Public Guaranteed Loans and Bank Risk-Taking*

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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 encourage riskier lending, pushing banks to lend to riskier borrowers or worsening incentives to prevent write-offs of loan applicants. Investigating the risk-taking channel of PGLs at the extensive margin, we find that smaller and riskier firms had a higher probability of obtaining a PGL. Yet, isolating credit demand from credit supply at the intensive margin, we find that safer firms had higher amounts of PGLs, while banks that were more exposed to non-performing loans (NPLs) before the crisis made smaller PGLs to risky firms, thereby using the guaranteed loan program to improve their financial position and reduce exposure to NPLs. This result remains valid when looking at the total amount of outstanding credit. By examining the substitution effect of SGLs, we find that banks substituted more PGLs for unsecured loans when firms are sounder. Finally, at the bank level, we find that PGLs have no impact on the overall credit risk of banks credit portfolio.

Keywords: Loan guarantees, bank lending, COVID-19 pandemic, credit risk
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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 underwritten by firms with 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 both the business and the banking system. Indeed, the contraction in demand for goods and services due to the virus containment measures could have had negative 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 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.

From the banks perspective, PGLs have two main interests. First, banks benefit from substituting existing loans with guaranteed ones. New loans reduce bank capital absorption, as PGLs carry lower credit risk weights (e.g. zero in the case of the fully guaranteed loans). In turn, guaranteed loans are originated at lower interest rates than existing loans because the guarantee mitigates credit risk. Second, banks can use PGLs to support their risky borrowers that are likely to default during a crisis, in order to avoid weakening their capital base. 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.

In the case that banks actually used PGLs to support their low-quality insolvent creditors, there could be negative consequences for financial stability. As the French state guaranteed between 70% and 90% the loan granted, 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 charge-offs of loan applicants (moral hazard). This effect is likely to be stronger for weaker banks, with less skin in the game, i.e., those that are less capitalized and have more NPLs (Holmstrom & Tirole, 1997).

This paper addresses this issue by studying the case of France between spring 2020 and spring 2022. Using granular data on loans and their characteristics, combined with data on bank and firms balance sheets, we analyze in detail the risk-taking channel of PGLs .The French case is particularly interesting because in the space of a few months, between March 2020 and early 2021, more than 100 billion euros in PGL were issued (Figure 1).

We find that French banks did not take advantage of PGLs to support their risky borrowers. On the contrary, guaranteed loans improved the French banks balance sheets by granting larger amounts of PGL to the most liquid, best capitalised and most profitable firms. This was especially true for low-capitalized banks with higher ratio of non-performing loans before 2022.

More specifically, 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 stronger than average. On the other hand, firms with a higher probability of obtaining a PGL were smaller and more fragile - in a word, riskier - than average. 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 state guarantee.

We investigate this issue by running a set of panel regressions in which we focus on the intensive margin of PGLs, 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 are on average three times higher than non-guaranteed loans. Second, the best capitalised, most liquid and most profitable firms had higher amounts of PGLs. Third, banks with lower capitalization and higher NPL ratios were the ones that granted higher amount of PGLs. 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, thereby using the guaranteed loan program to improve their financial position and reduce exposure to non-performing loans.

We then want to understand whether these results, which are valid at the level of the individual new loan, remain valid when looking at the total amount of outstanding credit. To do so, we examine the substitution between non-guaranteed loans and PGLs at the bank-firm level. Controlling for the demand for credit by exploiting cluster fixed effects at the industry, location and size levels, we investigate whether the growth rate of unsecured credit decreases with the volume of PGLs and the riskiness of firms. First, for each bank-enterprise pair, a 1 percentage point increase in the ratio PGLs over total assets of the firm is associated with a reduction in the growth rate of unsecured loans of about 1.5 percentage point. Through the addition of interactions with firm characteristics in our model, we also find that firms who benefited most from this substitution are larger, more capitalised, more liquid and younger, i.e. generally less risky. Finally, we find that large banks substitute less unsecured credit for PGL loans when firms are riskier.

As a final step we assess the overall impact of PGL on the riskiness of credit portfolio at the bank-level. Focusing on the bank-level, we study the effect of PGLs on banks' risk taking by using a dynamic panel model. Controlling for bank-specific variables as well as past values of banks' risk-taking measures (i.e. the probability of default, the default rate, the non-performing loan rate 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 an impact on banks' risk-taking. This result is robust to all bank risk-taking measures that we employ and is consistent with the other analyses conducted at the firm-bank level in the rest of the paper.

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; in section four we present our datasets, and especially the European credit registry Anacredit; in section five we outline our four different empirical strategies; section six presents our results; in the Conclusion we outline some policy insights.

2 Related literature

Our paper first contributes to the literature on the effect of public guarantees on bank risk taking. Initially, studies on this subject focused on the effect of state deposit guarantees. The latter may reduce market discipline because creditors anticipate their bank's bail-out and therefore have fewer incentives to monitor the bank's risk-taking (Merton, 1977; Flannery, 1998). Analyzing the removal of deposit insurance guarantees for German banks, Gropp et al. (2014); Kelly et al. (2016) find evidence for this mechanism. At the bank-level, Saito & Tsuruta (2018) and Wilcox & Yasuda (2019) study more directly the impact of loan guarantees for small business in Japan in the late 1990s and find that they increase the risk taking of banks. Compared with their paper, the bank-level analysis of our paper leads to opposite conclusions. One of the main reasons is the different institutional context, as Japanese banks were guaranteed that the guarantee program would repay 100% of the loan balance. Furthermore, the granularity of our databases allows us to study bank risk-taking not only from the perspective of the banks themselves, but also at the level of individual loans.

With regard to the use of firm-level data, the recent empirical literature yields conflicting results. Gazaniol & Lê (2021) studied a French pre-Covid public guarantee scheme[1] and find that guarantees improve access to external finance but also mechanically increase the rate of bankruptcy procedures since they increase financial debt. Lelarge et al. (2010) focus on the French PGLs scheme "Sofaris" and show that loan guarantees significantly increases the recipients' probability of default, suggesting that risk shifting may be a serious drawback for such loan guarantee programs. By using regression discontinuity techniques De Blasio et al. (2018) show that guarantees provided by the Italian scheme "Fondo di Garanzia" to support SMEs during the Great Recession increased the likelihood that a firm is unable to pay back its loans. In the case of the United states, Bachas et al. (2021) use notches in the guarantee rate schedule for the Small Business Administration (SBA) lending program and find that lenders indeed do shift riskier loans to the notch, where the guarantee rate is higher. Even more recently, , during the COVID-19 crisis, Jiménez et al. (2022)

[1] "fonds création", "fonds développement", "fonds transmission", and "fons renforcement de trésorerie".

find that spanish PGLs were more likely to be extended by bigger banks, banks with lower capital ratios and lower return on assets, and by banks with higher NPL ratios, indicating that there is an association between PGL loan extension and bank weakness, consistent with risk shifting behavior. On the contrary, Cascarino et al. (2022) study the public loan guarantee programs implemented in Italy during the same period and observe that the adoption of these guarantee schemes was not associated with an increase in risk-shifting by banks. Consistent Baena et al. (2022) find that French PGLs enabled a partial disconnection between firms' soundness and their risk parameter during the pandemic, we find that French banks, encouraged by the partial state guarantee, did not relax the terms of their loans.

