Banks' Credit Losses and Lending Dynamics

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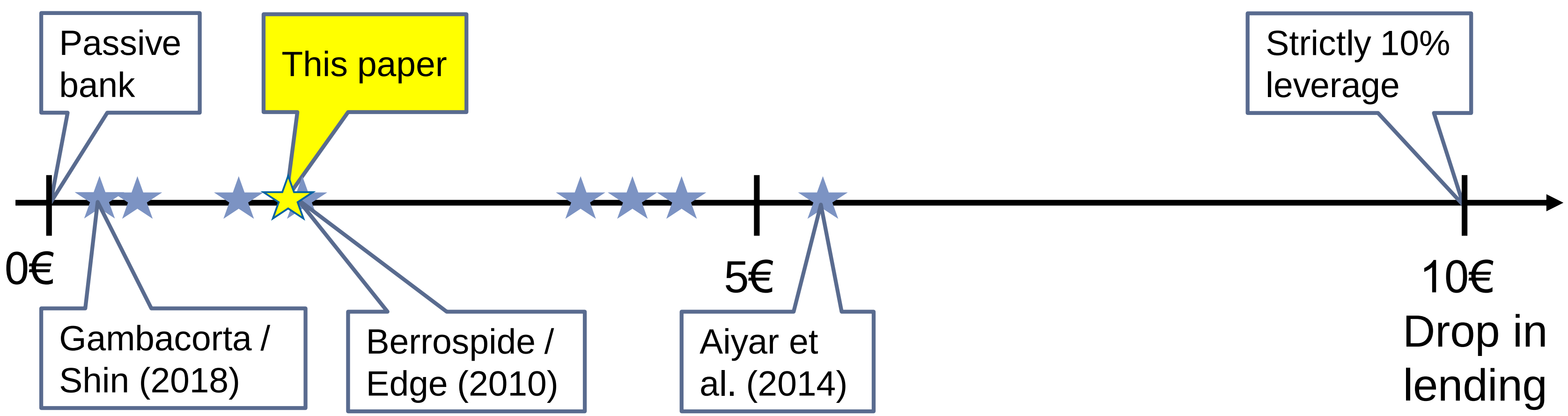
General research question

Broader interest: Bank capital ➔ Lending
Problem: Capital is highly endogenous!
Our solution: *Unexpected* credit losses

The direct link Credit loss ➔ Lending is interesting in its own right: calibration of macro stress tests (“satellite model”)

A bank has a credit loss of 1 euro (➔ Capital shrinks by ≈ 1 euro, c.p. ➔)
Effect on lending?



Data

- Loans of all German banks to domestic non-financial firms ($N = 1774$)
  - Exposure
  - Value changes (mainly write-downs, no market factors)

