THE RAMSI MODEL: RISK ASSESSMENT FOR SYSTEMIC INSTITUTIONS

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Bank of England
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Plan

- Motivation and background
- Model overview
- Key model components
- Application: predictive distributions
- Conclusions and discussion
Motivation

- Develop a **unified quantitative framework** to guide and sharpen the BoE’s risk assessment work

- Provide an **internally consistent view** of key risks to the UK banking sector
  - Modular approach to integrate different sources of risk.
  - Adding-up constraints from BS and P&L identities
Motivation

RAMSI could be used in internal risk assessment to:

- Track overall risks in the financial system over time
- Produce a ranking of banks (in terms of overall vulnerability, and vulnerability to particular risks);
- Stress testing;
- Identify structural vulnerabilities (what are the sources of tail risk?);
- Simulate policy exercises.
Plan

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Devleop a unified quantitative framework to guide and sharpen the BoE’s risk assessment work

Provide an internally consistent view of key risks to the UK banking sector by:
- describing different sources of risk
- capturing correlations across them
- imposing basic BS and P&L constraints
Key features of RAMSI

- Focus on 10-12 major UK banks
- Modular approach to integrate risks
- Emphasis on risks over and above those naturally priced and managed by financial institutions, i.e. feedbacks/externalities across banks.
- Closest model in this spirit is OeNB (2006), but
  - More limited modelling of P&L and feedbacks.
  - Static model (one quarter horizon).
Plan

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- Application: predictive distributions
- Conclusions and discussion
Structure of the model

Shocks/scenarios
(Macroeconomic/financial)

Credit losses
Available for sale assets
Trading income
Net interest income
Non-interest income and expenses

Feedbacks
Asset-side
("market liquidity risk")
Liability-side
("funding liquidity risk")

Network model of UK banks and LCFIs

Effects on bank lending

System asset / loss distribution
Structure of the model: plain

Shocks/scenarios (Macroeconomic/financial)

- Credit losses
- Available for sale assets
- Trading income
- Net interest income
- Non-interest income and expenses

Effects on bank lending

System asset / loss distribution
Structure of the model: complete

Shocks/scenarios (Macroeconomic/financial)

- Credit losses
- Available for sale assets
- Trading income
- Net interest income
- Non-interest income and expenses

Feedbacks

- Asset-side ("market liquidity risk")
- Liability-side ("funding liquidity risk")

Network model of UK banks and LCFIs

Effects on bank lending

System asset / loss distribution
Balance Sheets

- 10-12 major UK banks (~80% UK lending)
- Each BS includes approx 400 asset and 250 liability classes
- Primarily constructed from published accounts — plus some interpolation

<table>
<thead>
<tr>
<th>Balance sheet dataset dimensions</th>
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<tbody>
<tr>
<td>Assets/Liabilities</td>
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<tr>
<td>Maturity buckets</td>
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<td>Repricing buckets</td>
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<tr>
<td>Annual data entries per bank</td>
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</tbody>
</table>
**INCOME STATEMENT**

- Net interest income
- Fees and commissions
- Trading income
- Other income

**Total operating income**

- Operating expenses
- Impairments
  - On loan book
  - On AFS book

**Profit before tax**

- Tax

**Profit after tax**

- Dividends

**Retained earnings**
The model includes:

- Credit losses (Credit Risk)
- Net interest income (Interest Rate Risk)
- AFS impairments (Market Risk)
- Feedbacks (Contagion Risk)

We abstract from trading, other income, bank-specific funding spreads, and assume no hedging of interest rate risk.
P&L and Balance Sheet dynamics

- **Net profits:**
  \[ NP_t = (\text{Int.Income}_t - \text{Int.Expense}_t) \]
  \[- \text{CreditLoss}_t - \text{Impairments}_t \]

- **Balance sheet evolution:**
  \[ \Delta \text{Shareholder Funds}_{t+1} = NP_t \]
  \[ \Delta \text{Assets}_{t+1} = f(NP_t) \]
  \[ \Delta \text{Liabilities}_{t+1} = g(NP_t) \]
Plan

- Motivation and background
- Model overview
- Key model components
  - Macro-economy and “fundamental” risks
  - Contagion
- Outputs and applications
- Open discussion and Q&A
Macro-model: Bayesian VAR

The variables:

<table>
<thead>
<tr>
<th>US</th>
<th>Euro Area</th>
<th>World</th>
<th>UK</th>
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<tbody>
<tr>
<td>GDP</td>
<td>GDP</td>
<td>Oil price</td>
<td>GDP</td>
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<tr>
<td>CPI</td>
<td>CPI</td>
<td>Equity price</td>
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<tr>
<td>Policy rate</td>
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<td>Yield curve slope</td>
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<td>Equity price</td>
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<td>Unemployment</td>
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<td>House price</td>
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<td>Commercial property price</td>
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<td></td>
<td>Income gearing</td>
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<td>Lending gap</td>
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<td>10 year corporate spread</td>
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<td>Undrawn equity</td>
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<td>HH unsecured debt</td>
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<td></td>
<td></td>
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<td>LIBOR spread*</td>
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<td>£ERI*</td>
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Variables that potentially could be included in BVAR, but are excluded in the baseline version of the model are denoted by *.
Macro-model: Bayesian VAR

- Sample 1984q1– 2008q4.