We also add to the literature that investigates how public intervention can intervene efficiently to ease credit market frictions, with positive macroeconomic effects. The use of PGLs to alleviate credit constraints is not new. These types of government interventions became increasingly popular after the 2007-08 financial crisis(Beck et al., 2010). In the presence of information asymmetries between borrowers and their lenders, government intervention can result in a more efficient allocation of resources, even if the government has no informational advantage over the lenders (Mankiw, 1986; Philippon & Schnabl, 2013; Philippon, 2021). The reason is that without government intervention, credit rationing can occur, and government interventions could correct this market failure. In this respect, 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 extend this literature by providing information on the profile of firms and banks that are most involved in such programs.

Finally, we contributes to the recent literature that studies 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 closest paper to ours is by Altavilla et al. (2021), which build on the same database (AnaCredit) to study the substitution effect between public guaranteed and unsecured loans during the pandemic, in four different European countries. In particular, they find that Banks extending guaranteed loans reduced non-guaranteed credit by about 40% more than other banks lending to the same firm. Our paper differs from theirs for three reasons. First, our research question focuses on bank risk taking, not substitution; second, using a different empirical strategy, we broaden the analysis to the study of single-bank firms instead of limiting it to multi-bank firms. This difference is particularly important in a country like France where single-bank firms account for 60 % of total firms in the credit register (Beatriz et al., 2018). Finally, their paper focuses on the very first months of the crisis, while we follow the PGLs scheme during two years of its life. The other study that comes close to us is the one by Jiménez et al. (2022) which highlight the importance of relationship lending in the effectiveness of PGLs during the COVID-19 crisis using granular loan-level information. We complement their analyses by investigating in depth the risk shifting effect of PGLs at both the firm-bank and bank level.

3 PGE: The French loan guarantee scheme during the pandemic

The French PGL scheme, *Prêts Garantis par l'Etat* (PGE), was announced on March 16, 2020, with the aim of countering on the one hand the negative economic effects of the Covid-19 pandemic that was beginning, and on the other hand the restrictive measures (lockdowns and business closures) decided by the French government as in the rest of Europe. The PGE scheme became effective on March 23, 2020[2]. It was originally to last until June 30, 2021, but was extended once until the end of December 2021, and a second time until June 30, 2022.

Each PGL request had to be validated by the French public investment bank BPI France[3]. In practice, almost all applications were accepted: the final rejection rate was 2.9%[4], a percentage in

[2] Arrêté du 23 mars 2020 prescrivant les mesures d'organisation et de fonctionnement du système de santé nécessaires pour faire face à l'épidémie de Covid-19 dans le cadre de l'état d'urgence sanitaire

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

[4] Le coût réel des PGE reste incertain, AGEFI, 17th February 2022

line with that of pre-crisis rejection rates. 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. Figure 3 shows 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. The spread between the rates applied to PGLs and the rates applied to non-guaranteed loans ranged from 1% to 1.5% over the period.

Enterprises 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 by another year. After these first two potential years, the maturity of PGE loans could be extended to a maximum of six years, with rates ranging from 1% to 2.5% depending on the agreed maturity.

From a formal point of view, the PGE scheme was allowed by the Communication of the EU Commission (2020/C 91 I/01) which stated that «Member States [..] may put in place [aid in the form of guarantees on loans] without the involvement of the Commission». The 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 initial PGE budget was set up to 300 billion euros, about 12 percent of French GDP in 2019, of which 143 billion were made available immediately. The amount of PGL available to each enterprise could reach up to three months of 2019 turnover. In the case of innovative enterprises or startups, the maximum loan amount could reach two years of payroll. In May 2020, the scheme was extended. On one hand, PGLs became available via FinTech platforms (IFP) too. On the other hand, a second type of PGL, called *PGE Soutien Innovation* was launched to help young innovative firms.

The PGL scheme was designed to support mainly small and medium-sized enterprises. Table 1 shows that the government guarantee covered different percentages of the loan depending on the size of the enterprise. For smaller firms, the coverage could reach 90 percent of the loan. For larger enterprises, the guarantee was only 70%. Figure 4 shows that as a result most of the loans were made to enterprises with a turnover under 1.5 billion euros, not only from the point of view of quantities, as is to be expected, but also from the point of view of volumes. About 65% of the total volume of PGLs allowed was given to small firms.

Figure 5 also shows that the program has been effective in supporting sectors particularly hard hit by the crisis. The figure shows only the top ten sectors in terms of volumes of PGL received. The lockdown actually involved store closures (retail sector), partial shutdowns in manufacturing and construction (one-third of the French workforce was on partial leave), while hotels and restaurants had to close. This is certainly good news from a macroeconomic point of view. However, this finding may raise concerns in cases where those being kept alive were not healthy firms, but firms that were already financially problematic before the crisis. The risk is once again that PGLs have been used to support risky lenders that are likely to default during a crisis. The rest of the paper aims to address this issue.

4 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 definition of the variables of interest are presented in Table 2.

4.1 Loan-level variables

Core data come from the AnaCredit[5] 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,

[5] 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`

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[6].

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 1998 the French credit gathers monthly data on credit exposures of all banks operating in France to all firms whose total credit exposure is higher than €25,000. Yet, it is not a loan-level database and granular information on new loans is not available. Overall, around 25 millions individual loans are reported monthly, granted by around 7000 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 2, which provides a comparison of the outstanding amount of credit to non-financial corporations (NFC) between the Banque 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 guarantees scheme provided by the government during the pandemic[7] and the protection identifier includes "PGE" (Prêt garanti par l'Etat). Selecting loans related to state guarantees in AnaCredit, Figure 1 shows that we capture almost 90% of the outstanding credit as reported by the European Banking Authority (EBA)[8]

[6] 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.

[7] 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)

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

In our analysis, we restrict our sample to new loans granted to NFC[9] 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[10] which represent 99% of observations related to PGL in AnaCredit.

4.2 Firm-level variables

We first match the AnaCredit dataset with firms' balance sheet information coming from the FIBEN 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. In 2017, 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[11]. Above all, a great advantage of FIBEN is that it enables to focus on non-listed SMEs that are often neglected by American studies based on the Compustat database [12]. 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 measures such as profitability (i.e. the ratio of cash flow over the sum of fixed and working capital), 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

[9] The associated institutional sectors is "S 11".

[10] To be precise, 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".

[11] 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)

[12] In this regard, 80% 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).

(i.e. the size and the age of the firm).[13]

4.3 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, 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).

4.4 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. 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 (i.e. private versus shared information). Like the length of the relationship, single-banking has sometimes been used as a relationship lending measure in the

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

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.

4.5 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 credit 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.

5 Empirical strategy

To assess the effects of PGL on bank risk-taking we take advantage of alternative empirical methodologies that are articulated among four 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 PGL change the distribution of new credit to risky firms and, if so, do weaker banks contribute more? The third part analyzes the potential substitution of non-state guaranteed loans for PGL among banks that grant a PGL to a firm. If there is indeed a transfer of risks, is the substitution effect stronger for riskier companies and weaker banks? Finally, the fourth 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?