- 72 quarters, 2002–2020
- 23 industry sectors

- Panel: Bank / sector / quarter

The shock – Definition

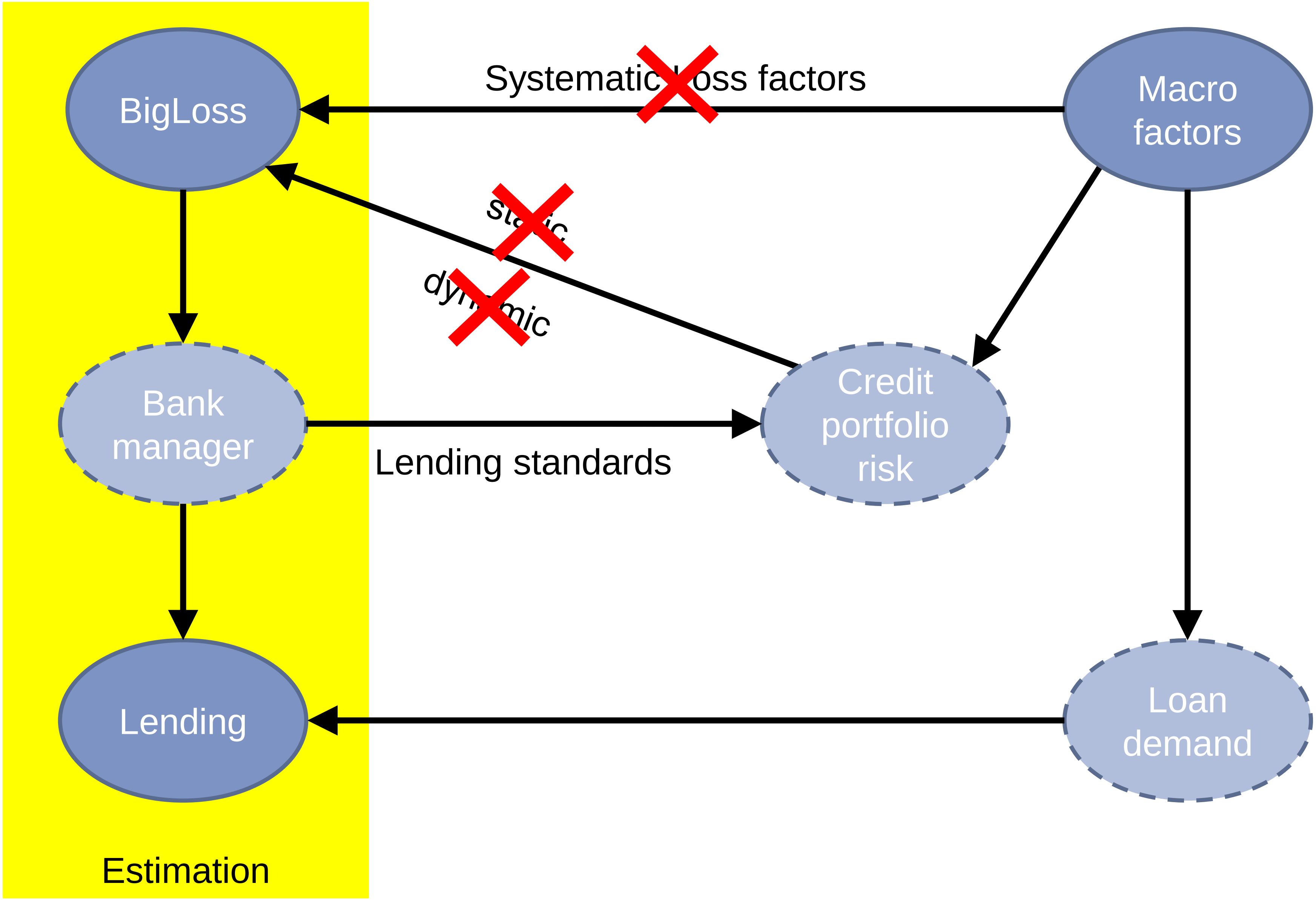
- We compare losses in a *single* sector with lending to all *other* sectors.

- Step 1: Boosting loss severity: Per bank and quarter, take the *largest loss in a single sector*, normalized by total assets
  Result: time series $\left[Loss_{\text{bk } i,2002\text{Q}4}, Loss_{\text{bk } i,2003\text{Q}1}, \ldots, Loss_{\text{bk } i,2020\text{Q}4}\right]$
- Step 2: The 10% largest losses in the bank's *individual* time series are its *Big Losses* (treatment dummy $BigLoss_{\text{bk } i,t} = 1$)
- Idea: Exceptional losses come as a surprise.

- Dependent variable: subsequent lending (1y) to the sectors not hit by the loss.

→ Simulation example

The shock – Causal interpretation?



The shock – Causal interpretation?

Endogeneity Concern	Solution
Choice of static credit portfolio risk	• By construction (same treatment intensity for every bank)
Dynamic lending standards → dynamic credit risk	• Simulation, showing: Portfolios are too static to give dynamic standards predictive power for $BigLoss$ dummy • Propensity score matching
Systematic loss factors	• $BigLoss$ mostly caused by single firms defaulting → mainly idiosyncratic • Variants of $BigLoss$, flattening treatment intensity across time and banks

Summary statistics

Variable	Mean			Standard deviation
	(all)	$BigLoss = 0$	$BigLoss = 1$	
Loss rate	0.04%	0.02%	0.16%	0.08%
New Lending	0.58%	0.63%	0.29%	1.69%

All normalized by total assets. Average profit: 0.055%

Empirical model

$$NewLending = \alpha + \beta_1\, BigLoss + \beta_2\, LowCapital + \beta_3\, BigLoss \times LowCapital$$
$$+controls + FEs + error$$

- $NewLending$: Change in lending (over the following year, excluding the sector with the loss)
- $LowCapital$: Dummy, indicating whether a bank counts to the 10% lowest capitalized banks in a given quarter; 1y lag
- FEs: time, bank, loss sector

- New approach to control for demand: (another talk...)
Lending of a *synthetic competitor*
(control variable; different from *synthetic control* method)

Main result

Variable	Coefficient
$BigLoss$ (dummy)	– 0.255***
$LowCapital$ (dummy)	– 0.240***
$BigLoss \times LowCapital$	0.421
…	
Observations	24,041
R^2 (within)	5.43%

- Linearization: 1.79 euro lending reduction for each euro lost
- 95% confidence interval: [1.30; 2.28]
- Interaction: insignificant throughout, regardless of specification

Further results

- Competing banks: No indication that other banks step in when banks hit by $BigLoss$ cut their lending.
- Crisis times: Little changes.
- Loan demand: Essential to control for.

