Macroprudential Surveillance of the European Banking System

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1. Early-warning models for European banks
   ▶ A framework for early-warning modeling with an application to banks (with J-H Lang and T Peltonen)

2. A network perspective to early-warning models
   ▶ RiskRank: Measuring interconnected risk (with J Mezei)

3. From micro to macro: Visualizing bank-level risk indicators
   ▶ Visual Macroprudential Surveillance of Banks
Motivation 1

- Financial crises triggered by various shocks (unpredictable)...
- ...but widespread imbalances build-up ex ante (identifiable)
- Early-warning models to identify systemic risk at early stages
- From micro to macro: bank-level models for a granular view
- Allows for various aggregations to higher hierarchical levels
Motivation 2

- Early-warning models to identify early stages of systemic risk...
- ...but the models focus on individual risk
- Network structure is essential as distress is not independent
- How to jointly measure the likelihood & impact of a crisis?
- RiskRank joins individual risk & interdependence to one metric
Motivation 3

- Macropru: supervision of the financial system as a whole
- Data: shift from firm-centric to system-wide analysis
- 3D cube: high-dimensional, large-volume, “high”-frequency

- How to visualize complex data for the system as a whole?
- SOTM visualizes how data structures evolve over time
Systemic risk

- Systemic risk along two dimensions (Borio 2009)
  1. Build-up of risk in tranquil times & abrupt unraveling in crisis
  2. How risk is distributed and how shocks transmit in the system

- Tools for measuring cyclical and cross-sectional systemic risk
  - early-warning models
  - macro stress-testing models
  - contagion and spillover models
1. Framework for early warning

**Pre-modeling:**
Aim & objective

- Modeling purpose
  - Ex-post: Explain the past
  - Ex-ante: Predict the future
- Forecast horizon
  - Early or late signals
- Events, indicators & sample
  - Event types to predict
  - Types of indicators
  - Entities & time span

**Modeling:**
Estimation & evaluation

- Evaluation criterion
  - Set signalling thresholds
  - Measure performance
- Modeling technique
  - Univariate or multivariate
  - Complexity of methods
- Model selection
  - Automatized or judgment-based
  - Degree of regularization
- Evaluation exercise
  - In-sample or out-of-sample
  - Recursive or cross-validate

**Post-modeling:**
Transformation & visualization

- Policy-relevant dimensions
  - Cyclical & cross-sectional
  - Model aggregation & decomposition
- Visual representations
  - Explore models
  - Communicate models
- Policy-relevant dimensions
  - Cyclical & cross-sectional
  - Model aggregation & decomposition
- Visual representations
  - Explore models
  - Communicate models
Bank early-warning model

Automatized model selection for forecasting purposes

- Model aim
  - Optimal prediction
  - European banks, horizon 1-8Q, $\mu = 0.9$

- Model selection and evaluation
  - Policymaker’s loss function of missing crises and false alarms
  - LASSO logistic regression for automatized model selection
  - Cross-validation to optimize model complexity for forecasting
  - Recursive real-time out-of-sample evaluation of the model

- Model output & visualisation
  - Assess time- and cross-sectional dimensions
  - Decomposition and aggregation of model output
~ 625 banks from 27 EU countries from 1999q1–2014q3

Unbalanced panel due to data gaps and entry/exit of banks

The dataset combines information from various sources:

- **Bank distress events**: Direct failures, state-aid cases and distressed mergers
- **Bank financial statements**: Quarterly and annual publicly available B/S and I/S variables from Bloomberg
- **Banking sector aggregates**: Quarterly aggregate assets and liabilities of MFIs by country from ECB BSI
- **Macro-financial variables**: Quarterly and annual data on interest rates, GDP, house/stock prices and MIP variables from various sources (through ECB SDW and Haver Analytics)
Both very complex and very simple models do not perform well.
The optimal out-of-sample model contains 11 variables.
LASSO logit model

- From 220 to 11 indicators
  - 3 bank-specific
  - 4 banking-sector
  - 4 macro-financial
- Coef. signs follow intuition
- Most coef. highly significant