5.1 The extensive margin of 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.

To study firm and bank characteristics associated with PGL, we construct a dataset at the firm-bank level to capture firms that have asked for a loan 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 60% 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)[14].The specification that we estimate is at the firm-bank level:

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

Where $APGL_{ib}$ is a dummy variable which takes the value 1 if firm i has obtained at least

[14] Note that a total of 95% of all observations corresponds to small and medium-size firms (SMEs).

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-unvarying heterogeneity among regions and sectors and ϵ_{ibr} is the error term.

5.2 The intensive margin of PGL: a fixed effect model

Looking at the intensive margin analysis (i.e., the amount of new credit granted), we construct a database building on the same sample period as previously but, this time we focus our analysis on the new loan-level. For every amount of new loans granted we distinguish whether the loan is a PGL or not. Indeed, we want to know if PGL are associated with higher amounts that can be linked to higher bank risk taking. Merging this loan-level database with firm and bank characteristics as well as relationship lending variables, we end up with 182,531 observations, composed of 126 banks and around 43,262 firms. Table 4 presents summary statistics of this new database. Following Beatriz et al. (2018), we use a panel data structure[15] on new loans using firm and bank fixed effects in our linear regressions to control for time-invariant unobserved heterogeneity[16]. As a result, the second specification that we estimate is at the new-loan-level:

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

Where $LN(CREDIT)_{ibt}$ 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

[15] 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.

[16] 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.

market power 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 viability of the bank. Under the bank risk taking hypothesis, weaker banks are likely to grant higher loan amount to risky firms in order to reinforce their capital base, thus benefiting from a windfall effect coming from PGL. To do so, we estimate both two-way and three-way interactions between our PGL dummy and our measures of firm and bank financial soundness.

5.3 Substitution between PGL and non-guaranteed loans: a cluster fixed effects model

The third issue addressed in this paper deals with the extent of credit substitution associated with PGE. To investigate whether weaker banks that grant a PGL to risky firms decide to reduce their exposure to non-guaranteed loans, we propose a different approach that needs another database. For each firm-bank pair, we calculate the growth rate of non-guaranteed credit between February 2020 and February 2022 and merge it with the volume of PGL as well as with the firm and bank characteristics used earlier. In the end, we obtain 72,629 firms and 132 banks representing 88,607 observations.Table 5 presents summary statistics of the credit substitution database. To estimate how much the non-guaranteed credit growth rate of a given bank-firm pair drop for an extra euro of guaranteed loans we use the following specification:

$$\Delta NG_{ib} = \alpha_{ILS} + \beta_b + \gamma F_{Q4-2019} + \delta G_{ib} + \epsilon_{ib} \tag{3}$$

Where the dependent variable ΔNG_{ib} is the firm-bank growth rate of non-guaranteed credit from bank b to firm i between February 2020 and February 2022. α_{ILS} is a "cluster-fixed effect" that captures the "firm-borrowing channel". Indeed, to include as many single-bank firms as possible into our estimations[17], we use industry–location–size (ILS) fixed effects as a time-varying demand control (Degryse et al., 2019). The industry bins are based on two-digit NACE classification codes; location bins are based on two-digit postal codes and the size bins are based on deciles of total assets of the firms. In that respect, the underlying assumption that we made is that the credit demand of firms belonging to the same industry–location–size group during our given time period is identical. β_b is a bank fixed effect that captures the "bank-lending channel" (Khwaja & Mian, 2008) and $F_{Q4-2019}$ is the same matrix of firms' credit worthiness controls that we used in our previous analysis. Finally $G_{ib} = \frac{GC_{ib}}{TA_i}$ is the amount of PGL received by firm i as a fraction of its total assets in December 2019.

To the extent that risk-shifting is at place, the substitution effect should be stronger for riskier firms and weaker banks. Thus, as for the intensive margin, we also estimate both two-way and three-way interactions between the volume of PGL G_{ib} and our indicators of firm and bank financial soundness.

5.4 A panel dynamic 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 109 banks representing 1,928 observations and 60% of corporate credit in March 2020. Since lagged values of risk taking 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:

$$RISK_{bt} = \alpha_1 RISK_{bt-1} + \alpha_2 PGLR_{bt-1} \alpha_3 CONTROLS_{bt-1} + \upsilon_b + \upsilon_t + \epsilon_{bt} \quad (4)$$

Where $RISK_{bt}$ denotes our indicators of banks' risk and $RISK_{bt-1}$ their past values. Hinging

[17] In France, single-bank firms represent 60% of the French credit register (Beatriz et al., 2018)

on the AnaCredit database we use three different measures as indicators of a bank's risk [18] For each bank and month, our first measure of its risks is the average probability of default of its credit portfolio[19]. Our second measure is the average default rate of the bank's credit portfolio[20], while our third measure is the average non-performing loan rate of the bank's credit portfolio [21]. We compute all these measures for each firm-bank pair and then weight them according to each firm's share of the total amount of credit granted by the bank. Finally, using the FIBEN database, we also compute the share of firms whose survival is threatened in the bank's credit portfolio according to the Banque de France rating. Considering that PGL 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 ratio of public guaranteed loan 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 loans ratio and its return on assets; υ_b is a bank-specific fixed effect; υ_t is a month-specific fixed effects and ϵ_{bt} is the idiosyncratic error term. The subscript b indexes banks while t indexes month, where t=2020:03-2022:02. Table 6 shows descriptive statistics of the above variables.

With such a model both the pooled and fixed effects estimator are likely to suffer from a dynamic panel bias (Nickell, 1981). We implement a dynamic panel methodology that 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, in a system, the regression in differences with the regression in levels [22]. The

[18] 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.

[19] The latter is provided directly by each bank and calculated following internal models specific to each institution.

[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))

[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

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 Eq. (4) as follows::

$$Y_{bt} - Y_{bt-1} = \alpha(Y_{bt-1} - Y_{bt-2}) + \beta'(X_{bt} - X_{bt-1}) \qquad (5)$$

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

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

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 in which we use 6 lags of instruments and collapse the instrument matrix, see Roodman (2009).

(m2). 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.

6 Results

6.1 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. We want to know what are the main firm and bank characteristics that drive the firm probability of obtaining a PGL from its bank. Our main findings are twofold. Firms with higher probability of obtaining a PGL were smaller and more fragile than average. For their part, banks with higher probability of granting PGLs were larger and more solid than average. Table 7 reports the 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 2.1% value can be interpreted as follows: For firms in an industry whose value-added growth rate between 2019 and 2020 was 4.93 percent (one unit below the average for all industries of 5.93 percent), the probability of obtaining a PGL was 2.1 percent higher. The other quantitatively important 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 lower than the average benefited from a 6 percent 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 0.5% higher probability to obtain a guaranteed loan), less profitable (a ROA higher by one point results in a 0.6% lower probability of obtaining a loan), and younger (marginal effect at the mean is 0.1%). These results show that the PGL program 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).

