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

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The risk of large exposures

- French macroprudential authority adopted a "large exposure limit" (art. 458 of the Capital Requirements Regulation) to limit the nexus between large corporates and systemic banks.
- It raises the question of systemic consequences of idiosyncratic corporate default.
- Can individual bank exposures have an impact on aggregates at the (i) bank level (ii) macro level?
- Which transmission channel? In this paper, we are analyzing the PD channel, more precisely the internal risk assessment by the banks.

PD Channel of transmission - Hypotheses

We test the following hypotheses:

- H1: Banks continuously adjust the probability of default (PD) of their corporate borrowers: the PD of firms experiencing an idiosyncratic shock should increase.
- H2: There are systemic firms whose idisoyncratic shock could affect the aggregated PD of bank's credit portfolios.
- H3: By impacting the CET1 Ratio (banking solvency ratio), banks should react to an increase of thEir aggregated PD by adjusting their credit supply.

  $\Longrightarrow$ Spillovers on other companies in the credit portfolio.

Literature review

- Credit supply shocks : Khwaja et Mian (2008)
- Loan portfolio concentration :
  - At the sectorial level : Agarwal et al. (2020)
  - At the investor level : Amiti et Weinstein (2018), Galaasen et al. (2020), Greewald et al. (2021)
- Corporate shocks identification :
  - Short-term funding shocks : Bureau et al (2021)
  - Productivity shocks : Guiso et al. (2005), Fagereng et al. (2018), Galaasen et al. (2020)
- On the link between RWA and credit supply : Thornton et Di Tommaso (2021)
- Regarding the use of *AnaCredit* : Altavilla et al. (2020), Altavilla et al. (2021), Da Silva et al. (2021)

Firm database: *FIBEN*

- Annual balance sheets and statements of profit and losses of French non financial corporations (NFC) with turnover exceeding 750,000 euros (2017-2020 included).
- Matched with the credit rating of the Banque de France
- Total bank debt of companies in *Fiben*: 675-720 billion euros.
- Consideration of the group structure with the Banque de France's database *Group Subsidiaries*.

Credit dabase: *AnaCredit*

- Granular credit registry (Instrument-by-instrument) covering all creditor relationships in the Eurozone with more than €25,000 of exposure.
- Period: September 2018 - December 2020 (monthly frequency). Not only at origination but all contracts.
- Agents: restriction to French credit institutions and French firms (90% of outstanding amount) to match with FIBEN.
- Instruments: restriction to credit lines and term loans (85% of outstanding amount).

Descriptive statistics of bank portfolios

- Loan portfolios range from 37mn to 27bn
- Significant concentration: top 10 represents 79% for half of portfolios

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max
Outstanding amount (million euros)	37.04	509.50	839.26	1,802.55	27,295.46
Number of loans	103	741	1,237	1,823	21,634
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.)	0.04	2.87	3.98	5.41	96.65
Ratio of NPL (pp.)	0.00	0.78	1.31	1.98	99.38

Note: $N = 2,829$.

Methodology

We start from a log-linearization of a production function for firm j:

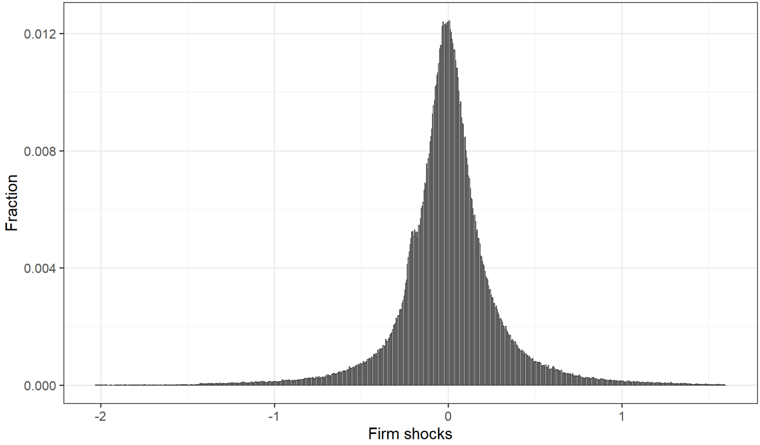
$$Y_{j,t} = \theta_j \eta_{j,t} K_{j,t}^{\beta_1} W_{j,t}^{\beta_2} \Longrightarrow \Delta y_{j,t} = \beta_1 \Delta k_{j,t} + \beta_2 \Delta w_{j,t} + \Delta \eta_{j,t} \quad (1)$$

Four components to $\eta_{j,t}$: macro, sectorial, expected and unexpected idiosyncratic firm shock $\varepsilon_{j,t}$.

$$\Delta y_{j,t} = \beta_1 \Delta k_{j,t} + \beta_2 \Delta w_{j,t} + \alpha_{s,t} + X'_{j,t-1}\gamma + \varepsilon_{j,t} \quad (2)$$

- $\alpha_{s,t}$: fixed effect Year x Sector
- $X_{j,t-1}$: bank's information set in t-1 (liquidity ratio, buckets of leverage ratio, credit rating, total assets and turnover)
- Wages and capital are positvely significant (as expected) as well as NFC balance sheet information

Idiosyncratic shocks distribution



Methodology

We estimate the following (basic) equation at the credit relationship level:

$$P_{i,j,t} = \alpha_{i,t,l,s} + \beta\varepsilon_{j,t} + \nu_{i,j,t} \tag{3}$$

With interaction terms (Bank x Sector x Credit type x Date) to control for supply factors. Also by controlling for the loan shares in portfolios.

