Macroprudential Surveillance of the European Banking System

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This talk

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

Bank early-warning model

Automatized model selection for forecasting purposes

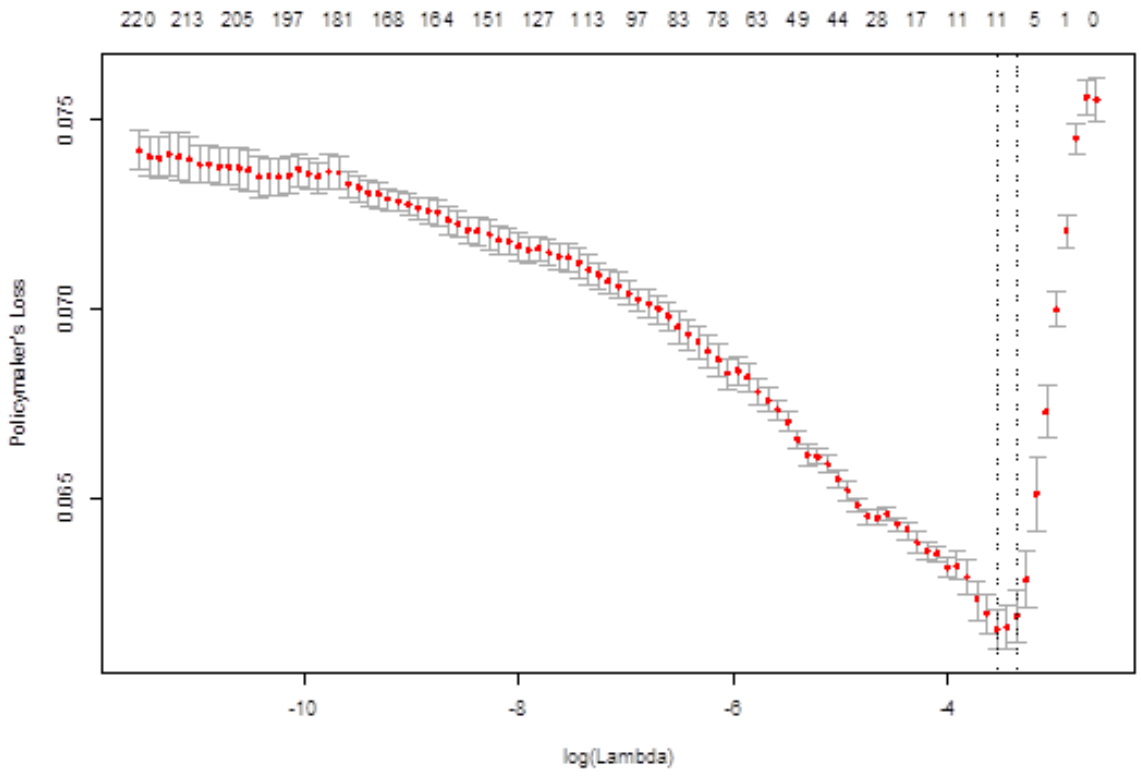
- Model aim
  - Optimal prediction
  - European banks, horizon 1-8Q, $\mu = 0.9$
- Model selection and evaluation
  - Policymaker's loss function of missing crises and false alarms
  - LASSO logistic regression for automatized model selection
  - Cross-validation to optimize model complexity for forecasting
  - 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

Data

- $\sim$ 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)

Bank early-warning model

- 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

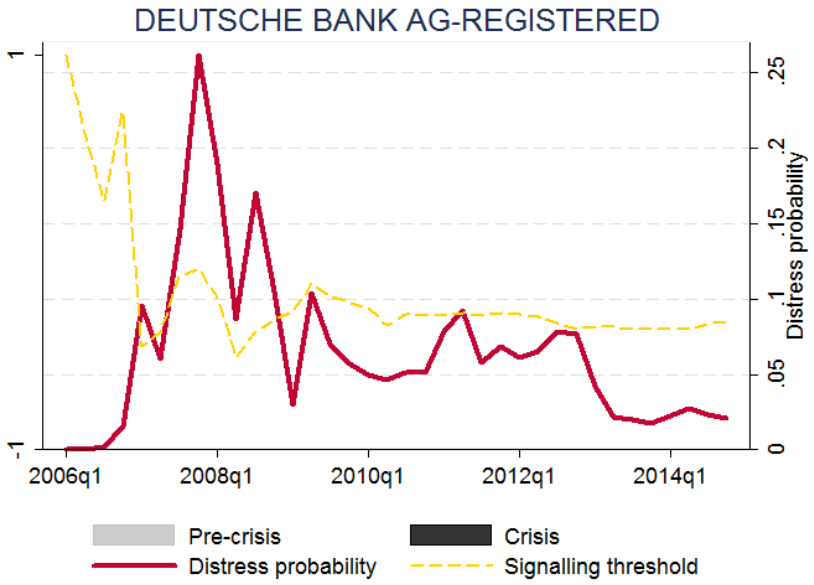
Variable	(1) Full sample	(2) Lasso sample
Intercept	-2.998***	-3.064***
	(0.152)	(0.215)
Bank-specific		
Tangible equity / Total assets, lag 2	-0.303***	-0.293***
	(0.0446)	(0.0666)
Interest expenses / Total liabilities, lag 2	0.125**	0.252***
	(0.0530)	(0.0876)
Reserves for NPLs / Total assets, lag 2	0.169***	0.355***
	(0.0593)	(0.0956)
Banking-sector		
Financial assets / GDP, lag 2	0.000864	0.00302***
	(0.000580)	(0.00105)
Loans / Deposits (1-year change), lag 1	0.00916	0.0148
	(0.00606)	(0.0104)
Mortgages / Loans (1-year change), lag 1	-0.414***	-0.269**
	(0.0841)	(0.132)
Issued debt / Total liabilities (1-year change), lag 1	-0.156**	-0.142*
	(0.0624)	(0.0804)
Macro-financial		
Total credit / GDP (3-year change), lag 2	0.0135**	0.0134
	(0.00647)	(0.00877)
House price gap (lambda = 1,600), lag 2	-0.0468***	-0.0544**
	(0.0173)	(0.0267)
MIP International Investment Position, lag 2	-0.0112***	-0.00802
	(0.00374)	(0.00574)
10-year yield (1-year change), lag 1	0.326***	0.385*
	(0.101)	(0.217)
Observations	7,987	4,176
Total number of banks	384	231
Number of SBGs	106	69
Number of LCBGs	23	20
Number of distressed banks	124	81
Number of pre-distress events	803	386