With respect to banks, the credit institutions more likely to grant a PGL were on average larger (a bank with total assets of € 90 billion higher than the average has a 1.1 percent higher probability of granting a guaranteed loan), more capitalized, more liquid, and more profitable. This result is in line with the findings of Altavilla et al. (2021), according to whom in the main Eurozone countries, public-guaranteed lending has mainly been offered by large, liquid and well-capitalized banks. Finally, the coefficient for the NPL ratio is slightly statistically significant and positive. The credit institutions more likely to grant a PGL have on average a (slightly) higher rate of non-performing loans in their portfolio.

As for relationship lending and credit markets controls, only the coefficient of our single-banking dummy turns out to be significant and negative: multiple-bank firms were 12% more likely to obtain a PGL, thus showing that diversification of borrowing may mitigate the volatility of credit supply during a crisis (Detragiache et al., 2000).

The results of the large PGL margin can be interpreted in at least two different ways. On the one hand, firms that may be considered riskier prior to the pandemic were more likely to obtain a PGL, which is consistent with the effectiveness of PGLs that were designed to prevent the failure of businesses that were most in need of financing. On the other hand, one should wonder whether the access to credit to the riskiest firms may have undermine banks' credit portfolio with higher banks' risk taking. To address this concern, is it particularly important to be able to give a supply side interpretation of the effects of PGLs. Hence, we focus on the extensive margin of PGLs in the next section.

6.2 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 are on average almost three times higher than other 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 the case. It is the better capitalized, more liquid and more profitable firms that have obtained the highest PGLs. Third, as for banks, it is those that are less capitalized and have higher NPL ratios that have granted the highest PGLs. This result could raise concerns about banks' risk taking. Nevertheless, we show that these banks provided loans to firms that were sound from the perspective of their investment grade. Finally, consistent with the importance of relationship lending in the PGL scheme (Jiménez et al., 2022), larger secured loans were given to firms with a longer relationship length.

Column 1 of Table 8 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 variations regarding the supply of credit that are bank-specific, as well as month fixed effects to take into account any variation common to all firm-bank pairs that are month-specific. The main result to note here is that the PGL dummy, which indicates whether the new loan is guaranteed by the state, has a magnitude of 1.872. This means that, *coeteris paribus*, guaranteed loans are almost three times higher than other loans.

In Column (2) of Table 8 we remove bank and firm fixed effects in order to observe the correlations between bank-specific and firm-specific variables and the loan amount received. One should note that here we observe all new loans, not just public-guaranteed loans. The main correlations we find are as follows. Larger and more profitable firms, on average, were the ones who obtained higher loans (PGL and non-PGL). The banks that granted higher loans were on average more capitalized, more profitable and with lower NPL rates. These results are intuitive and confirm the existing literature on the determinants of firms' acces to finance (Jiménez et al., 2012, 2014; Ferrando & Mulier, 2015). Nevertheless, they do not discriminate between PGLs and non-PGLs.

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) in 8 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 state-guaranteed nature of the loan[24]. Importantly, the main results in Column (1) of Table 9 are opposite to those we had found relative to the extensive margin. While at the extensive margin firms with the easiest access to PGLs were the most fragile ones, at the intensive margin, we found that it is better capitalized, more liquid, more profitable, and older firms that have obtained the highest amount of new credit loans, conditional on having obtained a PGL. All these effects are nonetheless quite small in magnitude. Alternatively, in Column (2) of Table 9, we include as regressor a variable summarizing the Banque de France rating and we interact it with our PGL dummy. The variable *investment grade* described in section 4, represents the assessment of firm quality calculated by the Bank of France on the basis of balance sheet and income statement characteristics of the firms themselves. In the context of this regression, the variable *investment grade* takes value 1 if the firm is considered as sound (i.e. the firm has an excellent ability to meet its three-year financial commitments) or 0 otherwise. The coefficient of 0.233 presented in Column 2 goes in the same direction as the coefficients shown in Column 1. Being creditworthy from the Banque de France point of view, significantly increased the amount of new credit obtained (on the condition that the firm had a PGL).

Turning to banks heterogeneity, we know look at the profile of banks that granted higher PGLs amount. 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[25].Table 10 presents the

[24] 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.

[25] 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.

results obtained by running this regression. Three coefficients are particularly worthy of interest. Let us first focus on the coefficient of the interaction between our PGL dummy and the capital ratio. This coefficient can be interpreted as follows: when considering two loans both guaranteed by the state, on average, loans granted by banks with a capital ratio one percentage point higher are lower by 10.5%. Second, PGLs granted by banks with a one percentage point higher NPL ratio are 52% higher than other PGLs. This result can have two distinct meanings. Either particularly risky banks have taken advantage of PGLs to increase their lending to the riskiest firms, thereby increasing their risk-taking; or these banks have used PGLs to improve the quality of their credit portfolio by lending to safer firms to improve their financial health.

To discriminate between these two possible explanations 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 11. 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 (0.661). Let us consider two PGLs granted by two different banks. The amount of the new loan granted by a bank with a one percentage point higher NPLR is higher by 66.1%. Now consider instead two PGLs to two different types of firms, one risky and the other non-risky, and granted by two banks with a one percentage point higher NPLR. In this case, the amount obtained by the safer company will be 17.8% higher.This result entails that banks that were more exposed to nonperforming loans before the crisis lent smaller loan amounts to risky firms to improve their financial situation and especially their exposure to nonperforming loans.

Finally, investigating the role of relationship lending on the amount of PGLs granted, we first interact, in column (1) of Table 12, 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 firms that exhibit higher relationship length with their bank before the pandemic received higher amounts of PGLs. 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 textitPGL,*investment grade* and *Duration* appears significant and negative while the simple interaction term between textitPGL and *investment grade* remains positive and significant, thus indicating that relationship lending mitigate the effects of firm riskiness on the amount of PGL granted.

6.3 Is there a substitution effect of PGLs to unsecured loans more pronounced for risky firms and financially weaker banks?

In this section, we analyse whether PGLs replaced maturing loans taken by the same firms from the same banks before the Covid-19 crisis. Unlike in Altavilla et al. (2021), who make this the focus of their analysis, we are interested in this question always from the perspective of risk-taking by banks. We are interested in finding out whether the substitution that has occurred at the firm-bank level between non-guaranteed credit and guaranteed credit has led to an increase in banks' exposure to risky firms.

The main results are as follows. First, we confirm Altavilla et al. (2021) findings that in France, as in the other major eurozone economies, banks have used the PGL scheme to replace some of the non-guaranteed credit with public-guaranteed credit in a dynamic of credit risk reallocation. More specifically, for each bank-enterprise pair, a 1 percentage point increase in the ratio PGLs over total assets of the firm is associated with a reduction in the growth rate of unsecured loans of about 1.5 percentage point. Using interactions between the volume of PGLS granted and firm characteristics in our model, we also find that those who benefited most from this substitution were larger, more capitalized, more liquid and younger (i.e. generally less risky). Finally, while we observe that bank characteristics alone do not influence credit substitution, we find that large banks substitute less PGLs for unsecured credit when firms are riskier.