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Full sample</th>
<th></th>
<th>(2) Lasso sample</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-2.998***</td>
<td>(0.152)</td>
<td>-3.064***</td>
<td>(0.215)</td>
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<tr>
<td>Bank-specific</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Tangible equity / Total assets, lag 2</td>
<td>-0.303***</td>
<td>(0.0446)</td>
<td>-0.293***</td>
<td>(0.0666)</td>
</tr>
<tr>
<td>Interest expenses / Total liabilities, lag 2</td>
<td>0.125**</td>
<td>(0.0530)</td>
<td>0.252***</td>
<td>(0.0876)</td>
</tr>
<tr>
<td>Reserves for NPLs / Total assets, lag 2</td>
<td>0.169***</td>
<td>(0.0593)</td>
<td>0.355***</td>
<td>(0.0956)</td>
</tr>
<tr>
<td>Banking sector</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial assets / GDP, lag 2</td>
<td>0.000864</td>
<td>(0.000580)</td>
<td>0.00302***</td>
<td>(0.00105)</td>
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<tr>
<td>Loans / Deposits (1-year change), lag 1</td>
<td>0.00916</td>
<td>(0.00606)</td>
<td>0.0148</td>
<td>(0.0104)</td>
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<tr>
<td>Mortgages / Loans (1-year change), lag 1</td>
<td>-0.414***</td>
<td>(0.0841)</td>
<td>-0.269**</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Issued debt / Total liabilities (1-year change), lag 1</td>
<td>-0.156**</td>
<td>(0.0524)</td>
<td>-0.142*</td>
<td>(0.0804)</td>
</tr>
<tr>
<td>Macro-financial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total credit / GDP (3-year change), lag 2</td>
<td>0.0135**</td>
<td>(0.00647)</td>
<td>0.0134</td>
<td>(0.00877)</td>
</tr>
<tr>
<td>House price gap (lambda = 1,600), lag 2</td>
<td>-0.0468***</td>
<td>(0.0173)</td>
<td>-0.0544**</td>
<td>(0.0267)</td>
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<tr>
<td>MIP International Investment Position, lag 2</td>
<td>-0.0112***</td>
<td>(0.00374)</td>
<td>-0.00802</td>
<td>(0.00574)</td>
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<tr>
<td>10-year yield (1-year change), lag 1</td>
<td>0.326***</td>
<td>(0.101)</td>
<td>0.385*</td>
<td>(0.217)</td>
</tr>
<tr>
<td>Observations</td>
<td>7,587</td>
<td></td>
<td>4,176</td>
<td></td>
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<tr>
<td>Total number of banks</td>
<td>384</td>
<td></td>
<td>231</td>
<td></td>
</tr>
<tr>
<td>Number of SBGs</td>
<td>106</td>
<td></td>
<td>69</td>
<td></td>
</tr>
<tr>
<td>Number of LCBGs</td>
<td>23</td>
<td></td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Number of distressed banks</td>
<td>124</td>
<td></td>
<td>81</td>
<td></td>
</tr>
<tr>
<td>Number of pre-distress events</td>
<td>803</td>
<td></td>
<td>385</td>
<td></td>
</tr>
</tbody>
</table>
LASSO logit performance

- Less than 1/3 of vulnerable states not signalled out-of-sample
- The conditional distress probability is fairly high at around 33%

<table>
<thead>
<tr>
<th></th>
<th>In-sample</th>
<th>Out-of-sample</th>
</tr>
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<tbody>
<tr>
<td>Signaling threshold</td>
<td>0.084</td>
<td></td>
</tr>
<tr>
<td>AUROC</td>
<td>0.844</td>
<td></td>
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<tr>
<td>Relative usefulness</td>
<td>0.529</td>
<td>0.324</td>
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<tr>
<td>Noise-2-Signal ratio</td>
<td>0.363</td>
<td>0.332</td>
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<tr>
<td>Type I error rate</td>
<td>0.168</td>
<td>0.306</td>
</tr>
<tr>
<td>Type II error rate</td>
<td>0.302</td>
<td>0.230</td>
</tr>
<tr>
<td>Conditional pre-distress prob.</td>
<td>0.236</td>
<td>0.328</td>
</tr>
<tr>
<td>Unconditional pre-distress prob.</td>
<td>0.101</td>
<td>0.139</td>
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<tr>
<td>Probability difference</td>
<td>0.135</td>
<td>0.188</td>
</tr>
<tr>
<td>True positives</td>
<td>668</td>
<td>551</td>
</tr>
<tr>
<td>False positives</td>
<td>2168</td>
<td>1130</td>
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<tr>
<td>True negatives</td>
<td>5016</td>
<td>3776</td>
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<tr>
<td>False negatives</td>
<td>135</td>
<td>243</td>
</tr>
</tbody>
</table>
Bank examples – time

DEUTSCHE BANK AG-REGISTERED

BANK OF CYPRUS PUBLIC CO LTD

BANCO COMERCIAL PORTUGUES-R

BANK OF IRELAND

Legend:
- Pre-crisis
- Crisis
- Distress probability
- Signalling threshold
Bank examples – cross-section

- CA = did not pass the ECB Comprehensive Assessment (CA)
- CA = Identified in the CA, but raised sufficient capital in 2014
- 6.8 = Capital ratio of 5.5% - 7.5% in CA adverse scenario
- X = Bank had a stress event in 2014

Distress probability (1q-8q ahead)

Signaling threshold
Euro aggregate

Weighted average probability for Euro Area, Lasso

- Bank-specific
- Banking-sector
- Macro-financial

Signalling threshold
2. RiskRank: Measuring interconnected risk

RiskRank as a measure of systemic risk for

- A hierarchical system of entities with...
- Risk levels for individual entities and....
- Interconnections among them.