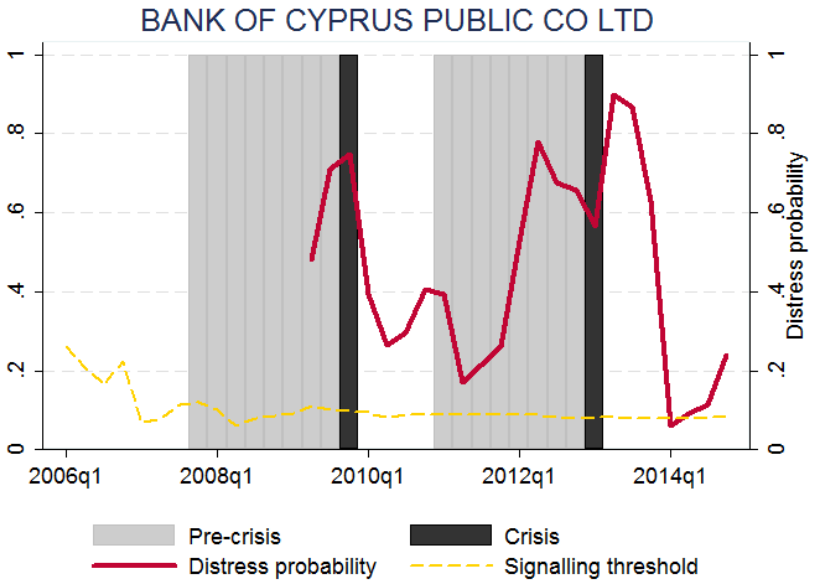
LASSO logit performance

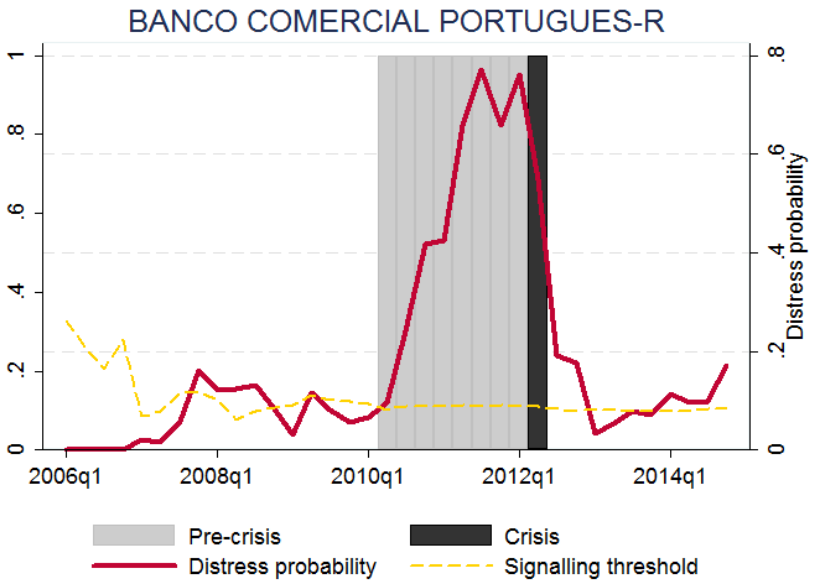
- Less than 1/3 of vulnerable states not signalled out-of-sample
- The conditional distress probability is fairly high at around 33%

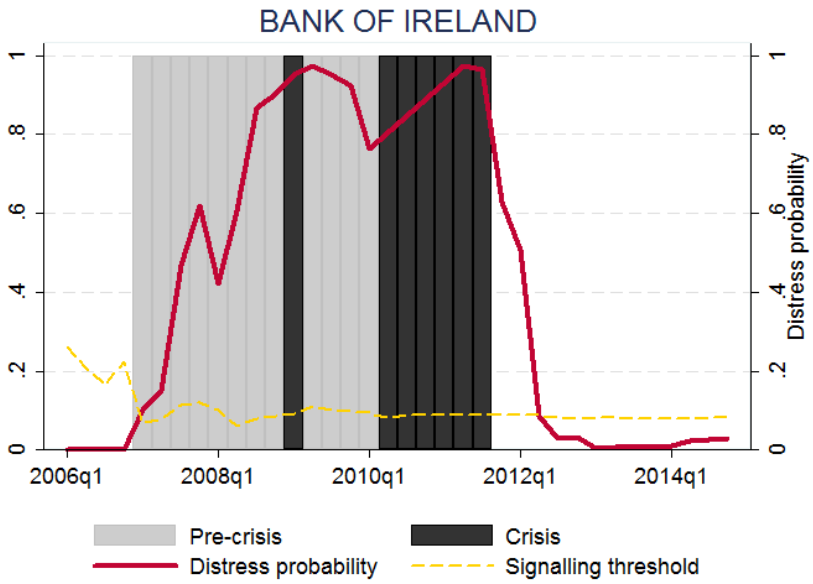
	In-sample	Out-of-sample
Signaling threshold	0.084	
AUROC	0.844	
Relative usefulness	0.529	0.324
Noise-2-Signal ratio	0.363	0.332
Type I error rate	0.168	0.306
Type II error rate	0.302	0.230
Conditional pre-distress probability	0.236	0.328
Unconditional pre-distress probability	0.101	0.139
Probability difference	0.135	0.188
True positives	668	551
False positives	2168	1130
True negatives	5016	3776
False negatives	135	243