Table 13 shows the results of the basic specification of equation 3. The coefficient of 1.525 can be interpreted as follows. For each bank-enterprise pair, a 1 percentage point increase in the volume of PGLs granted, normalized by the total assets of the firm, is associated with a reduction in the growth rate of non-guaranteed loans of about 1.5 percentage point [26]. The industry-size-location fixed effect ensures that we are not observing an effect due to loan demand but purely due to credit supply (Degryse et al., 2019). Including single-bank firms in the analysis, this finding is consistent with Altavilla et al. (2021) and indicates that PGLs have triggered a reallocation of credit risk in France.

Looking at the role of firm heterogeneity in this mechanism, we interact the volume of PGL G with firm characteristics in Table 14. The coefficients show that the firms for which loan substitution was most pronounced were those that were larger, better capitalised, more liquid and less young, i.e. generally less risky. This result implies that banks took advantage of the PGL scheme to substitute their own risk taking for that of the state but that they were less prone to do it for risky firms. Once again, this suggests that French banks did not increase their risk-taking through PGLs. Table 15 shows the results of a specification in which we interact the volume of PGL loans with some bank characteristics. The purpose is to understand whether the substitution phenomenon is higher for certain types of bank. None of the coefficients turn out to be statistically significant, indicating that the substitution affected all banks that participated in the program.

Finally, table 16 shows the results of a specification in which we introduce a triple interaction between the volume of PGL G, bank characteristics and the *Investment grade* of the Banque de France. Results are presneted in Table 16 and show that only the coefficient of the triple interaction between G, the *Investment grade* and the size of the bank is statistically signif cant and negative. This means that large banks replaced less unsecured credit with PGLs when firms were more risky. Thus, although there has been a partial substitution between non-guaranteed loans and PGLs, we argue that the latter have not been used by banks to take more risk.

[26] In this respect, on should note that the standard deviation of the growth rate of unsecured loans is 10 and the average is -0.87%.

6.4 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 banks' risk taking hypothesis. Yet, we have not assessed the impact of PGLs on the overall level of banks' credit risk. Focusing on the bank-level, we now directly study the effect of PGLs on banks' risk taking by using a dynamic panel model. Controlling for bank-specific variables as well as past values of banks' risk-taking measures, we find that granting more LGPs did not have an impact on banks' risk-taking. This result is robust to all bank risk-taking measures that we employ and is consistent with the other analyses conducted at the firm-bank level in the rest of the paper.

As outlined in section 5, we use four different measures as indicators of a bank's credit risk: the probability of default, the default rate, the non-performing loan rate and the share of firms whose survival is threatened in the bank's credit portfolio according to the Banque de France rating. For each specification, we include bank controls (defined in 2 and month fixed effects to capture movements common to all banks but specific to time. Finally, being in a dynamic panel model context, we add six lags of the dependent variable that captures banks' credit risk, from one to six months [27].

The results we obtained by running equation 4 are presented in Table 17. The first row shows that having granted more PGLs did not have any impact on banks' risk taking, as all coefficients are not statistically significant. In addition, only the lags of our dependent variables appear positive and significant, thereby highlighting the persistent effect of banks' risk taking strategy. 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 promote risky banking behaviour towards their clients.

[27] Note that the results are not sensitive to the choice of the number of lags

[28] It should be noted that in the Japanese case, the total amount of SME loans held by banks could be covered by the state guarantee, whereas the French PGL program covers at best 90% of loans.

7 Conclusion

In this paper, we estimate the effects of Public guaranteed loans (PGLs) on banks' risk-taking. To do so, we analyse the PGL program designed by the French government in response to the Covid-19 crisis. Using four different empirical strategies on granular loan-level data, we find that French banks did not take advantage of the PGLs to increase their lending to financially weak firms. On the contrary, thanks to the PGL program, French banks were able to transfer a part of their credit risk to the state while granting larger amounts of PGL to the most liquid, best capitalised and most profitable firms.

These results have policy implications. Guaranteed loans helped support credit to solvent but illiquid firms during the crisis, and in this way they served the purpose for which they were created. However, these guarantees are not neutral on banks' balance sheets. In the case of post-Covid France, the guaranteed loans improved the banks' balance sheets, especially for low-capitalized banks with higher ratio of non-performing loans before 2020. The most likely explanation is that in no case did guaranteed loans completely insulate banks from risk-taking. In fact, the guarantees covered between 70% and 90% of the loan, depending on the size of the firm. Complete loss insulation encourages banks to lend to low-quality borrowers, or even zombies, which increases banks' risk-taking. French banks, encouraged by the partial state guarantee, therefore continued to lend according to their own criteria and risk models. However, they did not relax the terms of their loans, knowing full well that in case of default, they would still have to bear part of the losses.

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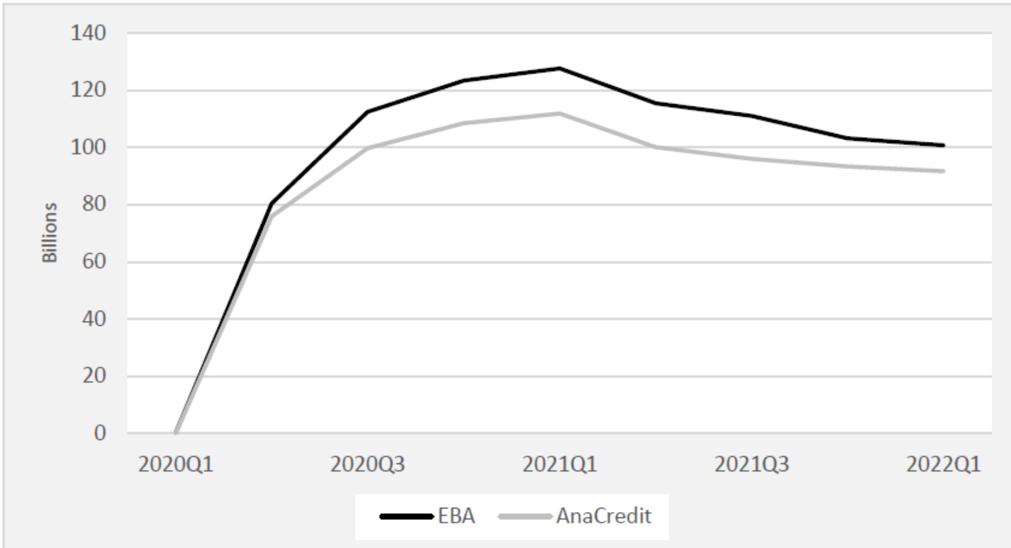
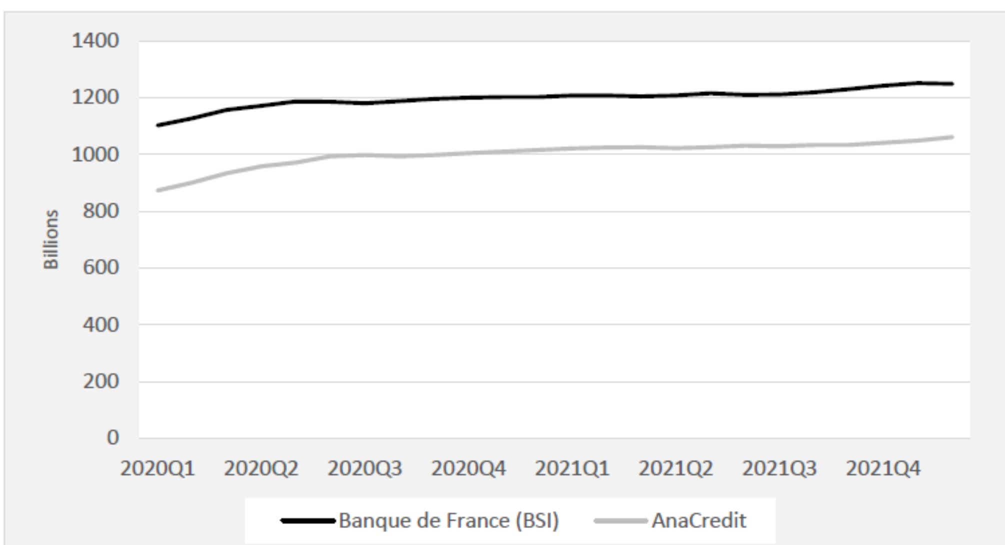
Appendix

