From Granular Credit Risk to Credit Supply: The Probability of Default Channel

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Abstract

We combine firm level data on balance sheets with *Anacredit* (EU credit register for NFCs) to investigate how idiosyncratic firm shocks affect bank portfolio credit risk and the aggregate credit supply. We show that the uncertainty bank face when setting single-name probability of default (PD) affects the level of risks of bank portfolios and the aggregate credit supply due to spillovers across firms. This is stronger when bank portfolio concentration is high given the presence of granular borrowers and when banks have low capital ratios. Firms with small loan shares in bank portfolios are the most affected by (indirect) credit restrictions. It implies that macroprudential authorities should be proactive in limiting portfolio concentration especially when bank capital ratios are low. We also focus on the Covid crisis: even if state-guaranteed loans were activated, this PD channel of transmission has still been active but with a lower intensity.

Keywords— Macroprudential policy, *Anacredit*, granular borrowers, credit risk

*Disclaimers: the views expressed in this paper are those of the authors and do not reflect the views of Banque de France

1 Introduction

The spread of Covid-19 and associated global prophylactic measures adopted around the globe have been one of the biggest challenges for non-financial corporations (NFCs) since World War II. Several supporting measures have been adopted to ensure the financing and survival of NFCs in 2020, particularly in France. Loan moratoria, state-guaranteed loans and tax reliefs are some examples. Most of these measures rely on relationships between banks and companies to alleviate short-term financing pressures for companies on the one hand, and by ensuring sustainable risk-taking behaviors by banks through state-guarantees on the other. These emergency measures were adopted when NFC-related risks were already a focus of the French macroprudential authority (*High Council for financial stability* - HCSF): since 2018, systemic banks have been required to maintain below 5% of their own funds some exposures to large and leveraged French corporations. This measure (as part of the large banking exposure regulation) aims to reduce the nexus between highly leveraged large firms and systemic banks. The HCSF thus considers that some firms could be systemic, or more precisely that some exposures or bank-firm relationships are sufficiently granular to generate (potentially negative) externalities for the rest of the financial system and other firms.

We analyze how NFC single-name exposures in banks' credit portfolios could affect the financing capacity of all firms through spillovers. Banks' portfolios are often characterized by a significant degree of concentration due to exposures to large firms: they are thus exposed to the distress and/or risk-taking behaviour of a few counterparties and this risk can spill over the rest of the credit portfolio. We address this issue by exploiting *Anacredit*, the recently available European credit register. It provides extensive information on NFC credit contracts (volumes, maturity, rates, guarantees for example) but also the associated risks parameters of the lenders such as the assigned probability of default. This data, in its "pilot version", have already been used for example in Altavilla, Boucinha, et al. (2020).

Our paper follows a step-by-step approach as in Galaasen et al. (2020). First, we isolate idiosyncratic firm shocks that are not foreseen by banks a the time of loan origination and until maturity. To do so, we exploit the *Fiben* database which is a *Banque de France* database compiling financial information of French firms aiming at providing banks with information on NFC-risk (including the NFC *Banque de France* rating of firms). Idiosyncratic firm shocks that we capture are thus exogenous with respect to banks' information set. In a second step, we investigate banks' responses to those shocks by focusing on the granularity of bank credit portfolio shares. Specifically, we focus on how probabilities of default (PDs) assigned by banks (as a regulatory risk parameter) are related to these idiosyncratic shocks, especially for so-called granular NFCs to which bank portfolios are significantly exposed. Our results suggest that the bigger the shock, the higher the PDs, regardless of the sign of the firm's idiosyncratic shocks. This U-shape pattern characterizes the impact of NFC uncertainty on bank risk parameters: the more difficult it is to make a proper assessment of credit risk, the higher the PD assigned. In a third step, we investigate how these links between NFC-risk and bank-risk parameters (PD) are still observed at the aggregate credit portfolio level. A common hypothesis is that portfolio diversification should decrease the impact of single-risk exposures, if there is no granular borrowers. We show, for our panel of French banks, that idiosyncratic risk exposures resist to the aggregation at the portfolio level. Related to this aggregate risk exposure, we show how granular single-risk exposures in a given portfolio spill over to other firms via lower credit supply and higher interest rates in case of shocks. We notably find that lower capitalized banks are the ones restricting credit conditions the most in case of shocks on one of their granular borrowers. On firms side, the ones with the lowest portfolio shares are the ones suffering credit restrictions the most. Finally, we investigate how supporting measures adopted during the covid-19 crisis have affected this PD channel of transmission. Soem papers have already started to analyze the impact of the crisis on firms balance-sheet (Bureau et al. 2021a, Bureau et al. 2021b) but still very few on lending conditions. Our results are robust to the covid crisis even when considering the impact of state-guaranteed loans: we find that probabilities of default still react to firm shocks but the effect is reduced by almost half. Accordingly, on aggregate, portfolio risk decreases as well but is still significant. In addition to being an effective tool for limiting the difficulties of firms in needs of liquidity, the state-guaranteed loan mechanism thus appears to be also effective in limiting spillovers from troubled firms to banks and then to healthy firms. In other words, it may be positive to maintain some zombies alive in crisis time through supporting measures, to avoid contagious credit restrictions to healthy firms. Our results thus confirm the need for macroprudential authorities to better account for potential negative externalities arising from individual bank-firm relationships and the need to specifically address concentration risks for weakly capitalized banks.

Our paper contributes to the literature that has already highlighted how firms are connected through a common financial intermediary, and has identified a set of channels through which banks' characteristics impact their credit supply. For example, Khwaja and Mian (2008) identified that banks transmit their liquidity shocks to firms. Greenwald, Krainer, and Paul (2021) identified that banks restrict credit primarily to small firms, following severe and negative macroeconomic shocks that impact their net income. According to Thornton and Di Tommaso (2021), banks with increasing risk-weighted assets tend to reduce credit supply to their clients. This literature is generally based on exogenous shocks that have nothing to do with banks' strategic portfolio composition choices. However, there is also a literature on how single-name exposure in banks' portfolios can impact aggregated banks' credit supply due to banks' portfolios concentration. For instance, Galaasen et al. (2020) argues that Norwegian banks' credit supply can be impacted by granular firms through the revenue channel. We add to this literature by showing that granular firms can also impact bank credit supply through other channels, such as the PD channel analyzed in this paper.

In section 2, we describe the granular datasets we use. In section 3, we present the methodology to extract idiosyncratic and unexpected firm shocks. In section 4, we present our main results and in section 5, we investigate how state-guaranteed loans deployed during the Covid-19 crisis may have affected the PD channel of transmission of idiosyncratic firm shocks. section 6 concludes.

2 Firms and Credit databases

2.1 Firm database

To estimate idiosyncratic and unexpected firm shocks, we use the *Fiben* (*Fichier Bancaire des Entreprises*) database of the *Banque de France*, which contains the annuals balance sheets and statements of profit and losses of French Non Financial Corporations (NFC) with a turnover of more than 750,000 euros for a given year. We merge this dataset with the credit rating of NFCs of the *Banque de France*. This credit rating is an indicator comprising twelve categories that assesses a company's ability to honor its credit commitments over a three-year horizon. The credit rating is available to any French NFC that requests it. This rating is commonly used (or even requested) by banks to grant credit to firms. For firms in *Fiben*, the rating process is more thorough, as it involves an individual assessment of accounting documents and interviews with managers by financial analysts from the *Banque de France*. In addition to the 12 ratings level, there is a category for firms that have not been thoroughly examined but have no payment incident reported. We treat this category as an additional category. Some firms are not rated because they are too small and have not requested it. This absence of rating is considered as a 14^{th} category, as the absence of such a widely spread rating is an information in itself.