Bank examples – time

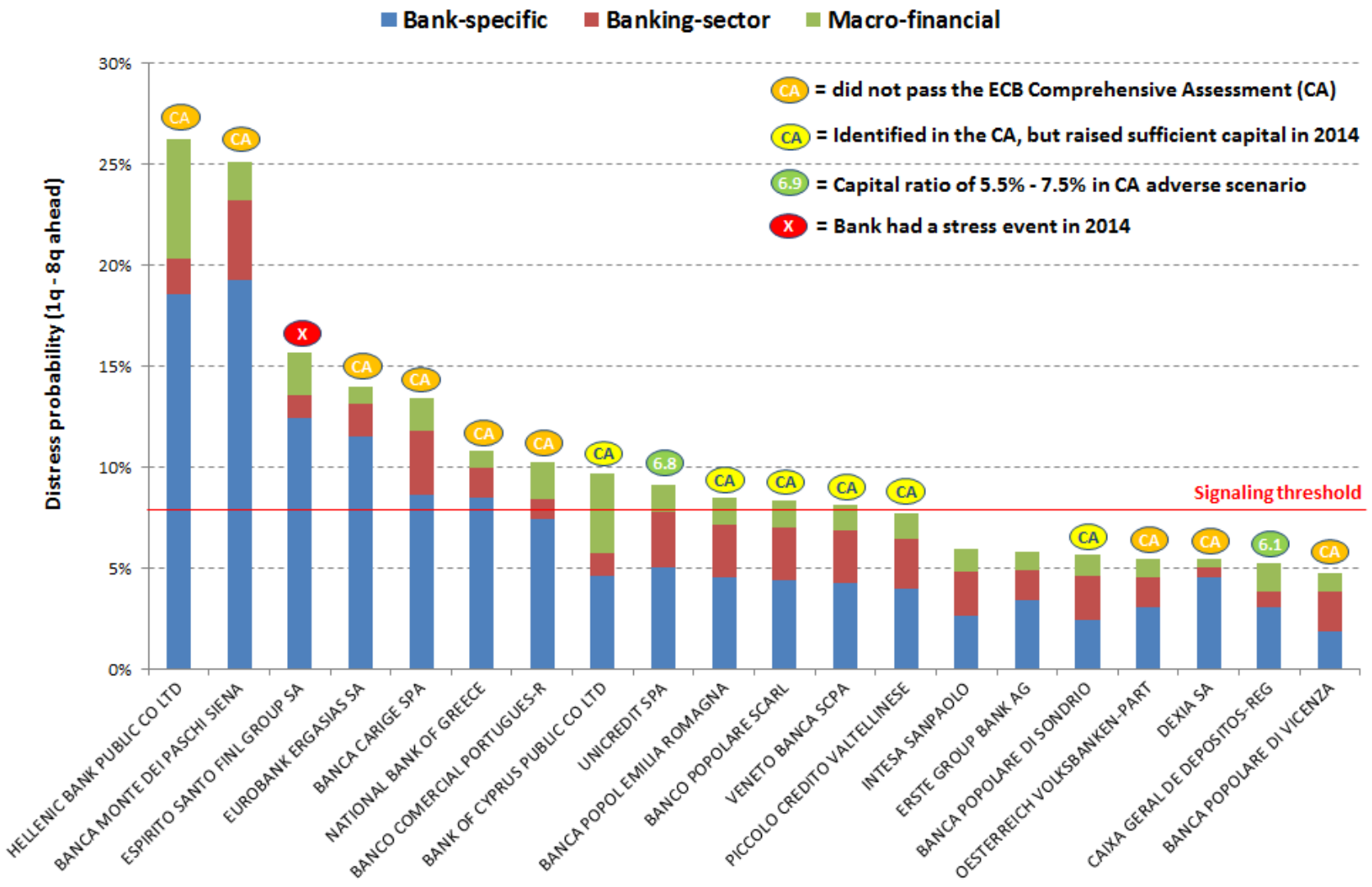




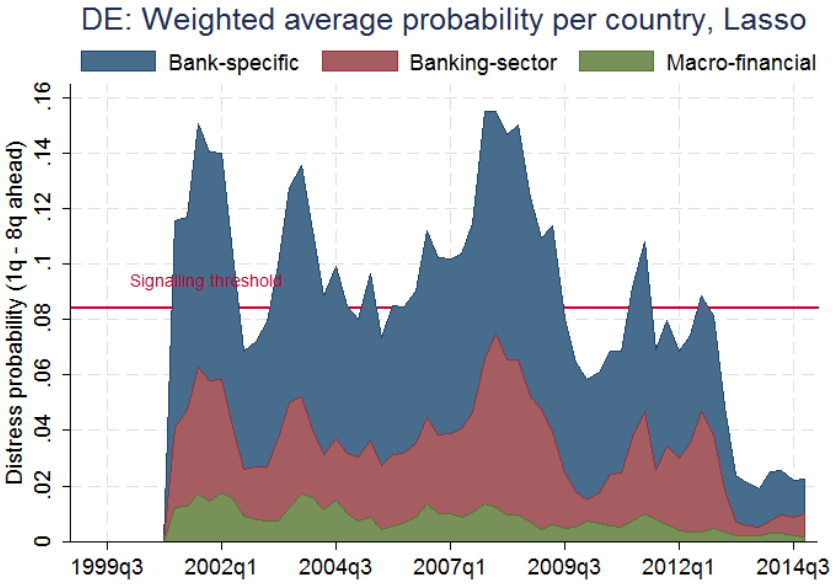


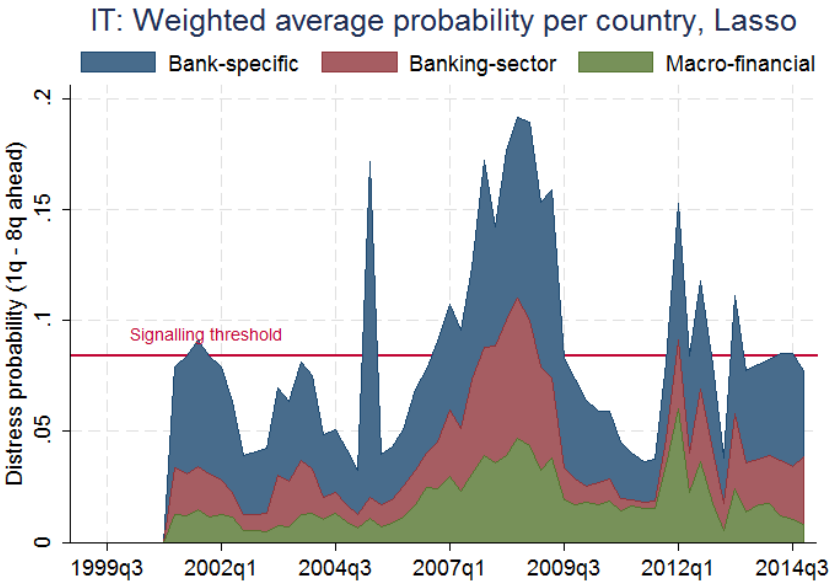


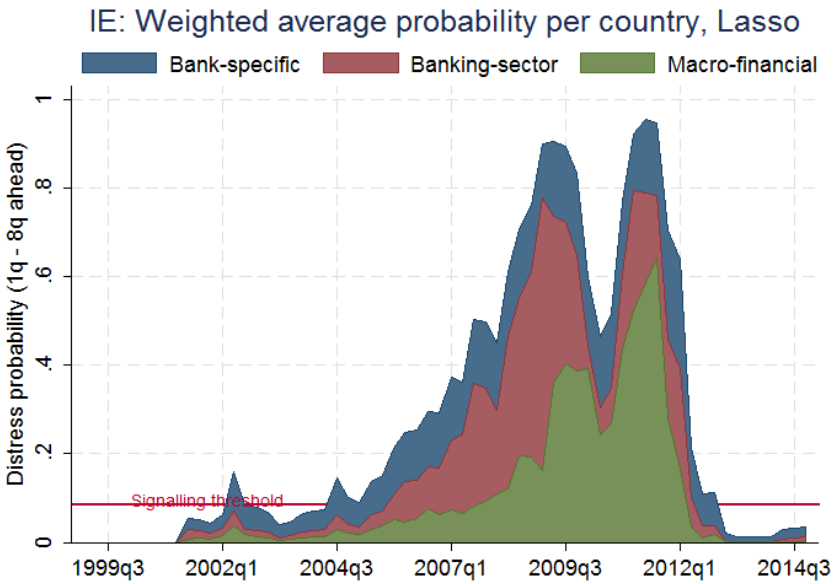
Bank examples – cross-section

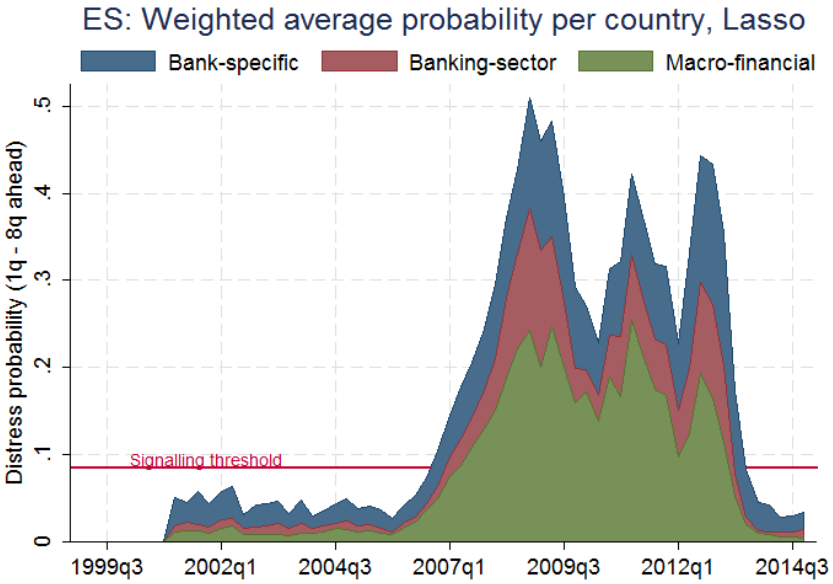


Country aggregates

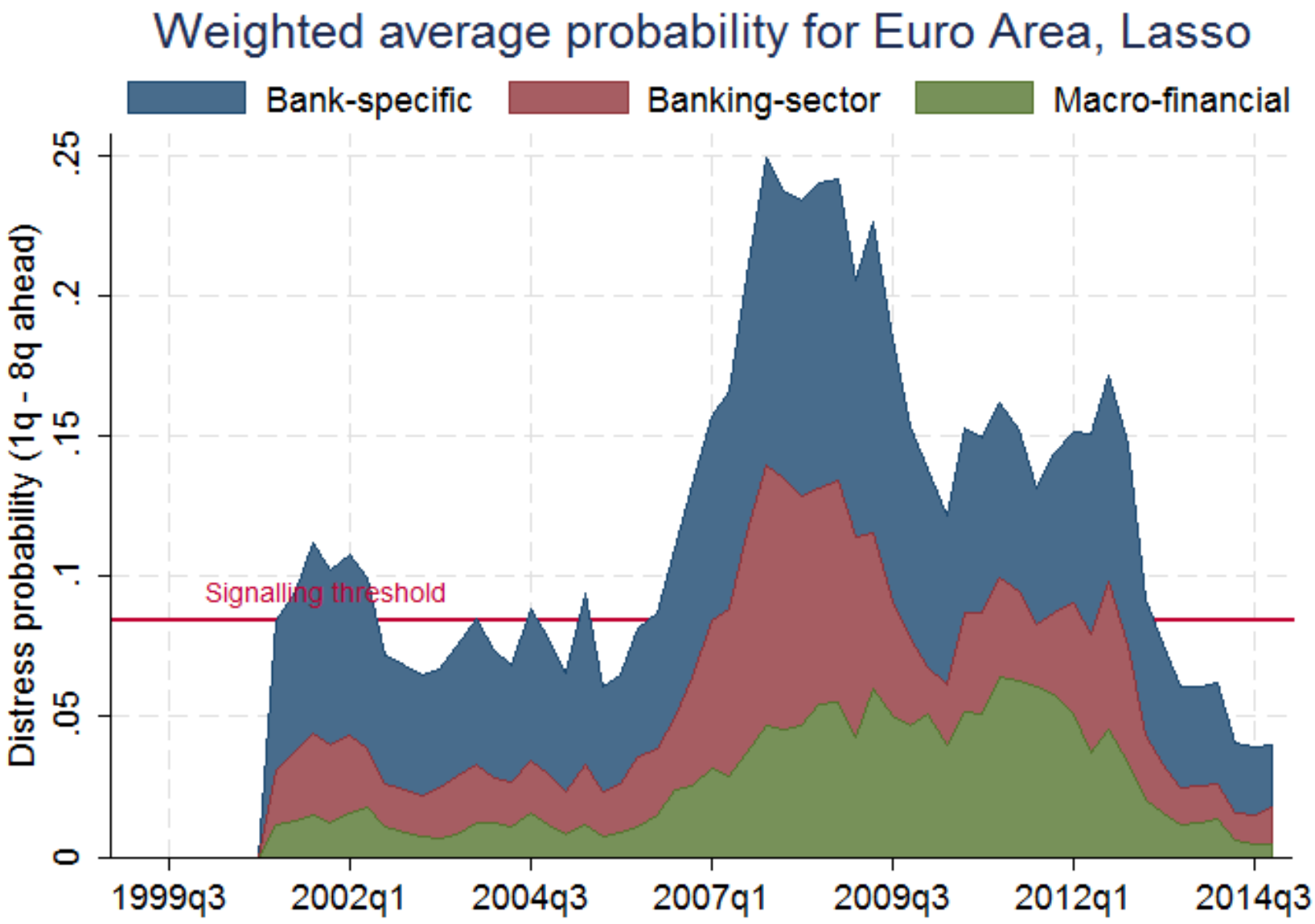








Euro aggregate



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 α 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 μ on the finite set $N = \{1, 2, ..., n\}$ is a set function $\mu : P(N) \to [0, 1]$ (where $P(N)$ is the power set of N) satisfying the following two conditions:

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

Definition

Discrete Choquet integral with respect to a monotone measure μ is

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

where $x_{(i)}$ denotes a permutation of the x_i values such that $x_{(1)} \leq x_{(2)} \leq \ldots \leq x_{(n)}$ and $C_{(i)} = \left\{c_{(i)}, c_{(i+1)}, \ldots, c_{(n)}\right\}$.

Additive Choquet integral

The additive Choquet integral is the weighted sum