Figure 1: Comparison of reported public guaranteed loans: EBA vs AnaCredit



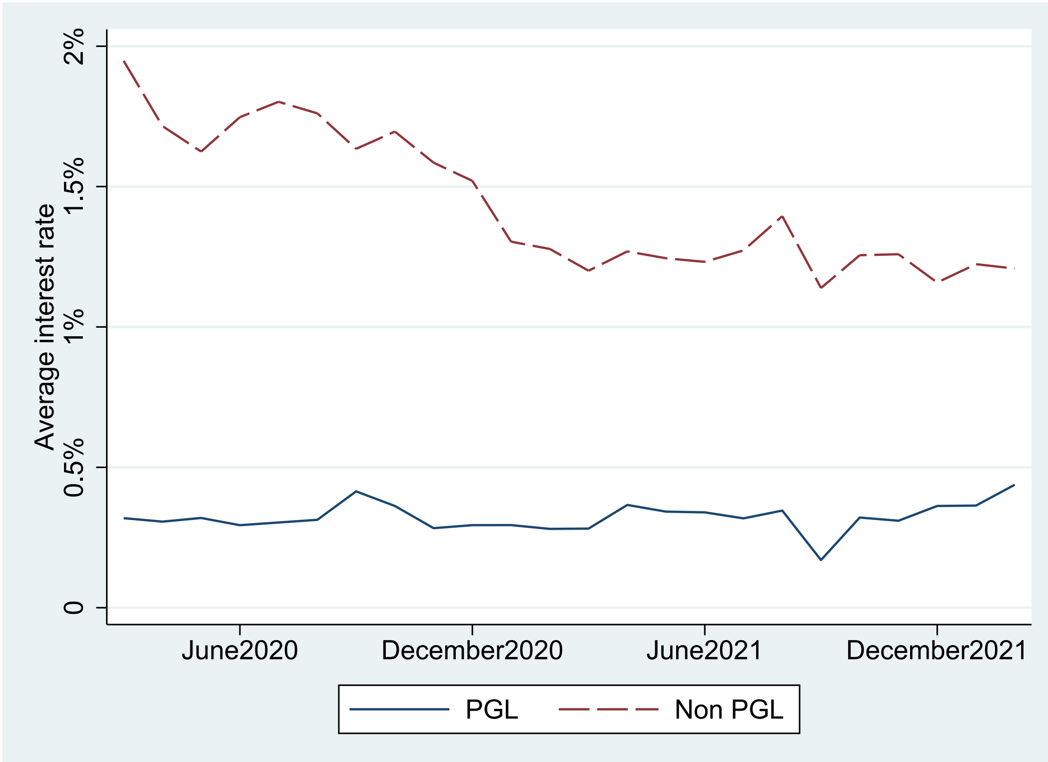
Notes: The EBA oustanding credit comes from its reporting and disclosure of exposures subject to measures applied in response to the COVID-19 crisis, while the other series is computed from AnaCredit.

Figure 2: Comparison of reported credit to Non-financial corporations: BSI vs AnaCredit



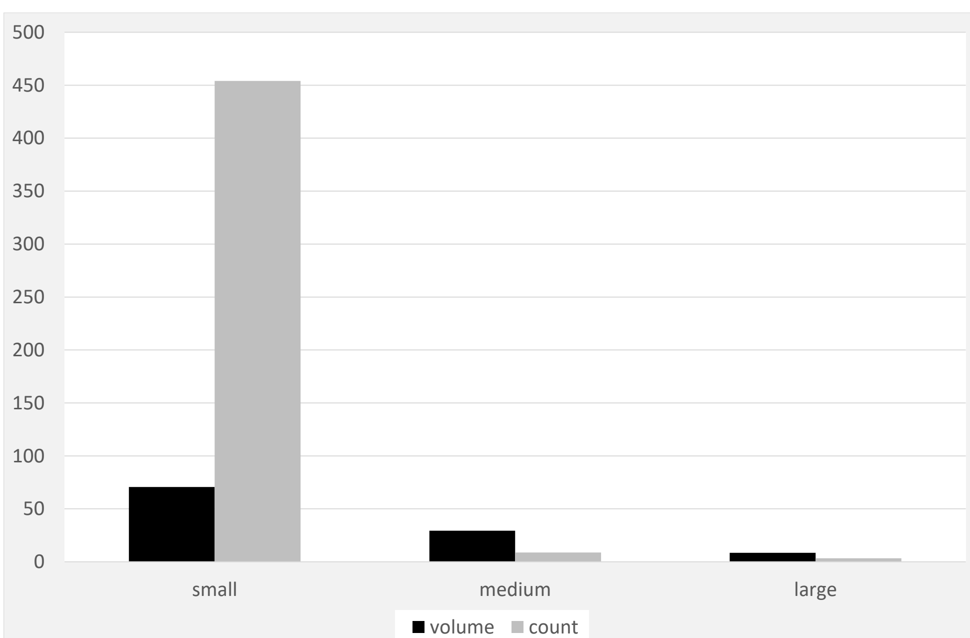
Notes: The bank balance sheet items (BSI) comes from Webstat (Banque de France) while the other series is computed using AnaCredit.

Figure 3: Average interest rates on new loans, March 2020 - February 2022



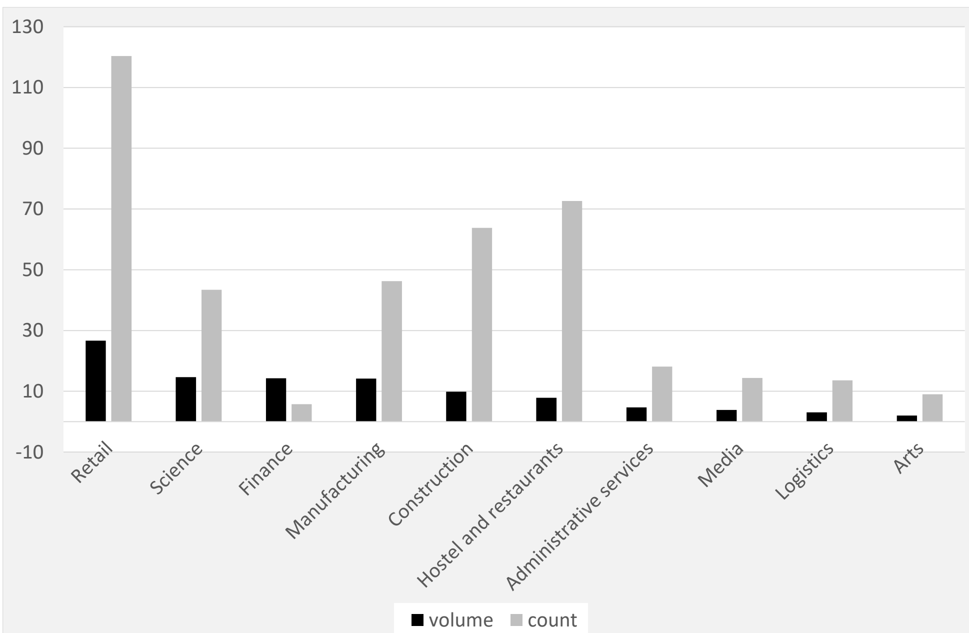
Source: Our elaboration on Anacredit data

