

Stress Testing and Calibration of Macroprudential Tools

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2020 ECB Macroprudential Stress Test Conference, Frankfurt, 5 and 6 February 2020

This presentation reflects the author's views and not necessarily those of the National Bank of Belgium

Overview

- 1. Main goals, relevance and findings
- 2. Comments
 - a) Robust inference and conclusions?
 - b) Main drivers of the loss rates?
 - c) Calibration of model
 - d) Macroprudential stress test/ calibration



Very interesting paper!

This paper takes a **more practical (forward-looking) approach** to risk evaluation and impact assessment of borrower-based macroprudential measures, addressing the various hurdles for policy makers (lack of sufficiently granular and up-to-date data)

- Applies stress testing techniques to provide forward-looking measure of a banking system's resilience (also in cases where standard statistical techniques become unreliable);
- Proposes a semi-structural model to guide the calibration of macroprudential policy tools;
- Integrates simple quantile-based techniques to inform the tail risk scenarios;
- Allows to study the effectiveness of specific macroprudential instruments in building resilience, taking into account countryspecific legal and operational issues.

The paper **convincingly develops this methodology** (TUI- approach by Harrison and Mathew (2008)) with **rich illustrations** through the Austrian and Suisse 'cases'



Main goals, relevance and findings Relevance

Very valuable contribution to operational macroprudential policy: allows to assess impact of country-specific measures



Eurosystem

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Two questions, four equations

Does the agent/portfolio face financial distress following micro or macro shocks? DSR critially modelling macro-sensitivity

 $\Pr(FD) = \beta_0(DSR) \cdot D + \beta_1 \Delta DSR^{\gamma} + \beta_0(\cdot)(\beta_2 U_{t-1} + \beta_3 \Delta U^{\alpha})$

 $LR_t = \Pr(FD) . I(default) . LGD_t.$

Conditional on financial stress, will an agent default?

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LTV determining default decision

 $\begin{aligned} \text{I(default)} &= 1 \text{ iff } HP_t - C + A_{liq} < NPV \big(L, r_f, r_l, T, legal \big) \\ \text{LGD:} \qquad LGD_t = NPV \big(L, r_f, r_l, T, legal \big) - (1 - \delta) \frac{HP_{t+n}}{(1 + r_f + \varphi)^n} \end{aligned}$

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Two questions, four equations

Build macrofinancial stress scenario conditioned on current (macro-)prudential stance $\Delta U_{\mu} \Delta HP_{\mu} \Delta r_{\mu} \Delta Y_{\mu} \Delta L$



Conditional on mild(er) macrofinancial scenario, assess the impact of the introduction of BBMs: *DSR*, *LTV*, *MAT*

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Two questions, four equations and many applications





Two questions, four equations and many applications



| | | | | | Stock of loans up to 2017 |
|-----|------------|-------------|-----------------|---|---------------------------|
| | | | | | Loan vintage 2018 |
| 4 | | | \bigwedge | 1 | Loan vintage 2019 |
| | | | | | Total |
| 3 | | | | | |
| 2 | | | | | |
| 1 | | $\times //$ | | | |
| | | | $/ \setminus /$ | | |
| 0 × | | // X | | | |
| | 10 | | $X \lambda$ | | 8 |
| | 8 | | | | 6 |
| | 0 | 4 | | | 4 |
| | LTVC (x10) | 2 | 2 | [| DSR (x10) |
| | | | | | |

Loss

estimate

12,95

8,27

10,61

31,82

Loss rate

0,8%

2,0%

2,8%

1,3%

Exposure

1704,72

414,98

382,31

2502,02

Overview

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- a) Robust inference and conclusions?
- b) Main drivers of the loss rates?
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Comments Robust inference and conclusions?

How robust are the results from this approach?

A substantial number of assumptions have to be imposed in the analysis to account for relevant (but messy) specific features

Constructing the data and vintage risk buckets

- p. 16 We *reconstruct* the vintages of mortgage flows (as data is only available from 2018 onwards)
- p. 16 We assume that a share α of the loan is interest-only
- P. 13 LTV (LTI) *data reflect all the segments* in banks' mortgage portfolios (including BTL and CRE) which may drive also the calibration of the results

Computing the DSR (in baseline and under stress)

- P. 17 We construct a matrix of re-princing of loans and apply a Student's t-distribution
- p. 17 Drawing on SNB statistics we consider that 75% of mortgages are fixed rate with maturities between 1 and 10 years

Accounting for behavioral dynamics

- p. 18 The banks are assumed to apply margin calls using a specific rule
- P. 26 We *assume* that there is a "bunching" of new loans just below the regulatory limits.