One of the concerns of researchers working on the French production system is the complex structure of groups that involve multiple layers of legal entities. In particular, it is possible for group heads to have relatively low activity (low sales, low material costs or wages but high external costs), while contracting a large share of credit (debt is centralized at the head level) before distributing it to its subsidiaries, thereby disconnecting the firm's productive structure and its borrowing capacity. To overcome this, we consider all the subsidiaries of a given group head, whether they are owned directly or indirectly by the group head. We then add the sum of the financial results of its subsidiaries to the financial results of the parent company as reported by Fiben (the accounting categories of interest are the turnover, the wage bill and intermediate costs).

Our dataset covers NFC from 2011 to the end of 2020, but we specifically use information between 2018 and 2020. During this period, the end-of-year credit of these firms is about 675-720 billion euros between. We exclude from this database firms than have balance sheets covering periods that are not exactly twelve months, that have total assets equal to zero and public administration. We keep firms that exist for more than one year, and that have a bank debt greater than 0. In the end, we retain a bit more than 50% of the balance sheets available in the database in 2018-2020, but more than 95% of the total banking debt. Summary statistics for the remaining firms are presented in Table 1.

Table 1: Summary statistics - Firm level

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max
Growth of gross profit	−20.73	−0.12	0.01	0.14	20.46
Sales (1000 euros)	0	1,202	2,194	5,429	101,659,157
Total assets (1000 euros)	2	1,162	2,281	6,020	289,789,433
Wages (1000 euros)	0	216	416	922	7,594,587
Equity (1000 euros)	−4,640,995	280	658	1,724	62,703,000
Gross debt (1000 euros)	1	460	965	2,590	102,992,996
Banking debt (1000 euros)	1	49	193	614	52,537,000
Liquidity ratio	0.00	0.02	0.10	0.22	1.00
Credit rating	1	4	5	6	14

Note: $N = 557,023$.

2.2 Credit database

To identify and analyze the characteristics of bank-firm credit relationships, we use *Anacredit*, an instrument-by-instrument credit registry that includes all Eurozone (EZ) banks and their affiliates, made available to researchers by the European Central Bank since 2019. This database had been used in its preparatory version in order to study supranational *vs* national banking supervision (Altavilla, Boucinha, et al. 2020), and in its final version to study recent monetary policy decisions (Da Silva et al. 2021) or the impact of state-guaranteed loans during the Covid-19 crisis (Altavilla, Ellul, et al. 2021). The database contains all credit instruments, regardless of whether the loan receiver is inside the Eurozone or not, as long as the total of credit granted by the bank to the counterparty is greater than 25,000 euros. The register is implemented on a monthly basis and has a sufficient and satisfactory coverage as of September 2018 (prior to that date, quality issues with reported data and partial coverage of banks/loans make it difficult to use).

We only keep loans issued by deposit-taking corporations except central banks (sector S122 in the European system of accounts of 2010). We focus on French banks and French firms only (sector S11) given limited availability of accounting data about foreign NFCs: there is no equivalent to *Fiben* dataset outside France providing counterparty risk information to banks when they grant/monitor credit. However, the share of French counterparties in the portfolios of French banks is higher than 90% over the period of study that it is not a major concern. In addition, *Anacredit* contains several credit instruments, ranging from standard term loans to reverse repos to overdrafts. We choose to focus on *(i)* credit lines, *(ii)* revolving credit lines and *(iii)* term loans, as these are the most common forms of bank credit to NFCs. Indeed, in December 2020, term loans accounted for 53% of outstanding credit and credit lines for 32% of outstanding credit[1]. Although such a perimeter is not new, pre-existing national credit registers were not as comprehensive and complete as *Anacredit* in terms of available variables. In particular, we consider in *Anacredit* information on interest rates, probability of default assigned by banks, performing status or collateral and guarantees.

We restrict our analysis to the counterparties for which we have the balance-sheet information provided by *Fiben*.[2] Overall, the outstanding debt amounts to about 250-375 billion euros. One of the key variables of our analysis is the loan share, defined as the amount of outstanding credit for one NFC, divided by the total amount of outstanding credit for a given bank at at given time.[3] Summary statistics for the final dataset are presented in table 2. Figure 1 presents an histogram of the top 1% in the pooled distribution of loan share (removing values greater than 10% for the clarity of exposition, representing roughly 5% of observations in the top 1%).

Overall, the distribution of loan shares is highly skewed. Fitting a Pareto distribution on these data, we find a skewness parameter of 0.05. Trimming the upper and lower 10% of the distribution, the parameter rise to 0.38, but remains significantly lower than the estimates of Galaasen et al. (2020), which finds a parameter of 1.16. Whether this is linked from the inner characteristics of the French system, the place of

[1]Financial leases accounted for 6%, Overdraft for 5%, and trade receivables for 2%.

[2]Most excluded counterparties are micro-firms and firms in the housing sector, suggesting that we get rid of mainly *Sociétés Civiles Immovilières* (SCI).

[3]To obtain a consistent estimate, we remove credit portfolios with fewer than 100 counterparties. This represents less than 1% of observations in the database.

Table 2: Summary statistics - Credit level

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max
Outstanding amount (1000 euros)	0.00	58.16	163.90	471.82	2,310,627.00
Off balance amount (1000 euros)	0	0	0	0	2,300,000.00
Loan share (pp.)	0.00	0.002	0.01	0.03	88.03
Probability of default (pp.)	0.00	0.49	1.25	3.67	100.00
Annualized interest rate (pp.)	-0.25	0.65	1.09	1.73	9.95

Note: $N = 5,239,959$. For annualized interest rates, some observations were dropped as they were deemed erroneous. For this variable, there remains $4,874,346$ observations.

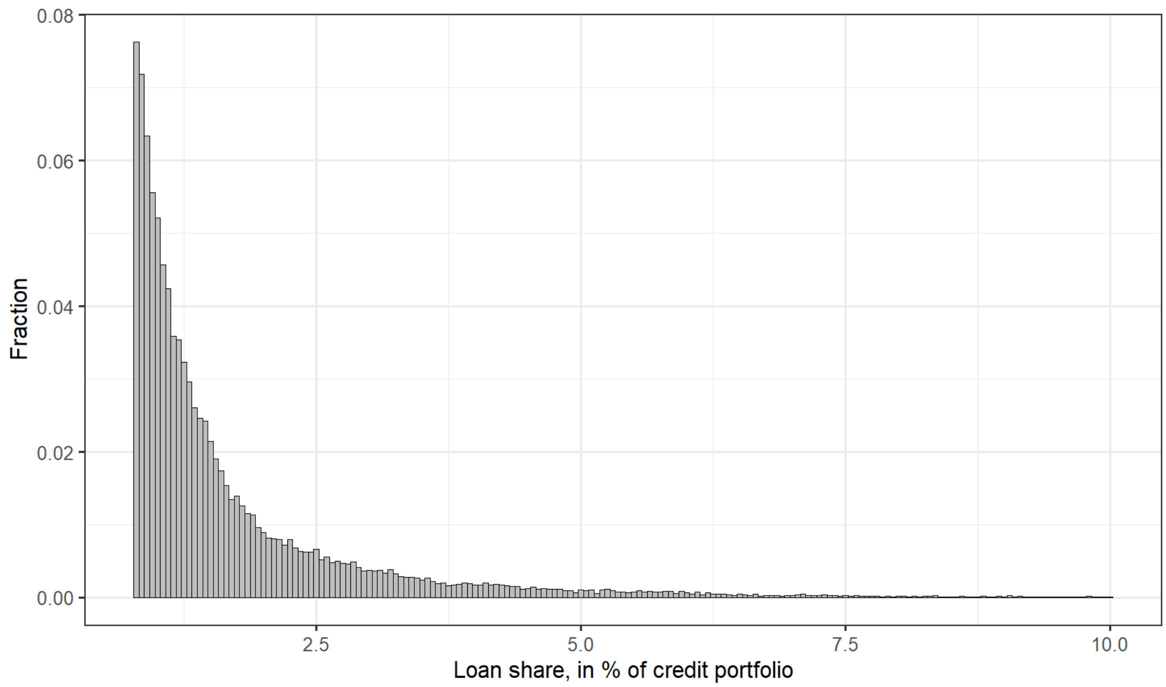

Figure 1: Distribution of loan share - Top 1%

our period of interest in financial cycles, or the particularly low reporting threshold of our credit register remains unknown.