Key features of RiskRank

- A general-purpose measure of interconnected risk
- Beyond entities, aggregates upward in the hierarchy
- Allows disentangling individual, direct & indirect effects
- Allows multiple indirect effects and feedback loops
Systemic risk aggregation

- Risk indicators into probability
  - Signaling: Monitor univariate indicators
  - Non/linear approaches for combining indicators
  - Ensemble learning for model aggregation

- Interlinkages into centrality
  - In, out & total strength/degree
  - Betweenness, closeness & eigenvector centrality
  - DebtRank (Battiston et al 2012)

- How to combine probabilities and links?
Aggregation operators

- Conventional aggregation operators
  - Min/max: con-/disjunctive operators
  - Weighted mean: fix trade-off & compensatory
  - Quadratic/geometric/harmonic/power $\alpha$ mean
  - Ordered Weighted Average (OWA) (Yager 1988)

- Choquet (1953) integral as a general aggregation operator
  - Includes the above (and more) as special cases
  - Generalizes to non-linearity and non-additivity
  - Extends conventional operators with interactions
### Choquet integral

**Definition**
Fuzzy measure $\mu$ on the finite set $N = \{1, 2, \ldots, n\}$ is a set function $\mu : P(N) \rightarrow [0, 1]$ (where $P(N)$ is the power set of $N$) satisfying the following two conditions:

- $\mu(\emptyset) = 0$, $\mu(N) = 1$;
- Monotonic, non-decreasing: $A \subseteq B$ implies that $\mu(A) \leq \mu(B)$.

**Definition**
Discrete Choquet integral with respect to a monotone measure $\mu$ is

$$
C_\mu(x_1, \ldots, x_n) = \sum_{i=1}^{n} \left( \mu(C(i)) - \mu(C(i+1)) \right) x(i)
$$

where $x(i)$ denotes a permutation of the $x_i$ values such that $x(1) \leq x(2) \leq \ldots \leq x(n)$ and $C(i) = \{c(i), c(i+1), \ldots, c(n)\}$. 
Additive Choquet integral

The additive Choquet integral is the weighted sum

$$C_\mu(x_1, \ldots, x_n) = \sum_{i=1}^{n} \mu(c_{(i)}) x_{(i)}$$

2-additive case covers pairwise interactions and individual effects

$$C_\mu(x_1, \ldots, x_n) = \sum_{i=1}^{n} (v(c_i) - \frac{1}{2} \sum_{j \neq i} l(c_i, c_j))x_i + \sum_{l(c_i, c_j) > 0} l(c_i, c_j) \min(x_i, x_j) + \sum_{l(c_i, c_j) < 0} |l(c_i, c_j)| \max(x_i, x_j)$$

where $v(c_i)$ stands for the Shapley-index (average contribution of fixed element $x_i$ in any subset) and $l(c_i, c_j) \in [-1, 1]$ for the interaction. This relies on the Möbius transformation of $\mu$ and that it equals 0 on any subset with cardinality above 2 (Grabisch, 1997)
Case of utility theory

\[ C_\mu(x_1, \ldots, x_n) = \sum_{i=1}^{n} (v(c_i) - \frac{1}{2} \sum_{j \neq i} I(c_i, c_j))x_i + \sum_{I(c_i, c_j) > 0} I(c_i, c_j) \min(x_i, x_j) + \sum_{I(c_i, c_j) < 0} |I(c_i, c_j)| \max(x_i, x_j) \]

Positive interaction
Complements
\[ I(c_i, c_j) > 0 \]
\[ \min \text{ operator} \]

Negative interaction
Substitutes
\[ I(c_i, c_j) < 0 \]
\[ \max \text{ operator} \]

No interaction
Independent
\[ I(c_i, c_j) = 0 \]
no operator
From Choquet to RiskRank

For risk levels $x_i$ and links $l(c_i, c_j)$, 2-additive RiskRank is

$$RR_c = \underbrace{w(c)x_c}_{\text{Individual effect of entity } c} + \sum_{i=1}^{n} (v(c_i) - \frac{1}{2} \sum_{j \neq i}^{n} l(c_i, c_j)) x_i +$$

$$\underbrace{\sum_{i}^{n} \sum_{j \neq i}^{n} l(c_i, c_j) \prod(x_i, x_j)}_{\text{Indirect effects of } j \text{ via } i \text{ on } c}$$

which

- allows multiple indirect effects via $k$-additivity
- allows simulated feedback through dynamic iteration
RiskRank as a network
http://vis.risklab.fi/
Real-world examples

