$_{t-1}$	2.390	4.625***
	(2.001)	(1.591)
Lags of the dependent variable		
Default rate$_{t-1}$	0.932***	
	(0.033)	
NPL$_{t-1}$		0.927***
		(0.054)
Time F.E.	YES	YES
Bank controls	YES	YES
Number of instruments	55	55
H-test(p-value)	0.46	0.68
AR(2)(p-value)	0.78	0.85
Observations	576	576
Number of banks	96	96

Notes : The Table shows the regression results for the system-GMM estimation based on specification 3 which interact the *PGLR* with bank controls. The estimates use three lags of instruments and are robust to heteroscedastic standard errors. Column (1) presents the results for the default rate, while column (2) presents the results for the NPL rate. All specifications were estimated with a constant and with quarter fixed-effects. AR(2) shows the p-value of the test of serial correlation in the error terms, under the null hypothesis of no serial correlation. Values presented for the Hansen test are p-values of the test of overidentifying restrictions of the instruments, under the null hypothesis of instrument validity. See section 3 for exact definitions and data sources. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 14: Robustness: alternative measure of firm riskiness

	Dependent variable = Credit Amount (log)
	(1)
PGL	1.378***
	(0.196)
PGL x NPL dummy	- 0.197**
	(0.099)
Loan, relationship lending, and credit market controls	
Maturity	0.002**
	(0.001)
Duration	-0.006***
	(0.00)
HHI	-0.004
	(0.01)
Firm F.E.	YES
Bank F.E.	YES
Time F.E.	YES
Observations	182,757
Number of firms	43,294
Adjusted R2	0.655
Within R2	0.065

Notes : This table shows the regression results of a within estimation based on equation 2. Column (1) interacts the dummy *PGL* with the *NPL dummy.* The latter takes the value 1 if the firm had a NPL with the lending bank in December 2019, and zero otherwise. The regressions includes firm, bank, market and loan controls as well as firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 15: Robustness: alternative measure of bank risk-taking

	Dependent variable$_t$ = BDF risk
	(1)
PGLR$_{t-1}$	-0.012
	(0.045)
Controls	
Total assets$_{t-1}$	-0.004**
	(0.002)
Capital ratio$_{t-1}$	-0.063
	(0.063)
Liquidity ratio$_{t-1}$	0.005
	(0.014)
ROA$_{t-1}$	-0.256
	(0.210)
Lags of the dependent variable	
BDF risk$_{t-1}$	0.566***
	(0.069)
Time F.E.	YES
Number of instruments	35
H-test(p-value)	0.26
AR(2)(p-value)	0.15
Observations	576
Number of banks	96

Notes : The Table shows the regression results for the system-GMM estimation based on specification 3. The dependent variable *BDF risk* is the share of firms whose survival is at risk in the bank' credit portfolio, according to the Banque de France rating. The estimates use three lags of instruments and are robust to heteroscedastic standard errors. The specifications was estimated with a constant and with quarter fixed-effects. AR(2) shows the p-value of the test of serial correlation in the error terms, under the null hypothesis of no serial correlation. Values presented for the Hansen test are p-values of the test of overidentifying restrictions of the instruments, under the null hypothesis of instrument validity. See section 3 for exact definitions and data sources. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 16: Fixed-effects panel regression, no controls

	Dependent variable=Credit amount (log)
	(1)
	Coef./SE
PGL dummy	1.340***
	(0.187)
Constant	10.959***
	(0.022)
R2	0.746
Adjusted R2	0.666
Within R2	0.057
Observations	182 757

Notes : This table shows the regression results of a within estimation based on equation 2 but without controls. The regression includes firm, bank and time fixed effects (coefficients are not reported but available upon request). The Hausman test rejects the null hypothesis of random effect estimator consistency. Standard errors (in brackets) are double clustered at firm-level and bank-level and are heteroscedasticity consistent. *, ** and *** indicate significance levels at 10%, 5% and 1% respectively. All the definitions of the variables are summarized in Table 2.

Table 17: Robustness: stability of coefficient to the introduction of controls (Oster (2019))

Regressions	**Oster bound**	**Observations**
Simple panel (Table 7, column (1))	[1.360 ; 1.383]	182 757
Firm heterogeneity (Table 8, column (1))	[1.388 ; 1.752]	182 757
Firm heterogeneity - Investment grade (Table 8, column (2))	[1.077 ; 1.585]	182 757
Bank heterogeneity (Table 9, column (1))	[1.528 ; 2.509]	182 757
Bank heterogeneity + CET1 ratio (Table 9, column (2))	[0.852; 1.789]	179 147
Triple interactions (Table 10, column (1))	[0.955 ; 1.795]	182 757
Relationship lending (Table 11, column (1))	[1.383 ; 1.142]	182 757
Relationship lending with triple interactions (Table 11, column (2))	[0.490 ; 1.401]	182 757

Notes : This table presents the bounding sets for the estimates of equation 2. Bounding sets are built following Oster (2019), see Appendix A for more details.

A Intensive margin: Stability of coefficient

As an additional robustness test, we quantify the robustness of the coefficient associated with the PGL dummy to the presence of unobservable covariates in our extensive margin analysis. The objective is to understand whether the addition of various controls and fixed effects can change the value of the coefficient associated with the PGL dummy variable. If this is the case, we can question the bias of the omitted variables. This test, developed by Oster (2019), is based on the theoretical framework of Altonji et al. (2005) in order to quantify the robustness of the coefficient of a linear regression in the presence of unobservable covariates.

The test serves to formalize the following intuitive approach: when controls are included in a linear regression and the coefficient associated with the variable of interest remains relatively stable, it is unlikely that the omitted variables significantly influence the results. Specifically, this test allows us to examine whether the addition of bank, firm, loan, and loan relationship characteristics, as well as their interactions, has an impact on the stability of the coefficient associated with the PGL dummy variable.

To apply the Oster (2019) approach in our context, we define R_{ac} and γ_{ac} as the R-squared and the coefficient associated with the PGL dummy in the regression containing all controls (including fixed effects). On the other hand, we define R_{nc} and γ_{ac} as the R-squared and the coefficient associated with the PGL dummy in the regression containing only the fixed effects, but not the additional controls and interaction terms. The results of the latter can be found in Table 16. Instead, the results of the various regressions with controls are at column (1), Table 7, columns (1) and (2), Table 8, columns (1) and (2), Table 9, column (1) Table 10 as well as columns (1) and (2) in Table 11. Oster (2019) defines "treatment effect adjusted for approximate bias" as the coefficient

$$\gamma\left(\delta, R_{\max}\right)=\gamma_{ac}-\delta \cdot\left(\gamma_{nc}-\gamma_{ac}\right) \cdot \frac{R_{\max}-R_{ac}}{R_{ac}-R_{nc}}$$

where δ and R_{max} must be chosen by the researcher. R_{max} is the maximum R-squared that a regression including all observable and unobservable variables can achieve. We give R_{max} the most conservative value, i.e., 1. δ is a parameter that establishes the relative importance of the unobservable variables relative to the observable controls. Following Oster (2019), our bounds will be given by the betas obtained by setting $\delta = 0$ and $\delta = 1$ as extreme points for each test. Table 17 shows these "Oster bounds". The results indicate that these sets of bounds never contain 0. Consequently, our results on the impact of PGLs on the credit intensive margin (Section 7 .2) are robust to the presence of unobservable shocks.