To illustrate bank portfolios concentration, we present the Herfindhal-Hirschman index (Lütkebohmert 2009) and the shape parameter of a Pareto distribution fitted to each credit portfolio separately. The results are presented in Table 3. This confirms the strong concentration of credit. We note that the fitted shape parameter is relatively homogeneous and never gets greater than unity, suggesting that the assessment of credit concentration is not driven by a few portfolios. More naive measures confirm this: the top 10% loan shares for a given portfolio represents at least half of bank's credit. That said, even though all portfolios seems concentrated, significant heterogeneity along this dimension remains to explore.

Table 3: Summary statistics - Portfolio level

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max
Outstanding amount (million euros)	26.32	510.03	835.36	1,785.67	27,314.34
Number of loans	100	748	1,254	1,840.8	22,405
Top 10% share	0.52	0.75	0.79	0.83	0.97
Top 5 share	0.03	0.10	0.15	0.20	0.90
Herfindhal index	0.001	0.004	0.01	0.01	0.77
Skewness parameter	0.06	0.14	0.17	0.19	0.59
Probability of default (pp.)	0.02	2.87	3.98	5.39	11.29
Ratio of NPL (pp.)	0.00	0.78	1.31	1.98	99.39

Note: $N = 2,826$.

3 Identification of unexpected firm shocks

3.1 Methodology

A starting point for our identification strategy is to estimate idiosyncratic firm shocks, that are shocks in deviation of macroeconomic and sector factors, and which could not be anticipated by banks given their information set. In doing so, we follow closely the methodology developed by Galaasen et al. (2020). We start from the following production function:

$$Y_{j,t} = \theta_j \eta_{j,t} K_{j,t}^{\beta_1} W_{j,t}^{\beta_2} \tag{1}$$

Where $Y_{j,t}$ is the gross profit (that is sales minus intermediary costs) of firm j at time t, $K_{j,t}$ its level of equity, $W_{j,t}$ the book wages, β_1 and β_2 are parameters. We decompose remaining factors of production into two components: a time-invariant one θ_j and a time-varying one $\eta_{j,t}$. Taking the log-difference of this production function removes the time-invariant factor (small letters denote log-levels):

$$\Delta y_{j,t} = \beta_1 \Delta k_{j,t} + \beta_2 \Delta w_{j,t} + \Delta \eta_{j,t} \tag{2}$$

The time-varying component $\Delta \eta_{j,t}$ can then be decomposed into four components: a macroeconomic component, a sector-specific component, an anticipated idiosyncratic component and unanticipated idiosyncratic component. For our identification purposes, we want to isolate the shock component, which we will denote $\varepsilon_{j,t}$ in the following model:

$$\Delta y_{j,t} = \beta_1 \Delta k_{j,t} + \beta_2 \Delta w_{j,t} + \alpha_{s,t} + X'_{j,t-1}\gamma + \varepsilon_{j,t} \tag{3}$$

Where $\alpha_{s,t}$ is an interaction term of sector and year variables, while $X'_{j,t-1}$ is a set of variables lagged by one period (including a liquidity ratio, buckets of leverage ratio[4], credit rating, the logarithm of total assets and the logarithm of sales). The aim of the former is to control for the macroeconomic and sector specific components, while the aim of the latter is to control for bank's information set and thus remove the anticipated component of the gross profit variation.

3.2 Results

First, following Galaasen et al. (2020), we withdraw from the sample of firms some outliers in the distribution of costs. Indeed, firms may dump all their costs on one specific year to benefit from tax advantages. The resulting change in value added could then not be attributed to unanticipated change in performance, but would rather be an endogenous outcome. We thus remove the top and bottom 1% of each cost-to-total cost distribution by year and sector[5]. Second, we truncate the distribution of growth in gross profit at the top and bottom 1% by year and sector in order to avoid the estimation of shocks to be driven by outliers. These two restrictions still enable us to capture around 95% of bank debt from our NFC dataset. Results are presented in Table Table 4.

Overall, our production equation displays a strong influence of wages and equity, and in particular of the former: a 1% increase in wage growth rate generates a 0.26 % increase in gross profit. Another takeaway of these estimation is the determining weight of variables proxying banks' information set over a specific firm, as all the variables have coefficients significantly different from 0 at the 1% confidence level. Therefore, the resulting shocks can be considered as unexpected by banks. This is confirmed when estimating the relation between these shocks and the loan-share size of corresponding firms in a bank's portfolio. If shocks are unexpected, they should not be correlated to the corresponding loan share, at least at the time of the shock. We test for this assertion, with results displayed in Table 19 in Appendix. We thus rely for the rest of the paper on the shocks obtained with the second specification of Table 4.

Although the most extreme shocks are negative ones, the distribution is well centered around 0. In addition, it is to be noted that the heterogeneity of shocks varies from one sector to another and from one year to another (see table 17 in Appendix).

[4]We built four buckets of leverage ratio, defined as the ratio of equity on gross debt: one for negative equity (4.5% of observations), one for observations with a ratio greater than 1 (36.5%), one for ratios between 0 and 0.44, and one for ratios between 0.44 and 1 (0.44 being the median ratios for observations between 0 and 1).

[5]Costs include material costs, energy costs, other costs and wages.

Table 4: Estimating idiosyncratic unexpected firm shocks

	Yearly growth of gross profit	
	(1)	(2)
Wages growth rate	0.265^{***}	0.262^{***}
	(0.002)	(0.002)
Equity growth rate	0.032^{***}	0.034^{***}
	(0.001)	(0.001)
Lagged liquidity ratio		-0.075^{***}
		(0.011)
Lagged total assets		0.012^{***}
		(0.001)
Lagged turnover		-0.016^{***}
		(0.001)
Year x Sector Fixed Effect	Yes	Yes
Ratings	No	Yes
Buckets of leverage ratio	No	Yes
Observations	527,961	527,961
R^2	0.046	0.049
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5: Summary statistics - Firm shocks

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max
Shock - Version 2	517,397	−2.04	−0.13	−0.003	0.12	1.58

These shocks are then associated with data on bank-firm relationships. To each (monthly) observation in *Anacredit* corresponds the NFC shock on the basis of yearly *Fiben* information. By doing so, we mitigate concerns about the endogeneity problem of credit supply and firm shock, as we combine observations that precede and follow the occurrence of the shock.