Not 'just' an innocuous "academic" exercise?

Relatively <u>strong policy conclusions/recommendations can</u>follow from this type of analysis:

- "Under our stress scenario, including a 25% price correction and a rise in 5-year mortgage lending rates to 5.0% over 2019-20, the <u>capital depletion of 170 basis</u> <u>points</u> represents <u>5.5 times the size of the CCyB</u>, assuming a risk weight density of 20 percent for mortgage loans. Netting out the average provisions on mortgage loans, the amount of 'unexpected losses' would exceed the amount of projected losses under the scenario by 4.8 times..."
- " if the adjustment to self-regulation in 2014 had consisted of applying an amortization period to two-thirds of the LTV ratio within a maximum of 10 years rather than the current 15 years. We recalculate the stress test analysis under this counterfactual macroprudential rule for vintages originated at or after 2014. Results suggest that the average default rate of the portfolio would decrease from 3.0 percent to 2.2 percent during the 2019-20 horizon. This implies a saving in bank capital ratios of around 60 basis points."
- " we propose a simple "rules of thumb" that can be used to guide the selection of preferred macroprudential limits once the second-round general-equilibrium effects are accounted for. It is to compare the expected losses on new mortgages (those subject to macroprudential limits) with those on mortgages granted before the borrower limits are introduced. In our example, the loss rate on the total mortgage portfolio (a proxy of losses on "old" mortgages) is 1.1 percent. Among the macroprudential limits considered, <u>a combination of LTV- DSTI limits of 80-30 percent with a speed limit of 20 percent, and hard limits on LTV-DSTI of 90-40 percent achieve that rate for new loan issuances.</u>



Comments Main drivers of loss rates?

Figure 3. Stress Test Results in Switzerland



Main driver of increases in stress (loss rates)?

Changes in **financial distress** and (PDs) seem **the main driver** of increased stress and loss rates and puts the financial distress model on the foreground



Decomposition of changes in expected loss



Comments Calibration of financial distress model

 $\Pr(FD_{i,t}) = \beta_0 (DSTI_{i,t-1}) \times D + \beta_1 \times \Delta DSTI_{i,t}^{\gamma} + \beta_0 \times (\beta_2 U_{t-1} + \beta_3 \Delta U_t^{\alpha})$ (1)

| Table 1. Model calibration for Switzerland | | | | |
|--|---|-------------------|----------------|---|
| | equation (1) | equations (2)-(4) | | |
| parameter | value | parameter | value | |
| eta_0 | $= \begin{cases} 0 & DSTI_t < 0\% \\ 1 \cdot \frac{DSTI_t - 0\%}{50\% - 0\%} & DSTI_t \in [0\%, 30\%] \\ 1 & DSTI_t > 30\% \end{cases}$ | С | 10% · HP | - |
| D | 0.2 | Т | [1,2,3,,15] | |
| β_1 | 0.217 | rf | 0.05 % | |
| γ | 2 | spread | $r_{i,t} - rf$ | |
| β_2 | 0.06 | δ | 15% | |
| eta_3 | 0.66 | Q | 2 | |
| α | 1 | $\sigma_{ m HP}$ | 15% | |

Gornicka and Valderrama (2019)



How reliable is the calibration of financial distress model (also outside of the scope of the data on which it was calibrated?)

- ◆ Taking the model to the extreme: Lim_{DSTI -> 1} Pr(FD_{i,t}) << 1?
- Nonlinearity in model complicates the calibration of the model:
 - Granularity of the data will matter for calibration and the use of less granular data will lead to downward bias (Jensen's inequality)
 - ♦ Time horizon matters for the calibration as well
- How to credibly calibrate the model on event-poor data (lacking critical financial stress events)?
- How to measure financial distress in the first place? Only indirectly observed through banks' *realized* losses.
 - Need for complementing information from household balance sheets?