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

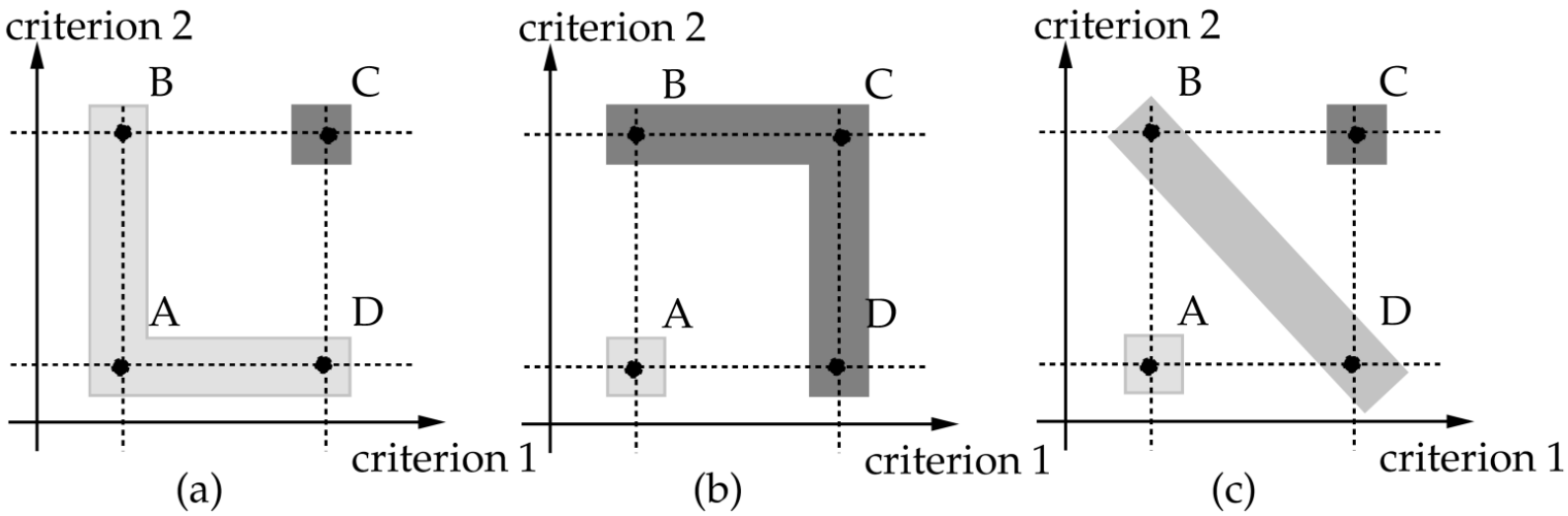
2-additive case covers pairwise interactions and individual effects

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

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

Case of utility theory

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



Positive interaction	Negative interaction	No interaction
Complements	Substitutes	Independent
$I(c_i,c_j) > 0$	$I(c_i,c_j) < 0$	$I(c_i,c_j) = 0$
min operator	**max** operator	no operator

From Choquet to RiskRank

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

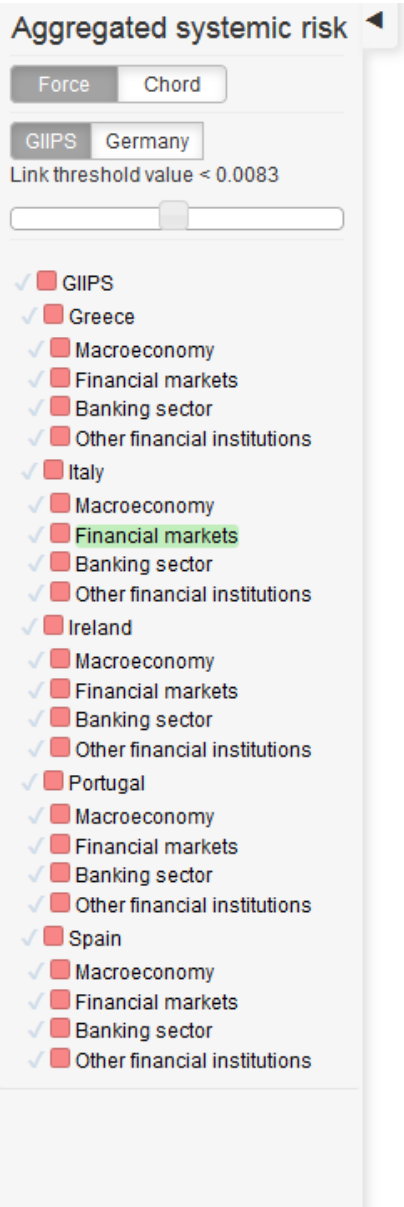
$$RR_c = \underbrace{w(c)x_c}_{\text{Individual effect of entity } c} + \underbrace{\sum_{i=1}^{n}\left(v\left(c_i\right) - \frac{1}{2}\sum_{j\neq i}^{n} I(c_i, c_j)\right)x_i}_{\text{Direct effects of entity } i \text{ on } c} + \underbrace{\sum_{i}^{n}\sum_{j\neq i}^{n} I(c_i, c_j)\prod(x_i, x_j)}_{\text{Indirect effects of } j \text{ via } i \text{ on } c}$$

