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DISCUSSION OF "ROBUSTNESS OF CREDIT RISK STRESS TEST RESULTS: MODELLING ISSUES WITH AN APPLICATION TO BELGIUM" BY STIJN FERRARI, PATRICK VAN ROY AND CHRISTINA VESPRO

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Summary

- **Issue**: Credit risk remains the main type of risk addressed in stress tests
- **Question**: How robust are stress test results to alternative modelling choices? *(EL = PD x EAD x LGD)*
- **Approach**: Look at impact in concrete stress scenario of changing
  1. How credit risk is measured
  2. The level of data aggregation
- **Findings and message**: Results are highly sensitive to modeling choices. Need for harmonisation.

Important topic

- The paper addresses an important topic in stress testing
- It does a nice job of conveying practical issues in stress testing, in particular the role of data availability
- The results should be somewhat disconcerting to anyone doing stress testing

Potential modeling choices

Credit risk variables

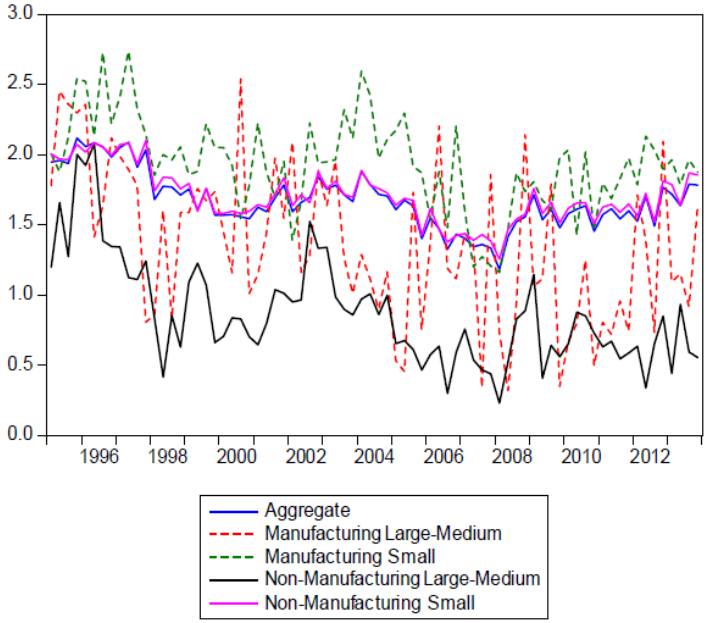
- Non-performing loans
- Loan loss provisions
  - Stocks and flows
- Bankruptcy rates

TABLE 1. Correlation among different credit risk variables, 1995Q1-2013Q4.

	BR	FLLP ratio	LLP ratio	NPL ratio
BR	1.00			
FLLP ratio	0.56	1.00		
LLP ratio	0.76	0.70	1.00	
NPL ratio	0.77	0.72	0.95	1.00

Level of aggregation

- Economy-wide
- Sectoral



The figure shows bankruptcy rates

Empirical strategy

Data

Quarterly data for each variable

Belgium

Estimation period: 1995Q1 – 2013Q4

Stress test horizon: 2014Q1 – 2016Q4 EBA scenario

Estimation

Autoregressive distributed lag model

Credit risk variable regressed on:

- own lags
- lags of macro variables

Results

EL = PD x EAD x LGD

Calculate ΔEL based on:

- estimation
- stress scenario
- simulated errors

Then identify tier 1 impact

Finally, **compare results!**

Results

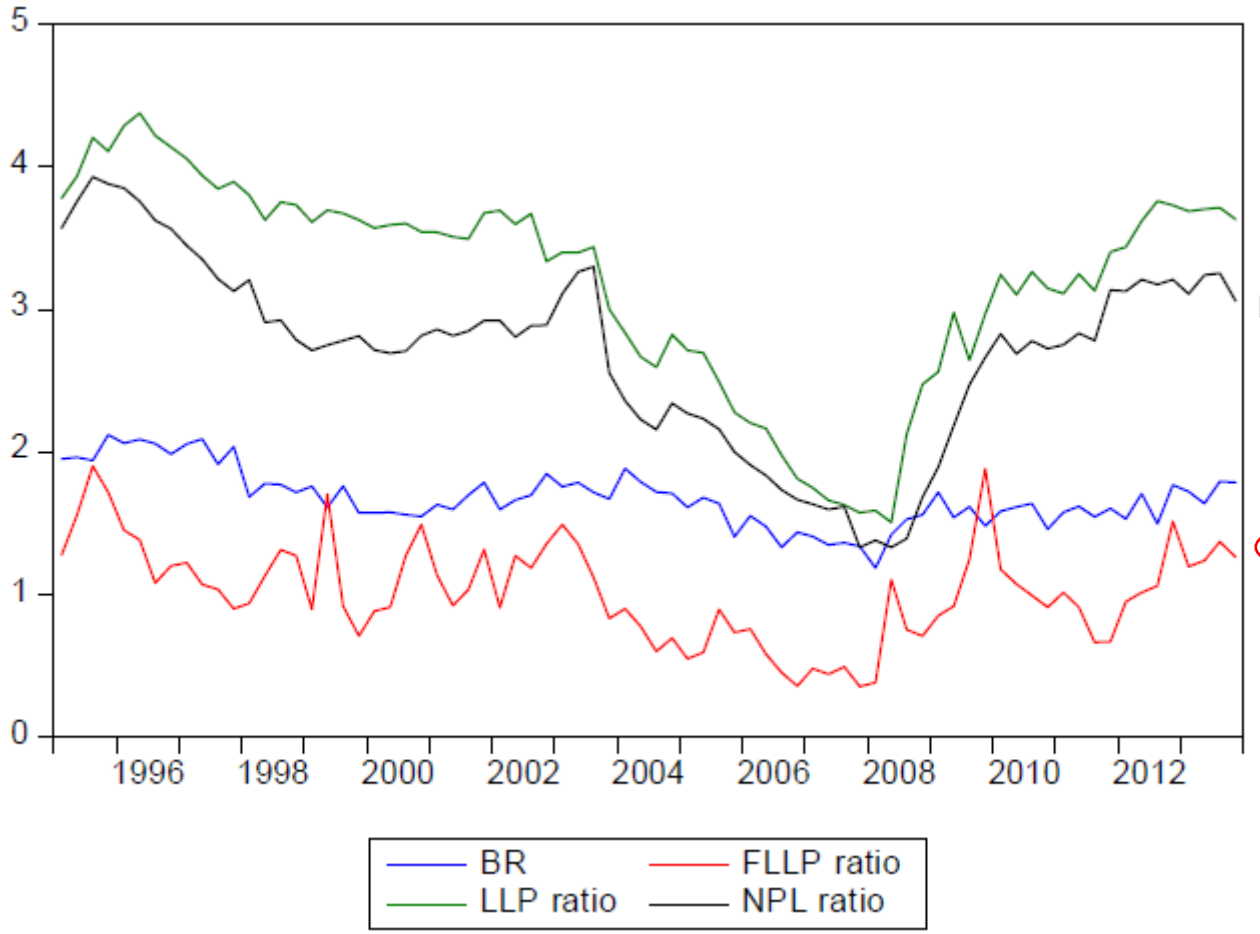
TABLE 5. The robustness of stress testing results.

	BR	FLLP ratio	LLP ratio	NPL ratio	Average	**Range**
A. Impact on Tier 1 capital ratio of different credit risk variables						
	Total EAD and REA					
50th percentile	-0.48pp	0.28pp	-1.25pp	-0.80pp	-0.56pp	**1.53pp**
75th percentile	-1.64pp	0.08pp	-2.93pp	-2.31pp	-1.70pp	**3.01pp**
	Corporate EAD and REA					
50th percentile	-0.33pp	0.19pp	-0.84pp	-0.54pp	-0.38pp	**1.03pp**
75th percentile	-1.10pp	0.05pp	-1.97pp	-1.55pp	-1.14pp	**2.02pp**

	Economy-wide	Industrial sector	Firm size	Sector and Size	Average	**Range**
B. Impact on Tier 1 capital ratio for different levels of data aggregation using BR as the credit risk variable						
	Corporate EAD and REA					
50th percentile	-0.33pp	-2.63pp	-0.31pp	-2.26pp	-1.38pp	**2.32pp**
75th percentile	-1.10pp	-3.58pp	-1.63pp	-3.86pp	-2.54pp	**2.76pp**

Robustness check with respect to lag structure

A reflection: A lot of the variation in the credit risk models is unexplained



LLP R^2: 0.13

NPL R^2: 0.16

BR R^2: 0.37

FLLP R^2: 0.55

Note: This is the model that give the strangest results! (previous slide)

Paper leaves questions unanswered…

- Paper identifies problem, but is silent about how to achieve robustness
- Authors suggest "a need to better harmonise the stress tests are conducted across institutions and supervisors" – but how?
  - … difficult to get around data availability issue…
- Which credit risk measures and levels of aggregation should then be used?
  - Authors could perhaps conduct backtests, e.g. comparing model performance during financial crisis?
  - One potential approach: Averaging across models?

Robustness

- What exactly do we mean by ”robustness”?
- Perhaps we can draw inspiration from literature on robust control
  - A set of plausible models
  - Fictitious ”evil agent” chooses (e.g.) worst distribution
  - Good decision rules, even in bad cases?

THANK YOU!