4 The probability of default channel

4.1 How does individual firm uncertainty affect bank risk parameters?

We start by investigating the link between firms idiosyncratic shocks and the PD set by banks as regards counterparty risks. Compared to Galaasen et al. (2020) which uses loan returns to measure how

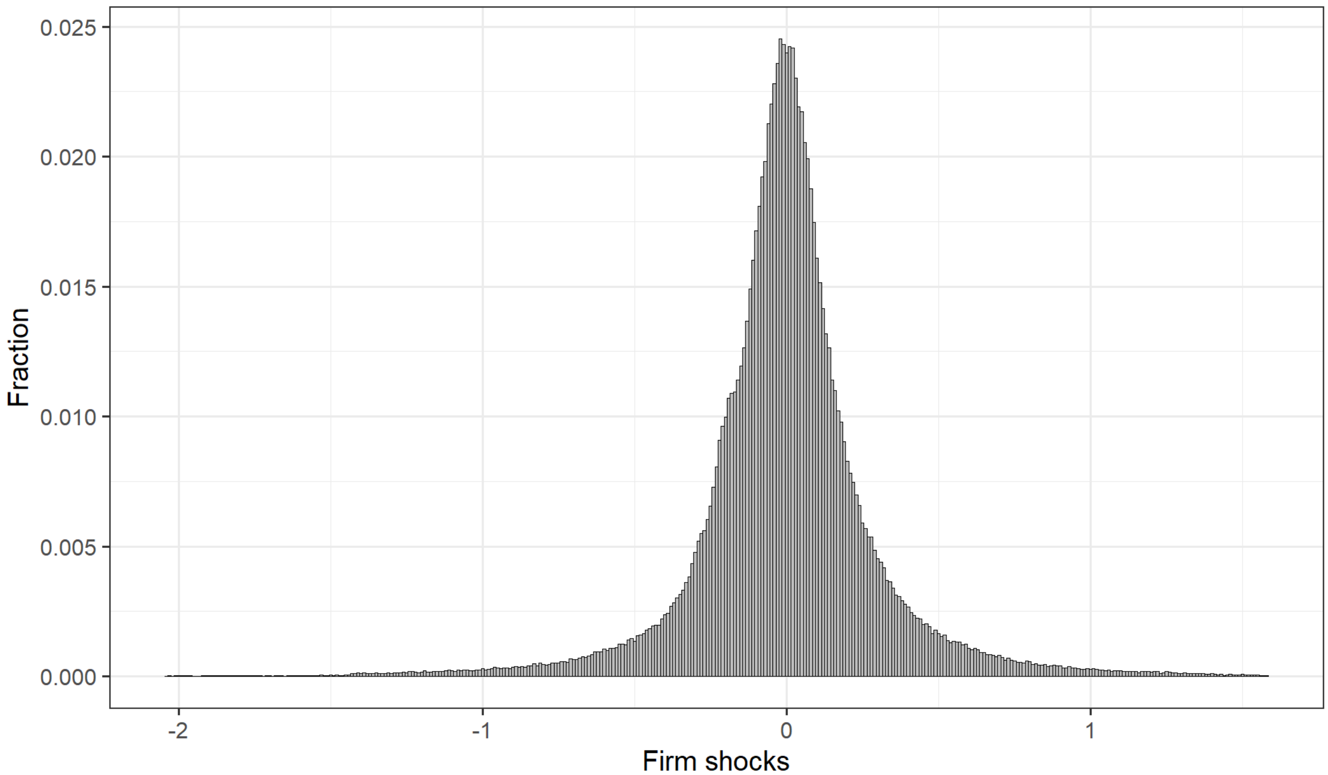

Figure 2: Idiosyncratic firm shocks

individual firm shocks affect bank balance-sheet, we prefer PDs since they better proxy the perceived risk associated with firm-bank relationship and reflect the ability of banks to measure/revise credit risks based on updated information. Loan returns have the disadvantage of measuring credit performance and not credit risk perception. More specifically, PDs allows to make a clearer bridge between credit risks and capital requirements since PDs directly translate into risk-weights. Finally, since we ultimately want to focus on the spillovers of idiosyncratic shocks on credit supply, PDs have the benefit to be revised as soon as banks consider it necessary and are forward looking indicators of risk perception/behaviours of the banks[6].

To asses the relation between shocks and credit risk, we estimate the following model:

$$P_{i,j,t} = \alpha_{i,t,l,s} + \beta\varepsilon_{j,t} + \nu_{i,j,t} \tag{4}$$

Where $P_{i,j,t}$ denotes the probability of default assigned by bank i to firm j at time t and $\varepsilon_{j,t}$ is the firm shock estimated in equation (3). A concern around this specification might be that of endogeneity

[6]Another limit to the return measure is that it mixes completely different types of debtor. Indeed, a effective low return is characteristic of defaulting firms but also firms with high credit quality benefiting from low interest rates. As a consequence, the relation between an idiosyncratic shock and effective returns might be difficult to interpret.

which would biased our estimates, namely that the probability of default at time t impacts the size of the shock, through either credit restriction or increased risk-taking behaviour from the firm. We thus consider supply-side fixed effects: we introduce $\alpha_{i,t,l,s}$, an interaction term between bank i, loan type l[7], sector s of firm j, and time t. The model thus compares the effect of a firm shock on the probability of default for a given sub-portfolio of banks, and thus isolates the effect of firm shocks on PDs.

Results are presented in Table 6, where standard errors are clustered at the firm and date levels. While the naive form of column (1) does not draw any distinction between negative and positive shocks, columns (2) to (4) do so. Column (3) accounts for the influence of loan share on bank's assessment, while column (4) controls for supply side factors. Finally, column (5) focuses on the absolute value of shocks. Overall, the naive regression yields a negative coefficient significantly different form zero, but which hides significant non-linearities. Indeed, the size of the shocks seems to matter more for the probability of default than its sign. This may be linked to the risk-taking strategy of the bank and especially the uncertainty surrounding the risk evaluation. Thus, banks could be particularly conservative in PDs also when facing innovative strategies in deviation from the norm. This is why our baseline specification considers shocks in absolute value. In short, a one standard deviation shock leads to an increase in 84 bps of the probability of default[8]. We also find that the higher the loan share, the smaller the impact of idiosyncratic shock on PDs. This relationship is linear and applies to negative as well as positive shocks. In short, there is evidence suggesting that banks reset less re-actively PDs for firms that weigh heavily in their portfolio, for a given value of shock.

[7]The loan type variables is a dummy variable equal to one if more than half of outstanding debt for relation $\{i, j\}$ at time t comes from credit lines.

[8]This transformation should not hide the fact that the coefficient is greater in amplitude for negative shocks than for negative shocks, although they were standardized by their respective standard deviation. This tends to confirm that shocks are informative of real difficulties faced by firms, but not only.

Table 6: Effect of firm shock on the probability of default

	Probability of default				
	(1)	(2)	(3)	(4)	(5)
Loan share			-0.346^{**}	-0.120^{**}	-0.118^{**}
			(0.138)	(0.058)	(0.060)
Firm shock	-0.218^{***}				
	(0.044)				
Positive firm shock		0.406^{***}	0.424^{***}	0.673^{***}	
		(0.063)	(0.067)	(0.065)	
Negative firm shock		-0.740^{***}	-0.766^{***}	-0.986^{***}	
		(0.060)	(0.062)	(0.060)	
Positive firm shock x Loan share			-0.077^{**}	-0.094^{***}	
			(0.039)	(0.030)	
Negative firm shock x Loan share			0.134^{***}	0.123^{***}	
			(0.036)	(0.033)	
Absolute firm shock					0.835^{***}
					(0.052)
Absolute firm shock x Loan share					-0.111^{***}
					(0.026)
Bank x Date x Loan-type x Sector	No	No	No	Yes	Yes
Observations	5,293,959	5,293,959	5,293,959	5,293,959	5,293,959
R^2	0.0002	0.001	0.002	0.151	0.151
Note:					*p<0.1; **p<0.05; ***p<0.01

These results are confirmed with several robustness checks. First, the asymmetric relation between shocks and probability of default is robust to the selection of sub-samples that removes extreme values. For instance, focusing on the bottom 75% of the distribution of probability of default (meaning a maximum value for the probability of default of roughly 4%) does not change our result, as evidenced by table 20 in the appendix. Second, we check for robustness by using the performing status of the loans instead of PDs with a Linear Probability Model: it yields similar results, displayed in table 21 in the appendix: the higher a positive shock is, the higher the probability for a loan to be non performing, while the smaller a negative shock is, the higher the probability to be non performing.