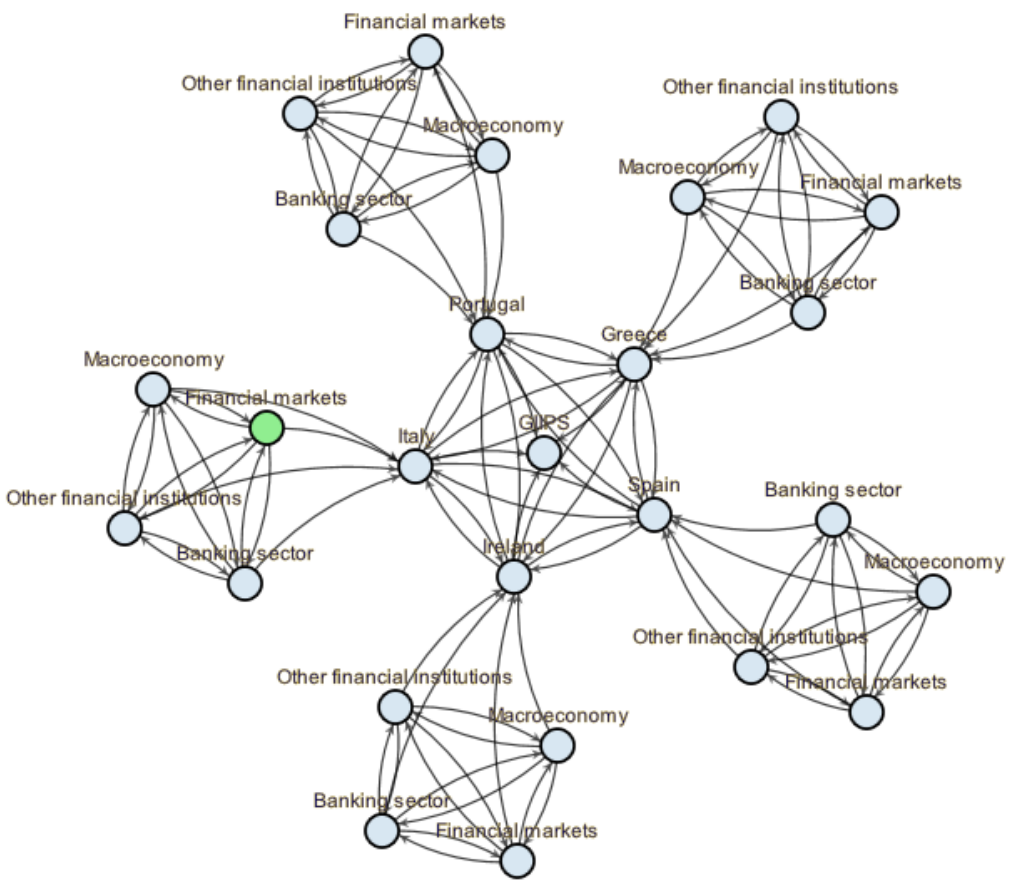
which

- allows multiple indirect effects via k-additivity
- allows simulated feedback through dynamic iteration

RiskRank as a network

http://vis.risklab.fi/



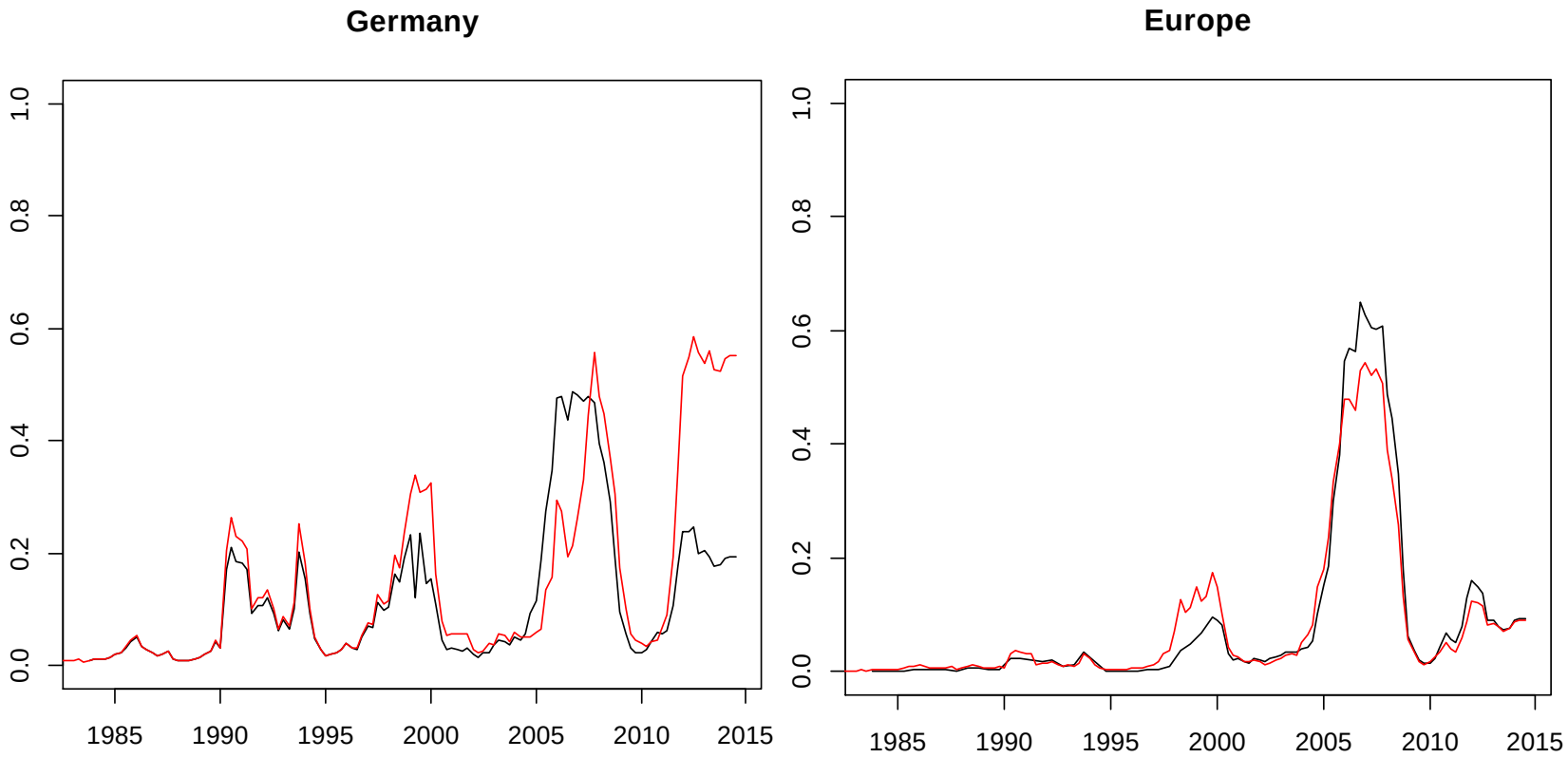


Real-world examples

- Country early-warning model: Holopainen & Sarlin (2015)
- Network: BIS foreign claims, immediate borrower

	Individual		RiskRank	
μ	$U_r(\mu)$	AUC	$U_r(\mu)$	AUC
0.0	0 %	0.915	0 %	0.934
0.1	-6 %	0.915	1 %	0.934
0.2	-3 %	0.915	3 %	0.934
0.3	6 %	0.915	14 %	0.934
0.4	12 %	0.915	28 %	0.934
0.5	15 %	0.915	37 %	0.934
0.6	25 %	0.915	47 %	0.934
0.7	44 %	0.915	59 %	0.934
0.8	60 %	0.915	69 %	0.934
0.9	73 %	0.915	78 %	0.934
1.0	0 %	0.915	0 %	0.934