- Bayesian estimation to cope with the large number of variables. Our priors (a variation of Minnesota):
  - Random walks
  - Small open economy
  - Taylor rule

  ➔ Intuitively appealing, better forecasting performance.

The model captures ‘macro risk’ in a plausible way – up to a point.
Predicting recessions: early 90s

UK GDP growth
Predicting recessions: 2008-9

UK GDP growth
Exposures are split by
- Region: UK, US, EA, RoW
- Type: mortgages, credit cards, other unsecured, corporate

For each type of exposure, we model:
- An aggregate default probability (PD)
- An aggregate credit loss rate (ACL)
- A bank-specific credit loss rate (CL)

ACL captures variation in recovery rates.
CL is introduced (and calibrated) to capture bank heterogeneity.
Example: UK mortgages

\[ PD_{t}^{\text{Sec}} = 7.97 + 0.26 \text{INCGEAR}_{t-4} - 14.6 \text{UNDRAWN}_{t-2} + 0.19 \text{UNEMP}_{t-2} \]

\[ ACL_{t}^{\text{sec}} = 0.003 + 0.06 PD_{t-2}^{\text{sec}} - 0.02 \left( \frac{P_{t}^{\text{res. prop}}}{P_{t-8}^{\text{res. prop}}} - 1 \right) \]

- PD\(_t\) = percentage of UK mortgages in arrears by six months or more.
- UNDRAWN\(_t\) = UK undrawn equity level (housing wealth minus debt).
- UNEMP\(_t\) = UK unemployment rate
- INCGEAR\(_t\) = UK income gearing (%)
- ACL\(_t\) = average credit loss rate at major UK banks, reported by MFSD.
Example: UK mortgage PD
Net Interest Income and AFS

Based on Drehmann-Sorensen-Stringa (2010)

- A and L priced as bullet bonds under risk-neutral measure.
- The implied coupons are riskless yields for L and default-adjusted yields for A:
  \[ C_i^L = r \]
  \[ C_i^A = f(r, ACL) \quad \text{s.t.} \quad A = EV(A) \]

One-period example:
\[ A = EV(A) \Rightarrow A = \frac{1}{1+r} \left(1+C\right)(1-ACL)A \Rightarrow C = \frac{r + ACL}{1 - ACL} \]
Key features of the NII/AFS model

- Spreads are set to cover expected credit losses (based on model-consistent forecasts for PD and ACL)

- But rates are sticky: only a subset of the balance sheet can be repriced at any time; hence:

- Unexpected changes in \((r, PD, ACL)\) generate
  - **Income risk**: volatility in interest income flows
  - **Market risk**: volatility in AFS values
AFS composition

- AFS include seven asset classes:
  - Equity
  - Treasury bonds and bills
  - Investment grade government securities
  - Investment grade mortgage securities
  - Investment grade corporate securities
  - Investment grade certificates of deposit
  - Investment grade other (ABS, etc)

- In all cases, we model the Economic Value of the exposures and obtain impairments as $\Delta EV$
Reinvestment

- Balance sheets are rebalanced at each $t$ using a set of reinvestment rules:
  - **Tier 1 ratio**: banks aim to achieve/maintain a predefined, bank-specific Tier 1 capital ratio
  - **Portfolio allocation**: Subject to the first rule, banks aim to maintain a constant portfolio composition
  - **Liability generation**: when assets and capital grow, all liabilities grow in proportion to their initial balance sheet shares

- The algorithm generates plausible “equilibrium” paths, but relies on strong assumptions, e.g.
  - No active disinvestment
  - No reshuffling of existing exposures
Implied Tier 1 capital ratios

Central forecast

Data

Maximum-minimum range
Interquartile range
Median
Plan

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Feedbacks overview

Three interlinked feedback mechanisms:

1. Interbank lending
   - Standard network model

2. Market liquidity
   - Reduced-form empirical equations

3. Funding liquidity
   - A ‘danger zone’ approach based on case studies
1. Interbank network

- Banks suffer interbank losses when counterparties fail, and may themselves default as a result.

- Network includes core banks, smaller UK banks, foreign banks and other LCFIs. These cannot generate contagion but can transmit it.

- Data and estimation:
  - Large exposure data
  - Missing exposures estimated by Maximum Entropy.
2. Asset Fire Sales

- Defaulting banks liquidate their AFS → asset prices fall → other banks may incur mark-to-market losses.

- Fire-sales affect three broad AFS exposures: equities, corporate bonds, ABS.

- Price responses are estimated using a simple non-linear (concave) equation.