Figure 4: PGL volumes and count per firm sizes



Notes: volumes are in billion euros and counts in thousands.

Figure 5: PGL volumes and count per sector



Notes: volumes are in billion euros and counts in thousand. Only the top ten sectors in terms of volumes are shown.

Table 1: Guarantee amount by 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

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
ΔNG	The firm-bank annual growth rate of non-public guaranteed credit between February 2020 and February 2022.
PGL ratio (G)	The firm-bank amount of public guaranteed loans received by a firm between March 2020 and February 2022 as a fraction of its total assets in December 2019.
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.
NPLR	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 rate 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	0.58	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
NPLR (%)	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					
State guaranteed loan (*0/1*)	0.22	0	0.41	0	1
Maturity (*months*)	43.12	11.96	106	1	680
Investment credit (*0/1*)	0.46	0	0.49	0	1
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 (Substitution of non-public guaranteed loan)

	Mean	Median	Sd	Min	Max
Dependent variable					
ΔNG	-0.87	-22.82	79.46	-95.79	324
Credit controls					
PGL ratio (G)($\%$)	7.25	3.15	10.04	0	47.92
Firm controls					
Age (*years*)	26	23	18	3	99
Total assets (*log*)	8.30	7.97	1.52	5.96	13.62
Total assets (*thousand euros*)	24,76	2,89	100,26	389	829,90
Capital ratio ($\%$)	28.28	27.13	15.52	0	69.87
Cash flow ratio (%)	4.55	4.48	8.31	-25.06	28.26
Cash ratio ($\%$)	10.55	6.83	11.11	0	51.08
Bank controls					
Total assets (*log*)	17.74	17.17	1.66	14.46	20.96
Total assets (*billion euros*)	52.31	27.12	0.01	1.90	1,267
Capital ratio ($\%$)	7.89	8.22	3.93	2.27	17.38
Liquidity ratio ($\%$)	17.62	11.97	18.35	0.62	58.11
ROA ($\%$)	0.42	0.42	0.18	0.10	1.33
NPLR ($\%$)	2.56	2.31	1.01	0	7.47

Table 6: Summary statistics (Bank risk taking)

	Mean	Median	Sd	Min	Max
Dependent variable					
PD($\%$)	7.47	5.34	4.61	0	17.95
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 control					
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
NPLR ($\%$)	2.32	2	1.11	0	7.08
PGLR ($\%$)	10.77	9.29	5.62	0.20	27.47

Table 7: Marginal effects at the means, probit estimation

	Marginal Effects, Probit Coef./SE
PGL dummy	
Firm controls	
Sector Growth Rate	-0.021***
	(0.00)
Firm Total Assets	-0.061***
	(0.00)
Firm Capital Ratio	-0.001***
	(0.00)
Firm Cash Ratio	-0.005***
	(0.00)
Firm ROA	-0.006***
	(0.00)
Firm Age	-0.001***
	(0.00)
Bank controls	
Bank Total Assets	0.011***
	(0.00)
Bank Capital Ratio	0.005***
	(0.00)
Bank Liquidity	0.001***
	(0.00)
Bank ROA	0.048***
	(0.01)
NPL Ratio	0.003*
	(0.00)
Relationship lending controls	
Duration	-0.001
	(0.01)
Single-bank	-0.128***
	(0.00)
Credit market control	
HHI	0.231
	(0.343)
Observations	140,901
Pseudo-R2	0.10

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Panel F.E. and Cross-section

	Credit Amount (log) Coef./SE	Credit Amount (log) Coef./SE
Credit variables		
PGL dummy	1.872***	1.711***
	(0.27)	(0.22)
Maturity	0.003***	0.002*
	(0.00)	(0.00)
Firm controls		
Firm total assets		0.658***
		(0.04)
Firm Capital Ratio		-0.001
		(0.00)
Firm cash ratio		-0.003
		(0.00)
Firm ROA		0.005**
		(0.00)
Firm Age		0.000
		(0.00)
Bank controls		
Bank total assets		0.034
		(0.13)
Bank Capital Ratio		0.089**
		(0.03)
Bank liquidity ratio		0.011
		(0.01)
Bank ROA		0.985***
		(0.09)
NPL Ratio		-0.321**
		(0.10)
Relationship lending variables		
Duration	-0.007**	-0.029***
	(0.00)	(0.01)
Single-bank		-0.020
		(0.04)
Credit market control		
HHI	-0.007	0.016
	(0.01)	(0.01)
Constant	10.801***	4.191
	(0.12)	(2.18)
Firm F.E.	YES	NO
Bank F.E.	YES	NO
Time F.E.	YES	YES
R2	0.773	0.379
Adjusted R2	0.702	0.379
Within R2	0.161	0.362
Observations	182 531	182 531

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Panel Regression - Firm heterogeneity

	Credit Amount (log) Coef./SE	Credit Amount (log) Coef./SE
PGL dummy	1.852***	2.041***
	(0.27)	(0.28)
Interactions with firm controls		
PGL x Firm Assets	-0.047	
	(0.03)	
PGL x Firm Capital Ratio	0.004**	
	(0.00)	
PGL x Firm Cash Ratio	0.014***	
	(0.00)	
PGL x Firm ROA	0.009*	
	(0.00)	
PGL x Firm Age	0.006***	
	(0.00)	
PGL x Investment grade		0.233***
		(0.04)
Loan, relationship lending, and credit market controls		
Maturity	0.003*	0.003*
	(0.00)	(0.00)
Duration	-0.007***	-0.007***
	(0.00)	(0.00)
HHI	-0.007	-0.007
	(0.01)	(0.01)
Constant	10.802***	10.804***
	(0.12)	(0.12)
Firm F.E.	YES	YES
Bank F.E.	YES	YES
Time F.E.	YES	YES
R2	0.773	0.773
Adjusted R2	0.703	0.702
Within R2	0.164	0.162
Observations	182 531	182 531