These results suggest that a good proxy for banks' exposure to idiosyncratic shock is not so much the average of firm shocks weighted by their loan share, but rather the weighted average of their absolute value. This means that shocks cannot cancel out, as it is the case when considering *ex-post* indicators of performance such as loan returns or revenues.

4.2 Do individual risk parameters affect portfolio aggregate risk?

As shocks cannot cancel out anymore, as we consider their absolute value, by construction the relationship can only be positive at the aggregate level. However, the degree of skewness in the distribution of portfolio shares can reduce or amplify this risk transmission on aggregate. If the relationship is significantly different from zero, this means that this amplification is at work.

To test this mechanism, we run the following model:

$$P_{i,t} = \alpha_{g(i)} + \alpha_t + \beta|\varepsilon_{i,t}| + \nu_{i,t} \tag{5}$$

Where $P_{i,t}$ stands for the weighted average PD, weighted by loan share, of bank i's credit portfolio at time t, α_t is a time fixed effect, $\alpha_{g(i)}$ a fixed effect for the banking group g of which bank i is part of, and $\varepsilon_{i,t}$ the average of absolute value of firms' shocks in portfolio i at time t, weighted by their respective loan share. A naive estimation could suffer from the endogeneity bias highlighted in the previous subsection. To address the issue, we use the Granular Instrument Variables (GIV) developed by Gabaix and Koijen (2020) and used in Galaasen et al. (2020). We therefore estimate the model by instrumenting bank shocks with the GIV. Denoting $s_{i,j,t}$ the loan share of firm j in portfolio i at time t, it can be written as the difference between the weighted and equally-weighted sum of firm shocks, using bank i loan shares:

$$GIV_{i,t} = \sum_j s_{i,j,t}|\varepsilon_{j,t}| - \frac{1}{N_j}\sum_j |\varepsilon_{j,t}| \tag{6}$$

The aim of this transformation is to get rid of bank's i supply effect on firm j, as shown by Galaasen et al. (2020). An important identifying assumption is that shocks are exogenous to the loan share which is verified in Appendix. [9]

Another caveat concerns the exclusion assumption of the IV procedure. Although the firm shock is by definition firm specific, the GIV recovers shocks that are specific to the bank-firm relationship at date t as it gets rid of bank's i supply effects on firm j. Put differently, this means that the GIV of bank i does not eliminate the effect of bank i' supply shock on firm j's shock. This means that there are situations

[9] We have such evidence when computing the correlation between these two variables, as evidenced by table 19 in Appendix : when controlling for bank information set contained in *Fiben* database, idiosyncratic firm shocks are independent to loan shares.

for which the exclusion assumption might be violated and which are worthy to control for. Indeed, in a case of a common supply shock to all banks, the variation in the GIV could go through this channel rather than only through the firm-specific shock. This concerns can be mitigated thanks to time fixed effect. However, if the supply shock is common to a sub-group of banks, this would not be enough. This needs particular attention in the case of France, as many banks are regional subsidiaries of larger banking group. This is thus mitigated thanks to a banking-group fixed effect, and even more robustly thanks to a time × banking-group fixed effect[10]. We thus proceed to the estimation, whose results are displayed in Table 7, with standard errors clustered at the bank level.

We find a significant relation. While column (1) performs a naive OLS estimation, column (2) uses the GIV for identification. A one standard deviation increase in the portfolio PD generates an 83 bps increase in the portfolio-level probability of default. Including the fixed effect interaction of time and banking group in column (3) does not change the order of magnitude for the effect. Column (4) includes two additional controls in the regression: the number of loans in the credit portfolio, and the Herfindahl-Hirschmann index of concentration. This is to ensure first that this is not only a sample problem, and that the result is not purely driven by concentration, but by shocks indeed hitting granular firms. The relation remains robust to the inclusion of these controls: a one standard deviation increase in the portfolio probability of default generates a 75 basis point increase in the portfolio-level probability of default.

Table 7: Effect of aggregated firm shocks on portfolios' probability of default

	Aggregated probability of default			
	(1)	(2)	(3)	(4)
Agregated firm shock	0.249	0.834***	0.820**	0.747**
	(0.287)	(0.320)	(0.329)	(0.310)
Time and Group FE	Yes	Yes	Yes	Yes
GIV	No	Yes	Yes	Yes
Time x Group FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Observations	2,714	2,714	2,714	2,714
R^2	0.333	0.297	0.335	0.377
Note:		*p<0.1; **p<0.05; ***p<0.01		

[10]This has however a cost, as two banks out of the 85 in the sample are the only one in their banking group, and have thus to be removed for identification.

4.3 Does individual risk-taking spillover to credit supply?

We measure the impact of an increase in PDs on the supply of creditTo do so, we restrict our sample to multi-banks firms to compare credit conditions heterogeneity for one firm depending on the aggregate risk of bank portfolios. We use similar methodologies as in (Khwaja and Mian 2008, Amiti and Weinstein 2018, Beaumont, Hurlin, and Libert 2019). More specifically, we consider:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta P_{i,t} + \eta_{i,j,t} \tag{7}$$

Where $y_{i,j,t}$ stand either for the logarithm of the quantity of credit or average interest ratesof bank i to firm j at time t.[11]. $P_{i,t}$ is the aggregated PD of the portfolio, $\alpha_{j,t}$ is the firm times date fixed effect needed for the identification of credit supply, while $\alpha_{i,j}$ is an interaction term that accounts for the unobserved heterogeneity associated to a particular firm-bank relationship. Results are displayed in Table 8, with standard errors clustered at the bank and firm levels. While columns (1) and (2) focus on quantity, columns (3) and (4) consider the effect of the aggregate probability of default on interest rate. Columns (1) and (3) do not include bank controls, while columns (2) and (4) do[12]. Overall, whether including bank controls or not, a one standard deviation increase in the probability of default of credit portfolio leads a to a 4.7% decline in the supply of credit and an increase by 4.3 bps of interest rates. When facing high default probabilities, bank contract their lending and raise their interest rates. Given the low interest rate regime over our period of interest, the increase is not negligible.

Table 8: Probabilities of default and credit supply

	Credit		Interest rates	
	(1)	(2)	(3)	(4)
PD	-0.045^{***}	-0.047^{***}	0.038^{***}	0.043^{***}
	(0.012)	(0.011)	(0.011)	(0.011)
Bank controls	No	Yes	No	Yes
Observations	2,914,321	2,914,321	2,670,938	2,670,938
R^2	0.960	0.960	0.940	0.941
Note:		*p<0.1; **p<0.05; ***p<0.01		

[11] Average means the average interest rates applied to firm j across its current loan contracts within bank i at time t.

[12] Controls include the number of credit relationships and the Herfindahl-Hirschmann index of concentration of the portfolio.

4.4 Which firms suffer credit restrictions when aggregate portfolio risk increases?

One possibility is that this channel (between PDs and credit supply) could differ across firms. Especially, it may be that the credit supply shocks lay more heavily on firms with small loan shares than on highly granular firms, as banks may be tempted to help those firms that matter in the aggregate at the expense of non-granular firms. To test for this, we create buckets of granularity based on quartiles of the loan shares distribution and run the following model:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta_1 Granular_{i,j,t} + \beta_2 (P_{i,t} \times Granular_{i,j,t}) + \eta_{i,j,t} \tag{8}$$

Results are displayed in Table 9, with standard errors clustered at the bank and firm levels. Overall, they confirm the assumptions formulated above, whether or not we include bank controls. While the bottom 25% of loan share sees its supply of credit cut by 9.3%, the top 25% of loan shares goes through a far more moderate contraction: there is not significant impact on the quantity of credit. Regarding rates, the less granular the firm, the higher interest rates in reaction to a rise in the portfolio's probability of default. This is however not true for firms that are the least granular: credit restriction seems to goes through quantities rather than price.