- Both positive and negative shocks (surprises) leads to higher PD (stronger for negative ones)
- The higher the loan share the lower the re-evaluation of PDs.

Results

	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

Methodology

- We estimate the following regression at the bank portfolio level for the weighted average PDs:

$$P_{i,t} = \alpha_{g(i)} + \alpha_t + \beta|\varepsilon_{i,t}| + \nu_{i,t} \tag{4}$$

- We use the Galasen et al. (2021) instrument to isolate the part of the shock independent of a credit supply shock:

$$GIV_{i,t} = \sum_j s_{i,j,t}|\varepsilon_{j,t}| - \frac{1}{N_j}\sum_j |\varepsilon_{j,t}| \tag{5}$$

Hypothesis : $|\varepsilon_{j,t}| = \lambda_i \eta_{i,t} + u_{i,j,t}$

- If there is transmission/amplification of shocks there are some skewness effects in loan shares.
- Behind the instrument, the "idea" is to get rid of bank shocks affecting NFC shocks.

Results

- Shocks to granular borrowers resist aggregation at the portfolio level.
- Diversification does not fully play its role
- Coherent with the concentration noticed in descriptive statistics

	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)
GIV	No	Yes	Yes	Yes
Controls	No	No	No	Yes
Time and Group FE	Yes	Yes	Yes	Yes
Time x Group FE	No	No	Yes	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

Methodology

We estimate the impact of portfolio PD on credit supply with the following regression:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta P_{i,t} + \eta_{i,j,t} \tag{6}$$

- NFC x Date to control for credit demand
- NFC x Bank to control for unobserved heterogeneity at the level of the credit relationship

We find:

- Rise in portfolio PD restricts credit supply and increases interest rates.
- 1 s.d. of portfolio PD decreases credit supply by 4,7% and increases interest rates by 4.3 bps.

General results

	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:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Results - Heterogeneity of firms

- We look for heterogeneous effects with respect to the granularity of firms:

$$y_{i,j,t} = \alpha_{j,t} + \alpha_{i,j} + \beta_1 Granular_{i,j,t} + \beta_2 (P_{i,t} \times Granular_{i,j,t}) + \eta_{i,j,t} \tag{7}$$

  Granular firms for bank i = firm j being in the top 25% of loan shares
- Stronger effect for "non-granular" than "granular": negative externality form granular borrowers to non-granular borrowers.
- Credit (quantity) effect for small firms and price effect (rates) for bigger ones with higher PDs.

Results - Heterogeneity of firms

	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

Results - Heterogeneity of banks

- We look for heterogeneous effects as regards bank solvency:

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

- Stronger effect for banks with low capital ratios.

	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

PD channel and state-guaranteed loan

- State-guaranteed loans (PGE) were introduced in April 2020, during the Covid pandemic.
- If PGE have an impact on our results, it means that we underestimate the PD channel.
- For firms with at least a PGE, PGE represents more than 60% of the outstanding for 75% of them.
- 70% of PGE are contracted between a bank i firm j with already existing credit relationship.
- Firm with PGE already had higher PDs compared to others in 2019.

PD channel and state-guaranteed loan

- We test how spillovers from granular borrowers to other counterparts are affected by PGE:

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

- As expected, PGE weaken the link between firm shocks and PD, which was intended as a policy device to moderate risk reappreciation.

Impact of public loan guarantee on individual PD

	Probability of default			
	(1)	(2)	(3)	(4)
Absolute firm shock	0.882***	0.439***	0.875***	0.896***
	(0.051)	(0.072)	(0.051)	(0.054)
PGE	0.588***			
	(0.143)			
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	3,611,979
R^2	0.151	0.223	0.150	0.146
Note:				*p<0.1; **p<0.05; ***p<0.01

Impact of public loan guarantee on aggregated PD

Transmission from idiosyncratic shock (through PDs reevaluation) to the Portfolio (on the aggregated PD) only valid without public guarantee.

	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
Controls	Yes	Yes	Yes	Yes
Time x Group FE	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

Impact of public loan guarantee on credit supply

As expected, interest rate of loans with a public guarantee don't react to the aggregated PD, however the impact on the average loan size still holds.

	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	Yes
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

Policy implications

- Banks respond to a negative idiosyncratic shock from a borrowing firms by reducing their aggregate credit supply (through prices and quantities).
- This could be transmitted to all firms in the same bank portfolio.
- Firms with smaller loan shares in bank portfolios are affected by credit risk evolution of other bigger loan shares (potentially bigger firms)

Policy implications

- This effect is stronger for banks with low CET1 ratio and this mechanism is stronger when the concentration of banking portfolios is high.
- State-guaranteed loans have been efficient in curbing this effect during covid: even targetted loans could be beneficial to all firms in the same portfolio to prevent contagion effects.
- Banks' capitalization and the "large exposure limits" are complementary: macroprudential authorities should closely monitor banks with sizeable exposures/ high concentration and thin management buffers.