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Bank heterogeneity

	Credit Amount (log) Coef./SE
PGL dummy	2.095***
	(0.25)
Interactions with bank variables	
PGL x Bank Capital Ratio	-0.105**
	(0.04)
PGL x Bank Liquidity ratio	-0.020
	(0.01)
PGL x Bank ROA	-0.308
	(0.49)
PGL x NPL Ratio	0.522**
	(0.19)
Loan, relationship lending, and credit market controls	
Maturity	0.002*
	(0.00)
Duration	-0.006**
	(0.00)
Single-banked	0.000
	(0.00)
HHI	-0.007
	(0.00)
Constant	10.909***
	(0.11)
Firm F.E.	YES
Bank F.E.	YES
Time F.E.	YES
R2	0.784
Adjusted R2	0.717
Within R2	0.204
Observations	182 531

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Triple interactions

	Credit Amount (log) Coef./SE
Maturity	0.002*
	(0.00)
PGL dummy	0.110
	(3.27)
Interactions with bank variables	
PGL x Bank assets	0.070
	(0.17)
PGL x Investment grade	-0.331
	(0.83)
PGL x Investment grade x Bank Assets	-0.000
	(0.04)
PGL x Bank capital Ratio	-0.092*
	(0.04)
PGL x Investment grade x Bank Capital	0.018
	(0.01)
PGL x Bank Liquidity Ratio	-0.019
	(0.01)
PGL x Investment grade x Liquidity	0.001
	(0.00)
PGL x Bank ROA	-0.338
	(0.50)
PGL x Investment grade x Bank ROA	-0.010
	(0.16)
PGL x NPL Ratio	0.661**
	(0.21)
PG Lx Investment grade x NPL Ratio	0.178***
	(0.05)
Loan, relationship lending, and credit market controls	
Duration	-0.006**
	(0.00)
Single-bank	0.000
	(.)
HHI	-0.007
	(0.00)
Constant	10.587***
	(0.45)
Firm F.E.	YES
Bank F.E.	YES
Time F.E.	YES
R2	0.785
Adjusted R2	0.718
Within R2	0.206
Observations	182 531

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Relationship lending

	Credit Amount (log)	Credit Amount (log)
	Coef./SE	Coef./SE
PGL dummy	1.711***	1.955***
	(0.25)	(0.27)
Interaction terms		
PGL x Duration	0.016***	0.007
	(0.00)	(0.00)
PGL x Single-bank	0.005	0.045
	(0.06)	(0.06)
PGL x Investment grade		0.309***
		(0.06)
PGL x Investment grade x Duration		-0.011*
		(0.00)
PGL x Investment grade x single-banked		0.077
		(0.08)
Loan and credit market controls		
Maturity	0.002*	0.002*
	(0.00)	(0.00)
HHI	-0.007	-0.007
	(0.01)	(0.01)
Constant	10.925***	10.924***
	(0.13)	(0.13)
Firm F.E.	YES	YES
Bank F.E.	YES	YES
Time F.E.	YES	YES
R2	0.773	0.773
Adjusted R2	0.702	0.702
Within R2	0.162	0.163
Observations	182 531	182 531

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Substitution between PG and non-PG loans

	Non-SG Credit Growth Coef./SE
PGL Volume	-1.525***
	(0.072)
Firm controls	
Total assets	0.385
	(1.406)
Capital ratio	0.067**
	(0.025)
Cash flow ratio	0.421***
	(0.056)
ROA	1.031***
	(0.055)
Age	0.041
	(0.021)
Constant	-8.106
	(11.961)
Industry-Location-Size F.E.	YES
R squared	0.250
Adjusted R2	0.119
Within R2	0.041
Observations	88 607

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Credit substitution, firm heterogeneity

	Non-PG Credit Growth Coef./SE
PGL Volume	-1.827***
	(0.101)
Interactions with firm controls	
PGL Volume x Total assets	-0.286***
	(0.048)
PGL Volume x Capital ratio	-0.008***
	(0.002)
PGL Volume x Cash flow ratio	-0.007**
	(0.003)
PGL Volume x ROA	-0.006
	(0.003)
PGL Volume x Age	-0.008***
	(0.002)
Constant	10.336***
	(0.55)
Industry-Location-Size F.E.	YES
R squared	0.249
Adjusted R2	0.118
Within R2	0.040
Observations	88 607

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Credit substitution, bank heterogeneity

	Non-PG Credit Growth Coef./SE
PGL Volume	-1.484***
	(0.100)
Interactions with bank controls	
PGL Volume x Assets	0.089
	(0.076)
PGL Volume x Capital Ratio	0.008
	(0.020)
PGL Volume x Liquidity ratio	-0.004
	(0.006)
PGL Volume x ROA	-0.155
	(0.238)
PGL Volume x NPLR	0.101
	(0.080)
Constant	9.981***
	(0.46)
Industry-Location-Size F.E.	YES
R squared	0.240
Adjusted R2	0.108
Within R2	0.029
Observations	88 607

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Credit substitution, triple interactions

	Non-PG Credit Growth Coef./SE
PGL Volume	-1.823***
	(0.093)
Interactions	
PGL Volume x Bank Assets	0.008
	(0.083)
PGL Volume x Investment grade	-0.549***
	(0.065)
PGL Volume x Investment grade x Bank Assets	-0.136*
	(0.066)
PGL Volume x Bank Capital	0.005
	(0.023)
PGL Volume x Investment grade x Bank Capital	-0.001
	(0.017)
PGL Volume x Bank Liquidity	-0.003
	(0.006)
PGL Volume x Investment grade x Bank Liquidity	0.003
	(0.005)
PGL Volume x Bank ROA	-0.153
	(0.373)
PGL Volume x Investment grade x Bank ROA	-0.056
	(0.416)
PGL Volume x NPLR	0.076
	(0.096)
PGL Volume x Investment grade x NPLR	-0.041
	(0.081)
Constant	20.501***
	(0.67)
Industry-Location-Size F.E.	YES
R squared	0.246
Adjusted R2	0.115
Within R2	0.036
Observations	88 607

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Bank risk taking, GMM dynamic panel regression

	PD Coef./SE	Default rate Coef./SE	NPL rate Coef./SE	BDF risk Coef./SE
PGLR_{t-1}	0.000	-0.001	-0.003	0.003
	(0.01)	(0.01)	(0.01)	(0.016)
Controls				
$\text{Total Assets}_{t-1}$	-0.003	0.000	-0.000	-0.002
	(0.00)	(0.00)	(0.00)	(0.003)
$\text{Capital Ratio}_{t-1}$	0.094	0.022	0.024	-0.030
	(0.11)	(0.03)	(0.02)	(0.029)
$\text{Liquid Ratio}_{t-1}$	0.016	-0.004	-0.005	0.012
	(0.02)	(0.01)	(0.01)	(0.016)
ROA_{t-1}	-0.696	-1.881	-2.415	0.125
	(2.35)	(1.87)	(1.59)	(0.781)
Lags of the dependent variable				
PD_{t-1}	0.906^{***}			
	(0.10)			
$\text{Default Rate}_{t-1}$		0.931^{***}		
		(0.09)		
NPL_{t-1}			0.949^{***}	
			(0.07)	
BDF Risk_{t-1}				0.689^{***}
				(0.176)
Time F.E.	YES	YES	YES	YES
Constant	0.051	-0.002	0.007	0.048
	(0.05)	(0.01)	(0.02)	(0.055)
Observations	1 928	1 928	1 928	1 927

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$