- Network: BIS foreign claims, immediate borrower

<table>
<thead>
<tr>
<th>$\mu$</th>
<th>$U_r(\mu)$</th>
<th>AUC</th>
<th>$U_r(\mu)$</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>0 %</td>
<td>0.915</td>
<td>0 %</td>
<td>0.934</td>
</tr>
<tr>
<td>0.1</td>
<td>-6 %</td>
<td>0.915</td>
<td>1 %</td>
<td>0.934</td>
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<tr>
<td>0.2</td>
<td>-3 %</td>
<td>0.915</td>
<td>3 %</td>
<td>0.934</td>
</tr>
<tr>
<td>0.3</td>
<td>6 %</td>
<td>0.915</td>
<td>14 %</td>
<td>0.934</td>
</tr>
<tr>
<td>0.4</td>
<td>12 %</td>
<td>0.915</td>
<td>28 %</td>
<td>0.934</td>
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<tr>
<td>0.5</td>
<td>15 %</td>
<td>0.915</td>
<td>37 %</td>
<td>0.934</td>
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<tr>
<td>0.6</td>
<td>25 %</td>
<td>0.915</td>
<td>47 %</td>
<td>0.934</td>
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<tr>
<td>0.7</td>
<td>44 %</td>
<td>0.915</td>
<td>59 %</td>
<td>0.934</td>
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<td>0.8</td>
<td>60 %</td>
<td>0.915</td>
<td>69 %</td>
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<td>0.9</td>
<td>73 %</td>
<td>0.915</td>
<td>78 %</td>
<td>0.934</td>
</tr>
<tr>
<td>1.0</td>
<td>0 %</td>
<td>0.915</td>
<td>0 %</td>
<td>0.934</td>
</tr>
</tbody>
</table>
Real-world examples

- **Red**: Individual probability
- **Black**: RiskRank

**Germany**

**Europe**
Let’s start from the underlying data.
Data & dimension reduction

- **Data reduction**, or clustering, vector quantization, etc.
- Exploring structures and tendencies in data
  - represent large-volume data as a reduced but representative set
- **Examples of reduction techniques**
  - *k*-means and hierarchical clustering
  - node filtering/grouping and edge bundling
- **Dimension reduction**, or mapping, projection, manifold learning, embedding, etc.
- Facilitate the visualization of high-dimensional data
  - represent data in two dimensions such that similar high-dimensional data are nearby and dissimilar distant
- **Examples of mapping techniques**
  - PCA, MDS, SOMs, Force layouting, etc.
Visual dynamic clustering

- Self-Organizing Time Map (Sarlin, Neurocomputing, 2012)
  - Focus on individual cross-sections and ...

A multivariate cross-section

Reduced number of mean profiles

Reduced dimensionality of mean profiles

Entities (e.g. Banks)

Risk indicators (e.g. micro, macro, banking sector)

Mean profile 1

Mean profile 2

Mean profile 6
Visual dynamic clustering

- Self-Organizing Time Map (Sarlin, Neurocomputing, 2012)
- ... and represent changes in mean profiles over time

Reduced number of low-dimensional mean profiles

Self-Organizing Time Map: visual dynamic clustering

Mean profile 1
Mean profile 2
...
Mean profile 6

Quarters (e.g. 2010Q1)

Q1 Q2 Q3 Q4
Application to EU banks

- Self-Organizing Time Map applied to bank-related data
  - 546 EU banks with at least EUR 1 bn in assets (26,852 observations)
  - Quarterly data from 2000Q1-2013Q1
  - Obtain 194 bank-quarter distress events
- SOTM: Emergence of macro patterns from micro data
- Weighting: Learning accounts for systemic relevance (assets)
- Framework: Visual surveillance of a macroprudential data cube
Visual dynamic clustering

- Evolution of bank, banking sector and macro conditions (24 indicators) in the cross-section (2005–2013, 546 banks)
  1. Similarity in color represents similarity in conditions
  2. Vertical distance represents similarity in conditions
Visual dynamic clustering

- SOTM grid as slices per indicator: Darker shade → larger value
Visual dynamic clustering

- SOTM grid as slices per indicator: Darker shade → larger value
Visual dynamic clustering

- SOTM grid as slices per indicator: Darker shade → larger value
Conclusion

- Bank early-warning model
  - Conceptual framework for early-warning modeling
  - Modeling solution for optimal predictive models
  - An application to predict European bank distress

- RiskRank as a measure of systemic risk
  - Brings together cyclical and cross-sectional systemic risk
  - Measures risk in any hierarchical & interconnected system
  - Allows disentangling effects & simulating feedback loops

- SOTM for visualizing risk indicators
  - Visualizes the 3D data cube (entities, variables, time)
  - Data & dimension reduction over time
  - Emergence of macro patterns from micro data
Thanks for your attention!
Appendix