- The impact is temporary: prices assumed recover at the end of each quarter (could be relaxed).

Note: serious data limitations and measurement issues
3. Funding Liquidity: ‘Danger Zones’

We model the closure of funding markets using a scoring system:

- At every $t$, banks are scored using a set of indicators:
  - solvency concerns (e.g. expected future capital)
  - liquidity position (e.g. wholesale maturity mismatch)
  - confidence (e.g. unanticipated profit shock)

- A bank accumulates “DZ points” as its position deteriorates.

- When the score crosses a predefined threshold, funding markets close and the bank goes in default.

Note: calibration based on case studies (inc. US, Japan); highly judgmental.
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Why predictive densities?

The object of interest is the future distribution of $x$ given today’s information:

$$p\left(x_{t+k} \mid X_t\right)$$

- Distributions are obviously central to FS issues
- They may offer a better way to evaluate systemic risk models (compared to central forecasts)
- They can shed an interesting light on “interconnectedness”
Generating predictive densities

\[
p(x_{t+1} | X_t) = \int p(x_{t+1} | X_t, \theta) p(\theta | X_t) d\theta
\]

- Out of sample prediction
  - No hindsight incorporated in estimation/calibration
  - No conditioning information on future \( x \) (unlike stress tests)

- “Parameter uncertainty” explicitly taken into account
  - Predicted probability do not depend on model parameters

Caveat: \( \theta \) is huge in RAMSI, and it includes calibrated parameters. We treat these as fixed.
Case study: 2008

Pre-Tax Profits for five large UK banks (Dec 2010 FSR, £bn)

In RAMSI, $\Delta$Capital $\approx$ Profits (no new equity, no recapitalisations).
Hence, we can compare predicted $\Delta$C to observed profits.
PD for Core Tier 1 Capital

Predicted change in aggregate capital (%)
PD for the aggregate CT1 ratio

Data

Predicted aggregate CT1 ratio in 2008Q4 (%)
### System-wide VaR and ES

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<th>0.1%</th>
<th>1%</th>
<th>5%</th>
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<tbody>
<tr>
<td><strong>Capital</strong></td>
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<tr>
<td>VaR</td>
<td>-17.3</td>
<td>-13.38</td>
<td>-8.83</td>
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<tr>
<td>ES</td>
<td>-17.8</td>
<td>-15.02</td>
<td>-11.44</td>
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<tr>
<td><strong>T1 Ratio</strong></td>
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<tr>
<td>VaR</td>
<td>5.97</td>
<td>6.25</td>
<td>6.57</td>
</tr>
<tr>
<td>ES</td>
<td>5.94</td>
<td>6.14</td>
<td>6.38</td>
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<tbody>
<tr>
<td><strong>Capital</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>VaR</td>
<td>-22.67</td>
<td>-16.40</td>
<td>-10.08</td>
</tr>
<tr>
<td><strong>T1 Ratio</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>VaR</td>
<td>5.28</td>
<td>5.72</td>
<td>6.12</td>
</tr>
<tr>
<td>ES</td>
<td>5.11</td>
<td>5.51</td>
<td>5.88</td>
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</table>

- Capital ~0.1% percentile, T1 ratio ~25% percentile
- All indicators predict a worsening compared to 2007
- The implied bank PD increases from 2.12% to 6.86%

... but is the signal strong enough?
PDs and interdependence (1)

Bank A vs Bank B:

- B is relatively safer
- Stable correlation

(→ common exposures)
PDs and interdependence (2)

Bank A vs Bank C:

- A is relatively safer

What is the correlation?
PDs and interdependence (2)

Bank A vs Bank C:

- A is relatively safer
- Good times: \( \rho \approx 0 \)

What is the correlation?
PDs and interdependence (2)

Change in Capital (%)

Bank A vs Bank C:

- A is relatively safer
- What is the correlation?
  - Good times: $\rho \approx 0$
  - Bad times: $\rho \approx 1$
Bank A vs Bank C:

- A is relatively safer
- Good times: $\rho \approx 0$
- Bad times: $\rho \approx 1$

What is the correlation?

Which distribution would VaR/CoVaR estimates refer to?
Plan

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- Key model components
  - Fundamental (1st round) risks
  - Contagion (2nd round) risks
- Application: predictive distributions
- Conclusions and discussion
RAMSI provides a quantitative framework for assessing systemic risk. The model:

- captures various sources of risk and key inter-risk correlations
- Emphasises feedbacks and externalities across institutions

Possible applications include:

- Stress testing
- Forecasting – distributions as well as central cases
- Policy experiments?
Conclusion

Application: predictive densities

- 2008 as a 0.1% probability event
- The model predicts worse tail outcomes for 2008
  \(\text{(But would a policy-maker act on that information?)}\)
- A useful way of exploring banks’ interdependence
  \(\text{(Is dependence more complex than you -or your model- think?)}\)

Next step: combining predictive densities from alternative, complementary models (e.g. VAR+RAMSI)