Comments Calibration of model

 $\Pr(FD_{i,t}) = \beta_0(DSTI_{i,t-1}) \times D + \beta_1 \times \Delta DSTI_{i,t}^{\gamma} + \beta_0 \times (\beta_2 U_{t-1} + \beta_3 \Delta U_t^{\alpha})$ (1)

| | Original | СН | AT |
|---------------------------|----------|-------|--------|
| D | 0,02 | 0,8 | 0,2 |
| DSR lin (β ₁) | 0,023 | 0,217 | 0,0003 |
| DSR nonlin (γ) | 2,5 | 1 | 2,5 |
| Delta U (β_3) | 0,7 | 0,66 | 0,006 |
| U (β ₂) | 0,08 | 0,06 | 0,007 |
| | | | |

How reliable is the calibration of financial disstress model?

 Substantial heterogeneity in the calibration of the financial distress models leads to significantly different risk drivers

Pass through of increase in unemployment in financial



Gornicka and Valderrama (2019)



Comments

Macroprudential stress test/ calibration

Micro-macro model (Gross and F. Garcia (2016)): impact of iimposing 85% LTV cap for Austria



Note: The figures show the impact on households' PDs, LGDs, and loss rates after having imposed an LTV cap at 85% along with loss-rate equivalent DSTI caps. The individual households' responses are aggregated to household sector estimates by taking EAD-weighted averages for each countrySee Section 3.2 for details.

Model applies stress test to <u>macroprudential</u> instruments

Stress test application is an important first step in assessing the overall impact of the measure....

But could/should be extended by enriching the macroprudential dimension (also acknowledged in this paper)

- Current analysis is embedded in a genuine macrofinancial scenario (house prices, gdp, credit, interest rates, unemployment... (generated by a DSGE model)
- No second-round effects (feedback) from macroprudential measures to real economy modeled (credit demand effects (?))
- Fully endogenizing credit demand (supply) is important given that the most recent vintages drive the overall loss rates
- But, this requires detailed data on individual financial and credit constraints (and hence very granular information on borrower characteristics)

- Great paper which offers a practical approach towards bridging the many hurdles that policy makers face
- It offers perspective to better assess risks in mortgage portfolios (by integrating and using the relevant information in risk parameters (LTV/DSR)
 - ♦ Risk assessment purposes related to evaluating capital adequacy
 - Impact assessment of introducing specific borrower-based measures
- But **requires a very careful approach** towards data construction (risk vintages), behavioral assumptions and calibration (especially of the financial distress model)
- And needs to be complemented with additional analysis which takes into account second-round effects (e.g. micro-macro interaction models)

Looking forward to seeing further developments in this modeling framework!



Additional slides



Comments Calibration of model

 $\Pr(FD_{i,t}) = \beta_0(DSTI_{i,t-1}) \times D + \beta_1 \times \Delta DSTI_{i,t}^{\gamma} + \beta_0 \times (\beta_2 U_{t-1} + \beta_3 \Delta U_t^{\alpha})$ (1)

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| | D | 0.2 | Т | [1,2,3,,15] | |
| | β_1 | 0.217 | rf | 0.05 % | |
| | γ | 2 | spread | $r_{i,t} - rf$ | |
| | β_2 | 0.06 | δ | 15% | |
| | β_3 | 0.66 | Q | 2 | |
| | α | 1 | $\sigma_{ m HP}$ | 15% | |

How reliable is the calibration of financial distress model (also outside of the scope of the data on which it was calibrated?

| Table 4: Model calibration for Austria | | | | | |
|--|---|-------------------|-------------------|--|--|
| | equation (1) | equations (2)-(4) | | | |
| parameter | value | parameter | value | | |
| β_0 | $= \begin{cases} 0 \text{ if } DSTI < 15\% \\ \frac{DSTI - 15\%}{30\% - 15\%} \text{ if } DSTI \in [15\%, 30\%] \\ 1 \text{ if } DSTI > 30\% \end{cases}$ | С | 5% of house value | | |
| D | 0.2 | Т | 25 | | |
| eta_1 | 0.0003 | rf | 0.1% | | |
| γ | 2.5 | spread | 2% | | |
| β_2 | 0.006 | δ | 0.2 | | |
| β_3 | 0.007 if $\Delta U_t > 0$ and 0 otherwise | Q | 1.25 | | |
| α | 1 | $\sigma_{ m HP}$ | 15% | | |

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