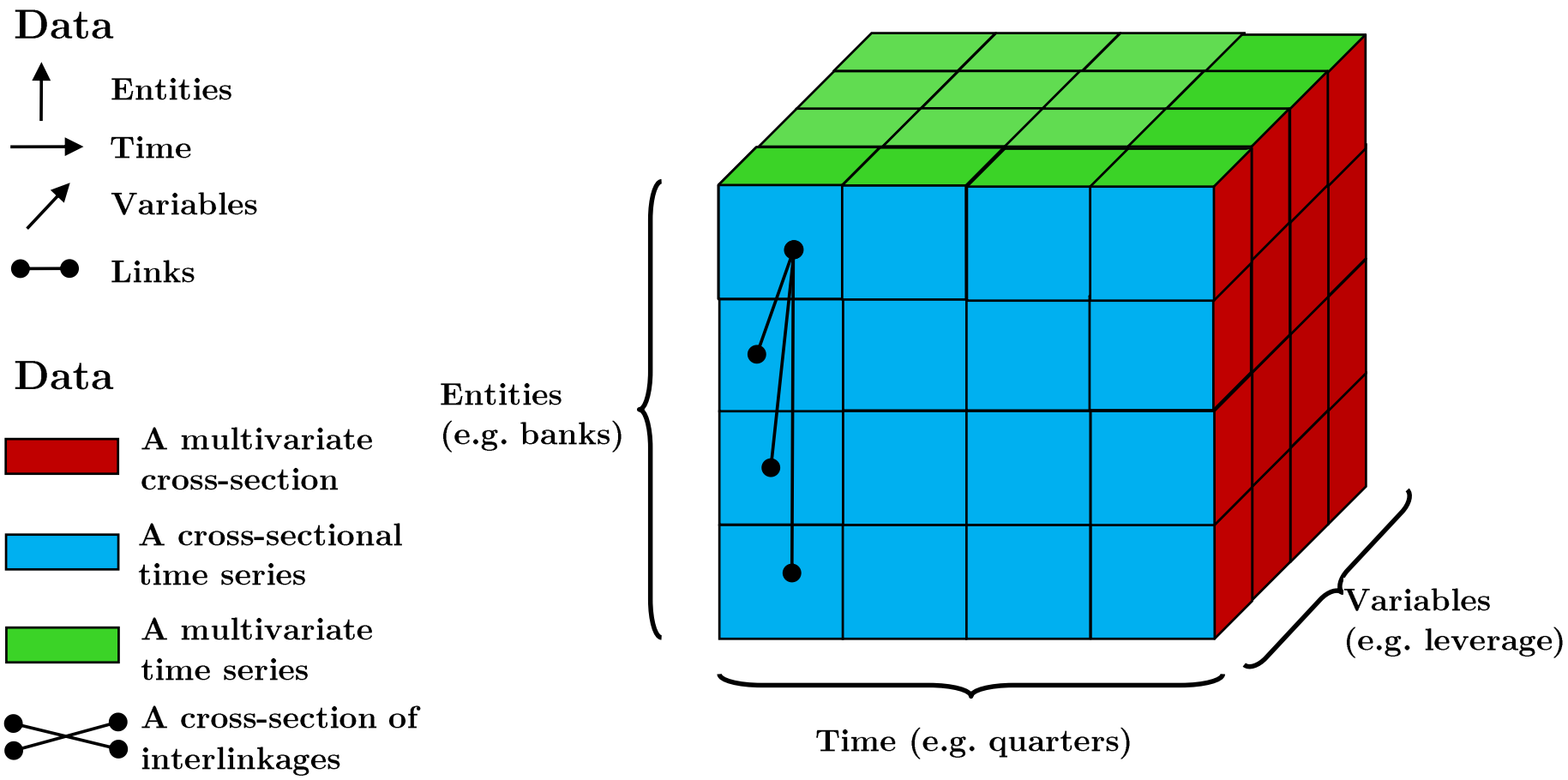
Real-world examples



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

3. SOTM:Visualizing risk indicators

- Let's start from the underlying data

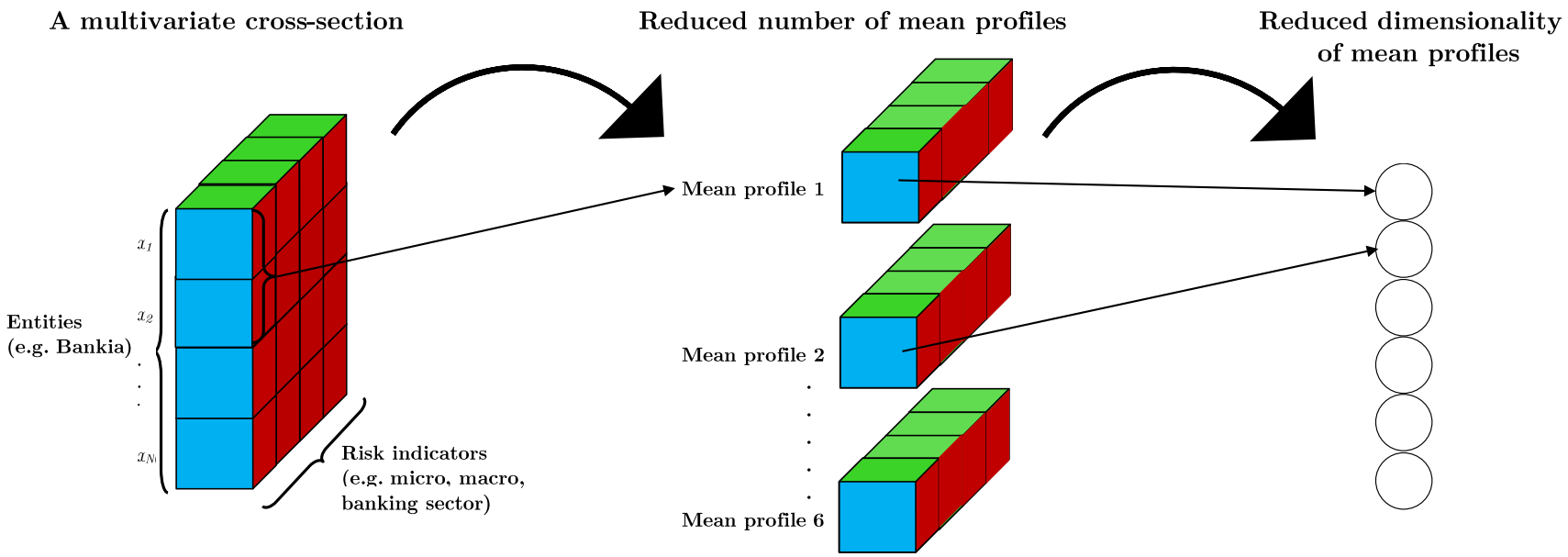


Data & dimension reduction

- **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.