- Robustness checks:
  - Other definitions of $BigLoss$: robust to changes.
  - Loss severity (x% loss tail rather than 10%): robust.
  - Horizon for $NewLending$: not much after 1Q, still an effect in year 2.
  - Propensity score matching for control sample: robust.
  - Model-based test for dependence of BigLoss on dynamic portfolio risk: negligible.
  - ...

Conclusion

- Exceptional single-sector losses are...
  - relevant shocks;
  - basically unpredictable;
  - not *external* but *exogenous* in the sense of Heckman, QJE (2000).

- Banks reduce lending after a big credit shock quite moderately;
  about 1.79 € for every euro of big losses.

- Scarce capital: similar lending cuts

- No evidence that low capital affects the lending response to tail losses.

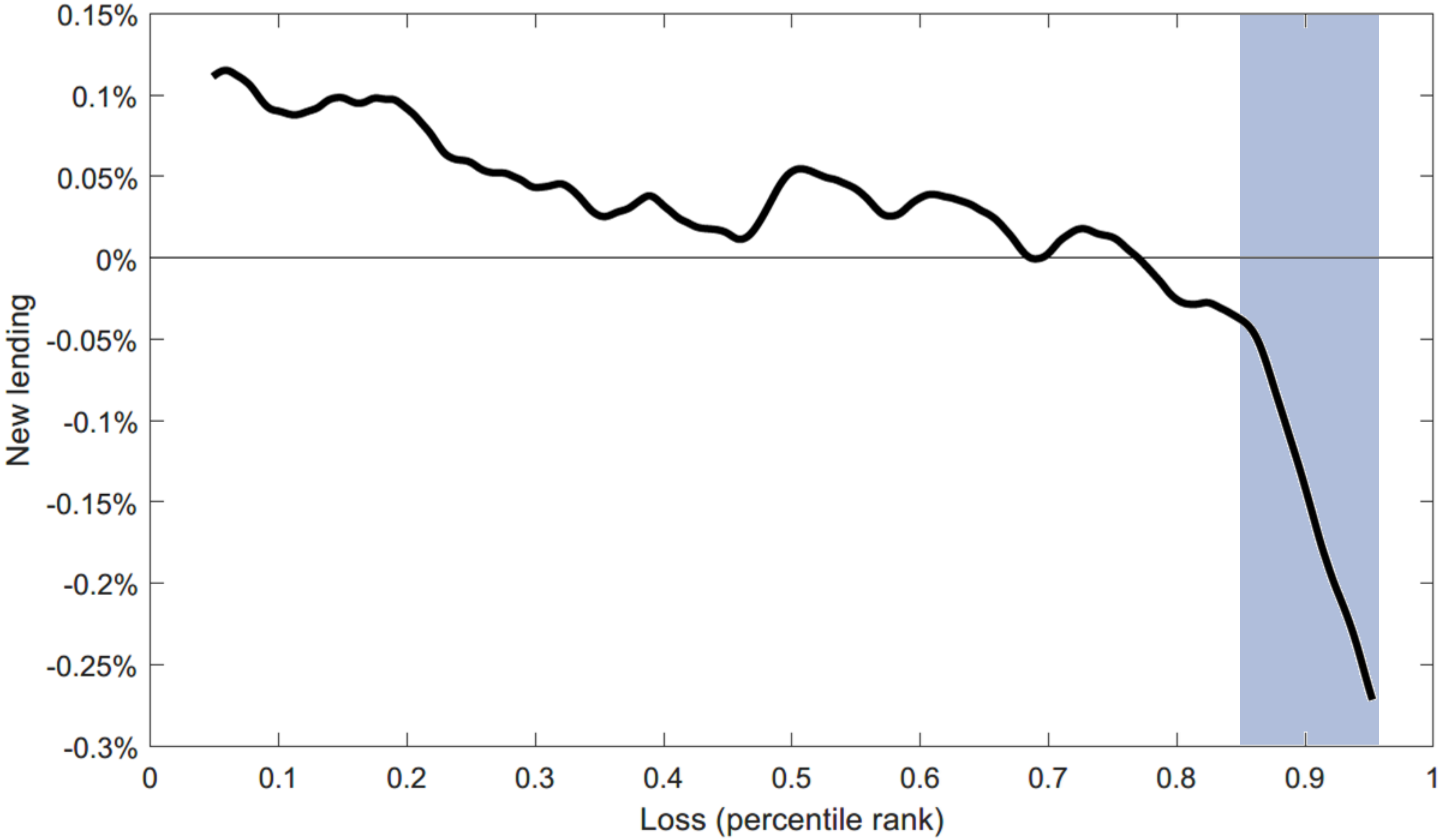
Supplement

Some answers from literature (and the industry...)

1 euro credit loss / capital gap ➔ change in lending?

Study /Assumption	Lending reduction	Driver	Sample
Constant leverage at 10%	10.00	(any)	–
Aiyar et al. (2014)	5.50	Capital shocks	Foreign subsidiaries of UK banks, 1999–2006
Hancock and Wilcox (1994)	4.63	Low capital ratios	US banks, 1991
Behn et al. (2016)	4.2	Cap. requir. shocks	German banks, 2008–2011
Bridges et al. (2014)	3.86	Cap. requir. shocks	UK banks, 1990–2011
Berrospide and Edge (2010)	1.86	Capital shocks	US banks, 1992–2008
Hancock and Wilcox (1993)	1.37	Large loan losses	US banks, 1990
Francis and Osborne (2009)	0.78	Cap. requir. shocks	UK banks, 1996–2007
Gambacorta and Shin (2018)	0.36	Capital shocks	Int. banks, 1995–2012
No constraints, passive bank	0	(any)	–

Loss severity vs. new lending*



* subject to kernel smoothing

Controlling for demand

- Key assumption: *Credit demand is homogeneous in each time × industry × county segment*.
  (≈ Peek and Rosengren, AER 1997; Degryse et al., JFI 2019)

- Standard approach à la Khwaja/Mian (2008):
  - FEs at time × industry × county level
  - Limited coverage by ≥ 2 banks per segment ➔ potential selection bias
  - Very different weighting of loans, depending on regional bank activity