Table 9: Probabilities of default and credit supply - The granularity factor

	Credit		Interest rates	
	(1)	(2)	(3)	(4)
Upper middle quartile	-0.569^{***}	-0.568^{***}	0.123^{***}	0.117^{***}
	(0.027)	(0.027)	(0.026)	(0.023)
Lower middle quartile	-1.187^{***}	-1.188^{***}	0.267^{***}	0.264^{***}
	(0.042)	(0.041)	(0.042)	(0.038)
Bottom quartile	-1.906^{***}	-1.911^{***}	0.444^{***}	0.447^{***}
	(0.074)	(0.073)	(0.049)	(0.046)
PD	-0.005	-0.007	0.024^{*}	0.029^{**}
	(0.008)	(0.008)	(0.013)	(0.013)
PD x Upper middle quartile	-0.013^{*}	-0.013^{*}	0.015^{*}	0.016^{**}
	(0.007)	(0.007)	(0.008)	(0.008)
PD x Lower middle quartile	-0.036^{***}	-0.035^{***}	0.025^{*}	0.024^{**}
	(0.010)	(0.010)	(0.013)	(0.012)
PD x Bottom quartile	-0.088^{***}	-0.086^{***}	0.021	0.018
	(0.016)	(0.016)	(0.016)	(0.015)
Bank controls	No	Yes	No	Yes
Observations	2,914,321	2,914,321	2,670,938	2,670,938
R^2	0.973	0.973	0.942	0.942
Note:		*p<0.1; **p<0.05; ***p<0.01		

4.5 Is low bank capital a driver of credit restrictions?

We consider heterogeneity in the reaction of banks with respect to their level of solvency ratios: we divide banks into two groups, those that are in a banking group with a CET1 ratio greater than the median, and those below it. We then run the following model:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta_1 Solvency_{i,t} + \beta_2 (P_{i,t} \times Solvency_{i,t}) + \eta_{i,j,t} \tag{9}$$

Results are displayed in Table 10, with standard errors clustered at the bank and firm levels. Results are clear cut: banks with a low CET1 ratio significantly cut their interest rates and their supply of credit, while banks with a high CET1 ratio do not, at least not significantly at the 5% confidence level. Low capitalized banks cut their credit supply by 3.4% and raise their interest rates by 6.4 bps on average, following a one-standard deviation increase in the aggregate probability of default, while highly capitalized banks do not. This confirms the idea that banks restrict credit to maintain CET1 ratio when facing granular credit risk[13].

Table 10: Probabilities of default and credit supply - The solvency factor

	Credit		Interest rates	
	(1)	(2)	(3)	(4)
Low CET1	0.163***	0.149***	−0.176***	−0.157***
	(0.026)	(0.023)	(0.036)	(0.036)
PD	−0.011	−0.016*	−0.014	−0.006
	(0.010)	(0.009)	(0.016)	(0.016)
PD x Low CET1	−0.037***	−0.034***	0.069***	0.064***
	(0.007)	(0.006)	(0.011)	(0.011)
Bank controls	No	Yes	No	Yes
Observations	2,874,111	2,874,111	2,631,458	2,631,458
R^2	0.960	0.960	0.940	0.940
Note:		*p<0.1; **p<0.05; ***p<0.01		

[13] A more precise way to asses this mechanism would require to analyze not directly the effect of the CET1 ratio, but of the share of the CET1 ratio which is in excess of regulation requirements. These two measures differ, as banks do not have the same capital requirements. This requires additional data that may be available in a later version of this paper.

4.6 How do bank behave to restrict credit: extensive or intensive margin?

The reduction of credit supply could be done in two ways: banks can grant lower credit volumes (intensive reduction of credit) or reduce the number of borrowers (extensive reduction of credit). The latter could highlight a phenomenon called ”bad apples cleaning”. Boualam and Mazet-Sonilhac (2021) show that during a period of recession (systemic shock), banks reduce their supply by reducing at the same time the amounts lent and their number of credit relationships.

To analyze this, we first adapt Equation 9 by interacting the aggregate PD with $Newclient$, a dummy equals to one if the borrower is a new client since less than three months. We report the results in column 1 of Table 11. Our results suggest that banks tend to reduce credit especially for client with a credit record of less than three months. Then, we estimate the same regression but with the number of unique loans as the independent variable. The objective is to identify whether the decline in the supply of credit is due to the non-renewal of loans or a decline in the number of clients. As we can see in column (2), the results suggest that a rise of the PD reduces the number of unique loans, which is two times more important for new clients (coefficient -0.025, p-value $< 0.01\%$). New clients would therefore suffer more from non-renewal of credit, while established clients would suffer more from a decrease in the average amount of credit granted.

Table 11: Decomposition of the credit supply

	Credit	Number of loans
	(1)	(2)
PD	-0.040^{***}	-0.022^{*}
	(0.008)	(0.012)
New client	0.026^{*}	-0.035
	(0.014)	(0.027)
PD x New client	-0.013^{***}	-0.025^{***}
	(0.005)	(0.008)
Observations	2,914,315	2,905,927
R^2	0.960	0.934
Note:	*p<0.1; **p<0.05; ***p<0.01	

5 Probability of default channel under public intervention

State-guaranteed loans aim at encouraging bank to lend by transferring credit-risk to the State.

Given that almost half of our study period is during the COVID-19 crisis, PGEs (stands for *Prêts Garantis par l'Etat*) can strongly influence our results. However, if we expect PGEs to have weaken the impact of portfolio credit risks on credit supply, it means that our previous results are affected downward and thus minimize the contagion effect we have identified. Given that the *Anacredit* database includes information on guarantees and guarantors allowing for PGE identification, we can insulate the impact of PGEs in our results.

5.1 Stylized facts on State-guaranteed loans in France

We first observe that among credit relations with at least one PGE instrument, PGE loans represent more than 60% of the outstanding amount of the credit relation for 75% of them. PGEs are thus quite concentrated on few credit-relationships (Table Table 12).

Table 12: Share of State-guaranteed loans in credit relations with at least one

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max
PGE share	524,488	0.03	60.57	87.32	100.00	100.00

Among the 114 902 credit relationships with a PGE in 2020 in our database, 79694 credit relations between a firm and a bank pre-existed the COVID-19 crisis, meaning that around 30% of PGE relationships are new relationships. This is partly linked to two dynamics: new firms entering the database, and firms creating new credit relations for the occasion, as the increase in the number of "PGE firms" is smaller than the increase in "PGE credit relations".

In addition, Table 13 shows that firms that benefit from PGEs after March 2020 were considered riskier by banks already before the covid shock. Finally, Figure 3 highlights that PGEs had a negative impact on borrowing rates due to the transfer of credit risks and a lower probability of default of the guarantor (the State).