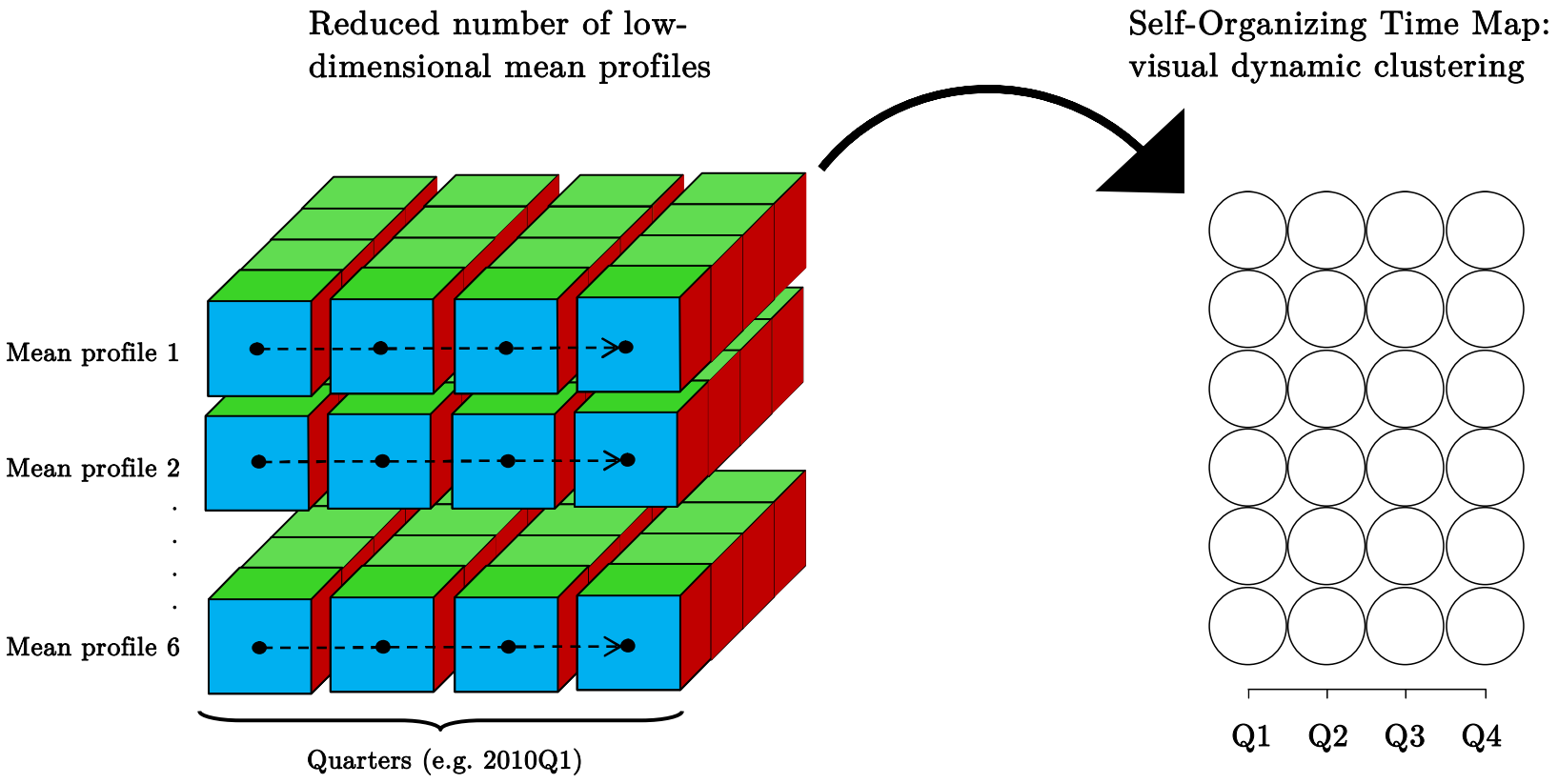
Visual dynamic clustering

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



Visual dynamic clustering

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

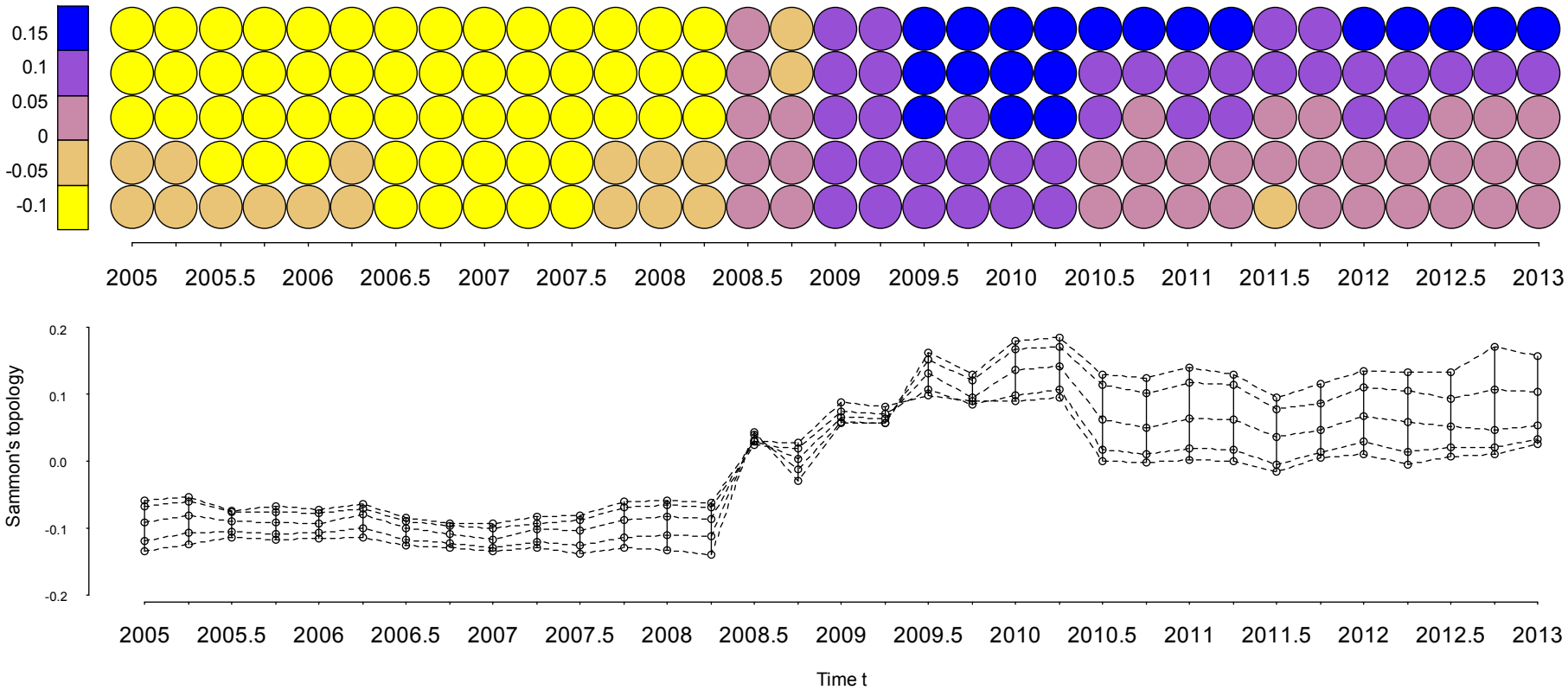


Application to EU banks

- 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

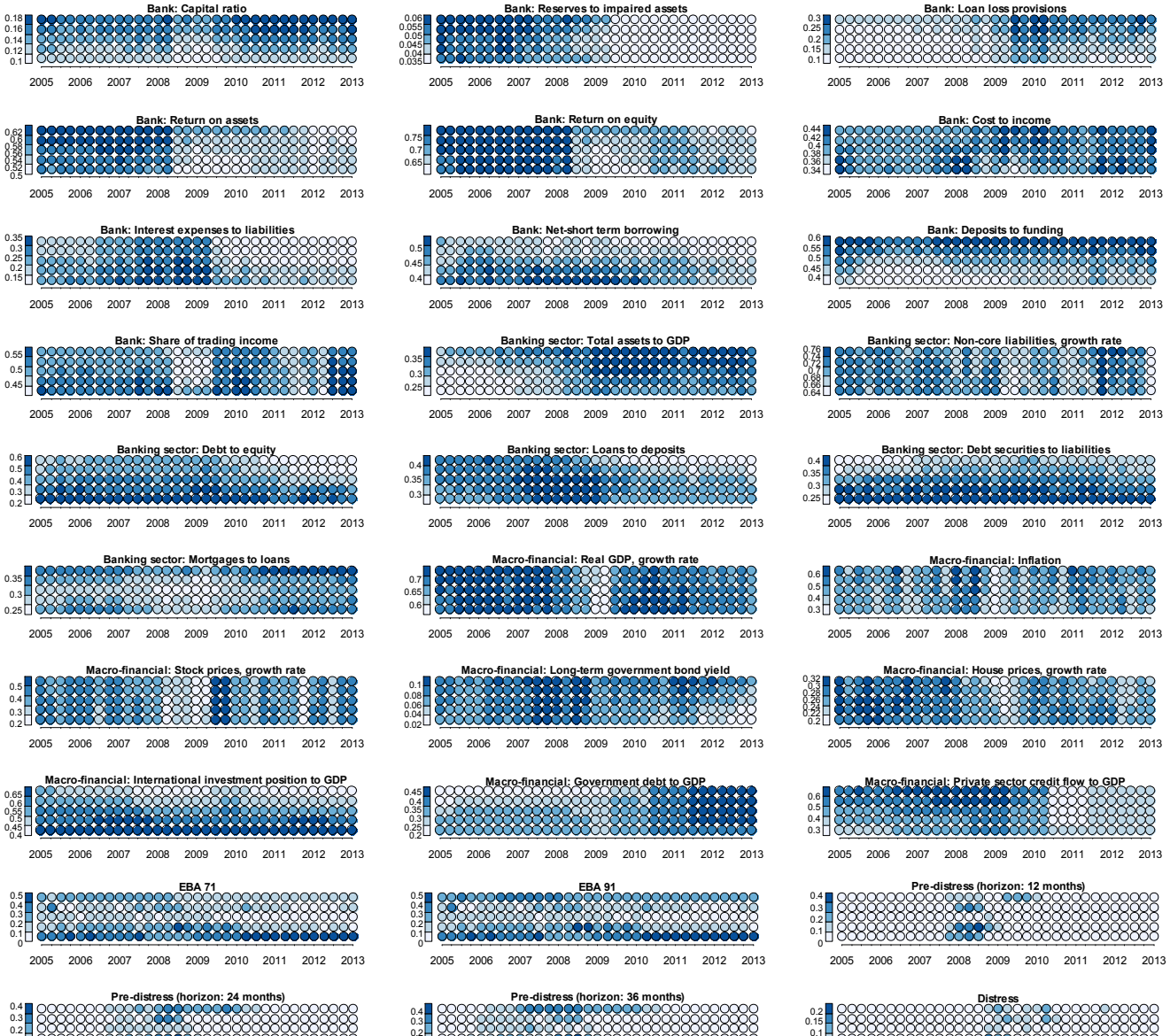