    ➔ strong bias towards large banks (1% of banks make up 25% of observations)
  - By contrast, lending supply decisions are made at bank level.

- What we do: assigning each bank a bespoke competitor (*benchmark bank*) with matching portfolio composition at industry × county × time level.

Constructing a benchmark bank – An example

Portfolio composition

Bank *i*	cty_1	cty_2
ind_1	-	50%
ind_2	50%	-

All other banks (aggregate)

ind_1	13%	25%
ind_2	33%	29%

Scaling factors

Benchmark bank *i* (competitor)

ind_1		
ind_2		

Net new lending

Bank *i*	cty_1	cty_2
ind_1	-	6
ind_2	3	-

All other banks

ind_1	3	–3
ind_2	8	7

Benchmark bank *i* (competitor)

ind_1		
ind_2		

Task: Rescale portfolio weights and, afterwards, net new lending of all other banks such that the outcome has the same weights as bank *i*.

Constructing a benchmark bank – An example

Portfolio composition

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ind_1	-	50%
ind_2	50%	-

Net new lending

Bank *i*	cty_1	cty_2
ind_1	-	6
ind_2	3	-

All other banks (aggregate)

ind_1	13%	25%
ind_2	33%	29%

Scaling factors

-	2.0
1.5	-

All other banks

ind_1	3	–3
ind_2	8	7

Benchmark bank *i* (competitor)

ind_1	-	50%
ind_2	50%	-

Benchmark bank *i* (competitor)

ind_1		
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1.5	-

Benchmark bank *i* (competitor)		
ind_1	-	50%
ind_2	50%	-

Net new lending

Bank *i*	cty_1	cty_2
ind_1	-	6
ind_2	3	-

All other banks		
ind_1	3	–3
ind_2	8	7

Benchmark bank *i* (competitor)		
ind_1	-	–6
ind_2	12	-

Constructing a benchmark bank – An example

Portfolio composition

Bank i	cty_1	cty_2
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ind_2	50%	-

All other banks		
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Scaling factors	
-	2.0
1.5	-

Benchmark bank *i* (competitor)		
ind_1	-	50%
ind_2	50%	-

Net new lending

Bank i	cty_1	cty_2
ind_1	-	6
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All other banks		
ind_1	3	-3
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Benchmark bank *i* (competitor)		
ind_1	-	–6
ind_2	12	-