5.2 State guarantee and the probability of default channel

The objective of PGEs was to disconnect credit conditions from firms' riskiness. Therefore, in this section, we test the following: *(i)* Are PDs less reactive to firm shocks in case of PGEs? *(ii)* Did the

Table 13: Distributions of probabilities of default in January 2020

Statistic	N	Min	Pctl(25)	Median	Pctl(75)	Max
State-guaranteed	41,958	0.00	0.56	1.69	4.80	100.00
Not State-guaranteed	85,332	0.00	0.43	1.10	3.26	100.00

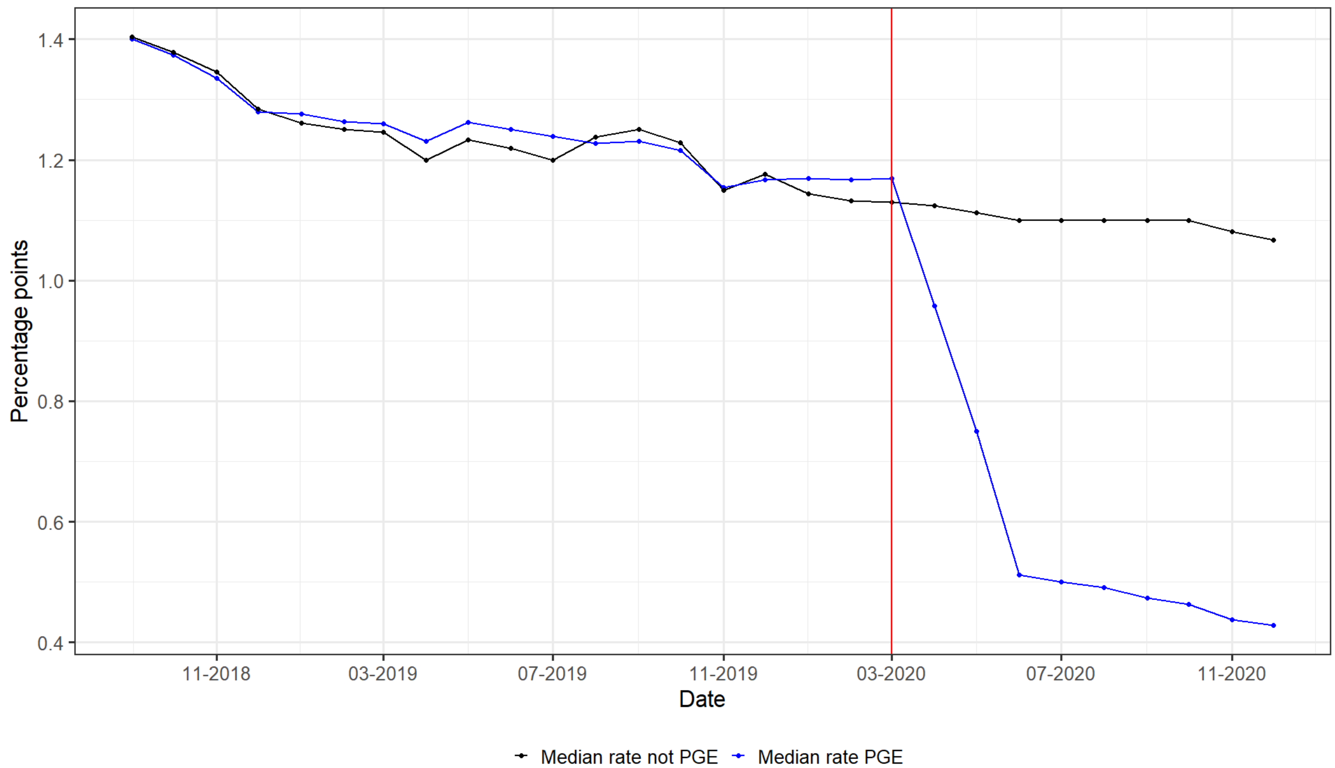

Figure 3: PGE and interest rates

guarantee provided to a granular borrower help protecting all firms from contagion effects? To test these hypotheses, we adapt Equation 4 by interacting the idiosyncratic shock with the fact to have a PGE:

$$P_{i,j,t} = \alpha_{i,t,l,s} + \beta_1 PGE_{i,j,t} + \beta_2(\varepsilon_{j,t} \times PGE_{i,j,t}) + \nu_{i,j,t} \tag{10}$$

Where $P_{i,j,t}$ denotes the PD assigned by bank i to firm j at time t and $\varepsilon_{j,t}$ is the firm shock estimated in equation (3). $PGE_{i,j,t}$ is a dummy variable equal to one if the credit relationship in t has at least one PGE loan.

Results are displayed in Table 14, with standard errors clustered at the firm and bank levels. our results are confirmed even if we single out the impact of PGEs: a one standard deviation shock implies a rise of probabilities of default by 88 bps, however this effect lowers to 47 bps (significant at the 1% confidence level) if the relationship has a PGE instrument (column 1). This result holds for different sub-samples provided in the rest of the table.

Table 14: PD and shocks for State-guaranteed loans

	Probability of default			
	(1)	(2)	(3)	(4)
PGE	0.588***			
	(0.143)			
Absolute firm shock	0.882***	0.439***	0.875***	0.816***
	(0.051)	(0.072)	(0.051)	(0.050)
Absolute firm shock × PGE	−0.474***			
	(0.076)			
Bank x Date x Loan-type x Sector	Yes	Yes	Yes	Yes
Sample	All	PGE	No PGE	Before COVID-19
Observations	5,293,959	516,536	4,777,423	5,293,959
R^2	0.151	0.223	0.150	0.151
Note:				*p<0.1; **p<0.05; ***p<0.01

The flow of credit to firms increased by 13.2% in 2020, a level not seen since 2007. As a consequence, the share of each loan in the total corporate portfolio of banks may have reduced, limiting contagion risks (with less granular borrowers). On the contrary, PGEs may have reinforced concentration if they primarily targeted granular risky borrowers. To test this, we consider estimations of equation Equation 6 on different sub-samples: (1) only credit relationships that contained at least one PGE (2) only credit relationships without PGE (3) All credit relationships before March 2020 and (4) All credit relationships after March 2020.

In Table 15, we confirm the impact of aggregated firm shocks on the aggregated probability of default when we consider credit relationships without PGE in banks' portfolios. This results does not hold, as expected, for the sub-portfolio pledged with PGE. Considering all credit relationships before and after Covid shocks we see that shock transmission from firm shocks to aggregate PD has decreased by around 40%, yet still statistically significant.

Finally, to test if PGEs helped firms to protect from shocks that may have suffered a granular borrower, we consider the following model:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta_1 PGE_{i,j,t} + \beta_2 (P_{i,t} \times PGE_{i,j,t}) + \eta_{i,j,t} \tag{11}$$

Table 15: Effect of aggregated firm shocks on portfolios' probability of default - The PGE impact

	Aggregated probability of default			
	(1)	(2)	(3)	(4)
Agregated firm shock	0.728	0.708***	0.872*	0.534*
	(0.512)	(0.267)	(0.450)	(0.319)
Sample	PGE	No PGE	Before COVID-19	During COVID-19
GIV	Yes	Yes	Yes	Yes
Time x Group FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	714	2,714	1,733	978
R^2	0.483	0.356	0.360	0.399
Note:				*p<0.1; **p<0.05; ***p<0.01

With $y_{i,j,t}$ denoting either the quantity of credit or interest rates. Results are displayed in Table 16, with standard errors clustered at the firm and bank levels. As expected given the stylized facts on interest rates of PGEs, interest rates are not reacting anymore to aggregate risk, thus protecting firms from contagion effects. However, the impact on credit supply holds: PGEs were not enough to completely compensate for the combined effect of the Covid-19 crisis and the high concentration of French banks' credit portfolio.