Visual dynamic clustering

- 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



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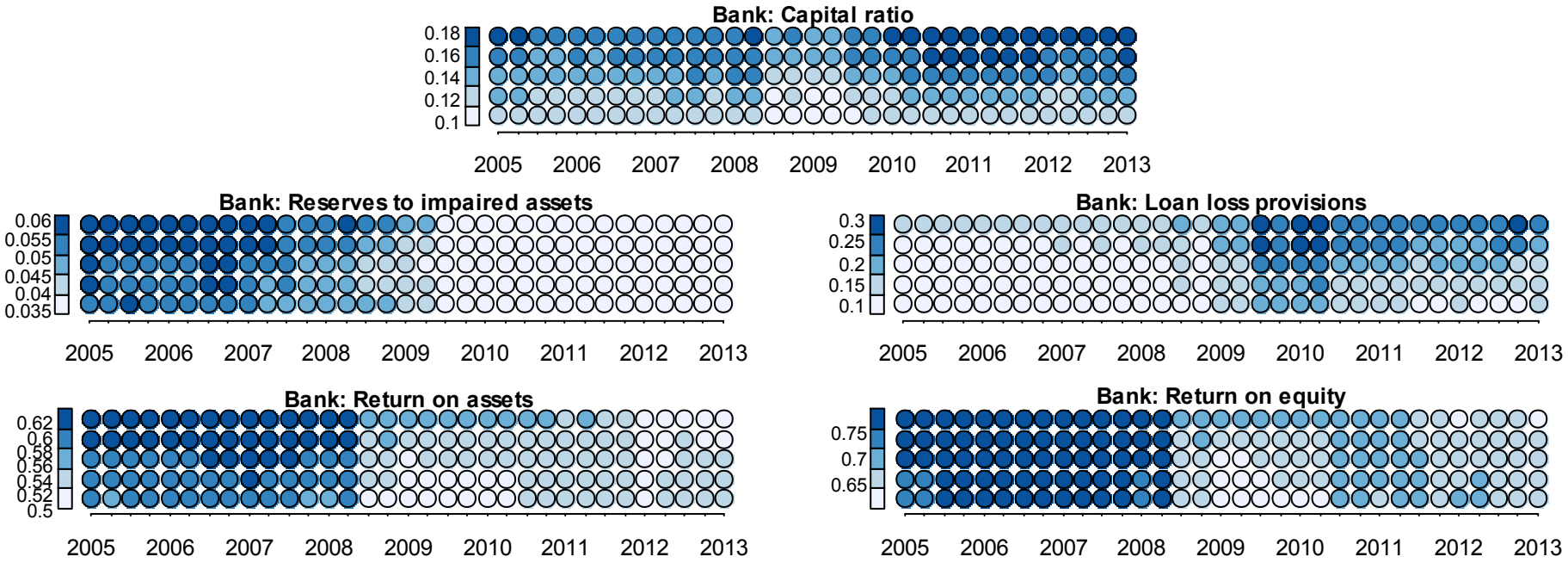

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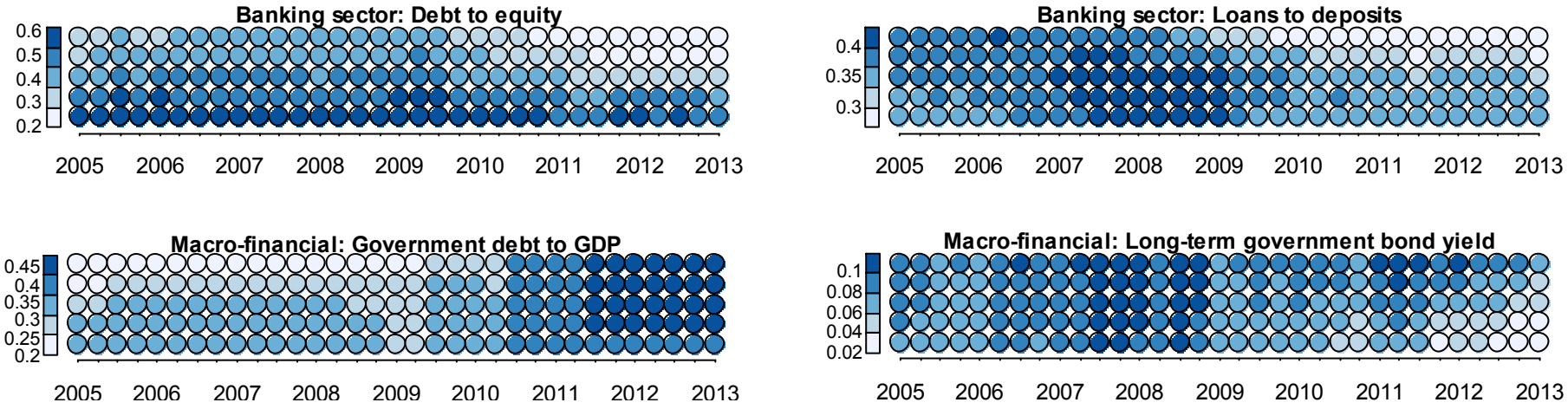

Conclusion

- 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