Table 16: Probabilities of default and credit supply - The PGE impact

	Credit		Interest rates	
	(1)	(2)	(3)	(4)
PD	−0.036***	−0.037***	0.038***	0.042***
	(0.009)	(0.009)	(0.008)	(0.008)
PGE	0.897***	0.893***	−0.315***	−0.302***
	(0.030)	(0.030)	(0.038)	(0.039)
PD x PGE	−0.005	−0.004	−0.043***	−0.045***
	(0.010)	(0.010)	(0.012)	(0.012)
Bank controls	No	Yes	No	No
Observations	2,914,321	2,914,321	2,670,938	2,670,938
R^2	0.964	0.964	0.942	0.943
Note:				*p<0.1; **p<0.05; ***p<0.01

6 Conclusions

In this paper, we have shown how idiosyncratic firm shocks may have systemic consequences on the supply of credit. In particular, we show that credit supply is affected through a probability of default channel of transmission: banks (using their internal models) set up higher PD when they face higher uncertainty as regards the financial soundness of a counterparty. The aggregate impact of single higher PD does not fade at the portfolio level, meaning that diversification is only partially effective, especially when portfolio concentration is high. This happens not only when firms are affected by negative shocks, but also in case of substantial positive shocks: what matters in setting the probability of default is the ex-ante uncertainty (positive or negative) banks face when they grant credit. Finally, we show that low capitalized banks are the ones restricting credit and increasing borrowing rates. Moreover, the credit restrictions are stronger for firms with small loan shares in bank credit portfolios.

Given that our sample partially overlaps the Covid-19, it has also been possible to investigate the impact of state-guaranteed loans on this probability of default channel: one hypothesis being that uncertainty could be reduced as soon as State-guaranteed loans benefit from a double screening of NFC financial soundness compensating for the heighten aggregate uncertainty faced by banks during the Covid-19 crisis and lock-downs. Moreover, the setting of probabilities of default by banks benefit from the State-guarantees. We show that indeed State-guaranteed loans enabled a partial disconnection between firms' soundness and their risk parameter. This induces lower contagion risks across firms that share the same credit provider. Therefore State-guaranteed loans by limiting PD increase in bank portfolio, especially for granular borrowers, have indirectly been beneficial to all firms including those not requesting state-guaranteed loans. However, if the effect of the PD channel of transmission is smaller, it remains significant.

Finally, in terms of policy recommendations, it is clear that macroprudential authorities should monitor single bank-firm relationships as soon as bank credit portfolios are highly concentrated and/or banks weakly capitalized. This remains true despite State interventions during the Covid-19 crisis. Policymakers should hence be particularly vigilant during the phasing-out of the support measures: if banks decide to revise their risk parameters against some granular exposures, it could create new spillovers across firms through credit restrictions. Restoring high capital buffers before phasing out state-guaranteed loans could dampen this risk, given that highly capitalized banks tend to be less affected by the PD channel of transmission identified in this paper.

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Appendix

A Data and descriptive statistics

Table 17: Intra-industry variation of shocks (1)

Year	Sector	Standard deviation
2018	Activités de services administratifs et de soutien	0.22
2019	Activités de services administratifs et de soutien	0.24
2020	Activités de services administratifs et de soutien	0.37
2018	Activités financières et d'assurance	0.28
2019	Activités financières et d'assurance	0.30
2020	Activités financières et d'assurance	0.34
2018	Activités immobilières	0.25
2019	Activités immobilières	0.27
2020	Activités immobilières	0.30
2018	Activités spécialisées, scientifiques et techniques	0.24
2019	Activités spécialisées, scientifiques et techniques	0.26
2020	Activités spécialisées, scientifiques et techniques	0.31
2018	Agriculture, sylviculture et pêche	0.36
2019	Agriculture, sylviculture et pêche	0.39
2020	Agriculture, sylviculture et pêche	0.43
2018	Arts, spectacles et activités récréatives	0.26
2019	Arts, spectacles et activités récréatives	0.30
2020	Arts, spectacles et activités récréatives	0.59
2018	Autres activités de services	0.14
2019	Autres activités de services	0.17
2020	Autres activités de services	0.36
2018	Commerce ; réparation d'automobiles et de motocycles	0.30
2019	Commerce ; réparation d'automobiles et de motocycles	0.32
2020	Commerce ; réparation d'automobiles et de motocycles	0.38
2018	Construction	0.26
2019	Construction	0.26
2020	Construction	0.29
2018	Enseignement	0.23
2019	Enseignement	0.24
2020	Enseignement	0.40
2018	Hébergement et restauration	0.15
2019	Hébergement et restauration	0.16
2020	Hébergement et restauration	0.45
2018	Industrie manufacturière	0.27
2019	Industrie manufacturière	0.28
2020	Industrie manufacturière	0.33

Table 18: Intra-industry variation of shocks (2)

2018	Industries extractives	0.30
2019	Industries extractives	0.31
2020	Industries extractives	0.33
Year	Sector	Standard deviation
2018	Information et communication	0.27
2019	Information et communication	0.29
2020	Information et communication	0.37
2018	Production et distribution d'eau ; assainissement, gestion des déchets	0.30
2019	Production et distribution d'eau ; assainissement, gestion des déchets	0.33
2020	Production et distribution d'eau ; assainissement, gestion des déchets	0.36
2018	Production et distribution d'électricité, de gaz, de vapeur	0.26
2019	Production et distribution d'électricité, de gaz, de vapeur	0.28
2020	Production et distribution d'électricité, de gaz, de vapeur	0.30
2018	Santé humaine et action sociale	0.13
2019	Santé humaine et action sociale	0.12
2020	Santé humaine et action sociale	0.15
2018	Transports et entreposage	0.16
2019	Transports et entreposage	0.17
2020	Transports et entreposage	0.25

B Identification of unexpected firm shocks

Table 19: Correlation between loan share and shocks

	Loan share			
	(1)	(2)	(3)	(4)
Shock - Version 1	0.005*			
	(0.003)			
Shock - Version 1 in absolute value		0.004		
		(0.006)		
Shock - Version 2			−0.001	
			(0.003)	
Shock - Version 2 in absolute value				0.009
				(0.006)
Observations	5,292,565	5,292,565	5,292,565	5,292,565
R^2	0.00003	0.00001	0.00000	0.00005
Note:		*p<0.1; **p<0.05; ***p<0.01		

C The probability of default channel

Table 20: Effect of firm shock for small probabilities of default

	Probability of default				
	(1)	(2)	(3)	(4)	(5)
Firm shock	0.001				
	(0.002)				
Positive firm shock		0.072^{***}	0.071^{***}	0.074^{***}	
		(0.003)	(0.003)	(0.002)	
Negative firm shock		-0.072^{***}	-0.073^{***}	-0.070^{***}	
		(0.002)	(0.002)	(0.002)	
Absolute value of shock					0.072^{***}
					(0.002)
Loan share			-0.030^{***}	-0.021^{***}	-0.021^{***}
			(0.011)	(0.006)	(0.007)
Positive firm shock x Loan share			0.005^{*}	0.002	
			(0.003)	(0.003)	
Negative firm shock x Loan share			0.003	0.004^{*}	
			(0.002)	(0.002)	
Absolute shock x Loan share					-0.001
					(0.002)
Bank x Date x Loan-type x Sector	No	No	No	Yes	Yes
Observations	3,966,155	3,966,155	3,966,155	3,966,155	3,966,155
R^2	0.00000	0.006	0.007	0.211	0.211
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 21: Effect of firm shock on performing status

The dependant variable of this regression is that the loan is defined as "non-performing" according to the bank. A positive coefficient indicates an increase in the probability that the loan will not be reimbursed totally.

	Performing status			
	(1)	(2)	(3)	(4)
Firm shock	-0.003^{***}			
	(0.0005)			
Positive firm shock		0.0004	0.004^{***}	
		(0.001)	(0.001)	
Negative firm shock		-0.004^{***}	-0.007^{***}	
		(0.001)	(0.001)	
Absolute value of shocks				0.006^{***}
				(0.0005)
Bank x Date x Loan-type x Sector	No	No	Yes	Yes
Observations	5,293,959	5,293,959	5,293,959	5,293,959
R^2	0.0001	0.0003	0.452	0.452
Note:		*p<0.1; **p<0.05; ***p<0.01		