Predicting Distress and Identifying Interdependencies among European Banks

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Motivation

- The global financial crisis has brought the banking system in several EU countries to the verge of collapse
- State interventions to EU banking sector peaked at 1.5 trl at the end-2009 ($>$13% of EU GDP)
- The costs in terms of lost output are even higher (20-25% of GDP, e.g. in Dell Arriccia et al. (2010), Laeven and Valencia (2010))

This Project. . .

- Presents one of the first early-warning models for European banks
- Introduces a new dataset of bank distress in Europe
- Applies a micro-macro perspective to predict bank distress, using macroeconomic and financial imbalances from the EU Macroeconomic Imbalance Procedure (MIP)
- Uses a state-of-the-art evaluation of early-warning signals, including importance of individual banks, as the policy maker needs to know how to interpret the signals of the model

Outline

1. Introduction

2. Data and Methodology

3. Results

4. Conclusion

5. Research in progress

Measuring bank distress

- Bankruptcies, liquidations and defaults
  - Captures direct bank failures (Sources: Moody's, Fitch and Bankscope)

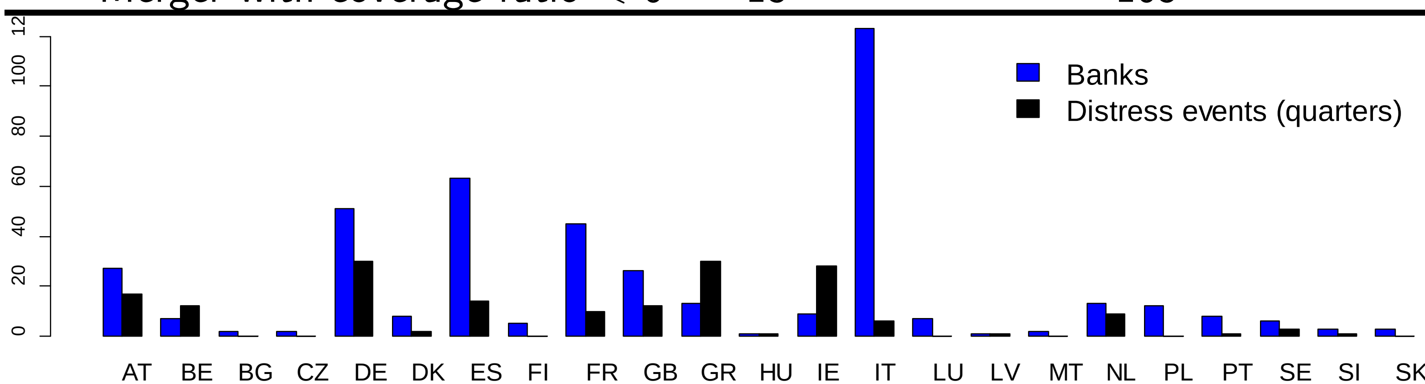
- State aid
  - A bank is defined to be in distress if it receives a capital injection from the state or participates in an asset relief programme (asset protection or asset guarantees). It does not capture liquidity support or guarantees on banks' liabilities (Sources: EC and ECB (using Bloomberg and Reuters))

- Mergers in distress
  - Merged entities are defined to be in distress if a parent receives state aid within 12 months after merger or if a merged entity has a coverage ratio < 0 within 12 months before the merger (where the coverage ratio is denied as the ratio of equity $+$ loan loss reserves - non-performing loans to total assets) (Sources: Bloomberg and Bankscope)

Sample & distress

- 546 EU banks with at least EUR 1 bn in assets (26,852 observations)
- Quarterly data from 2000Q1-2011Q4
- Obtain 194 bank-quarter distress events

Categories	Distress	Pre-distress
Direct failure	13	110
Bankruptcy & liquidation	3	24
Defaults	13	96
State aid	153	892
Capital injection	113	763
Asset protection	33	180
Asset guarantee	23	127
Distressed mergers	35	228
Merger with state aid	28	179
Merger with coverage ratio < 0	13	105



Explanatory variables

- Bank-specific balance-sheet indicators
  - Publicly available CAMELS variables (Capital Adequacy, Asset Quality, Management Quality, Earnings Performance, Liquidity, and Sensitivity to Market Risk)

- Country-specific banking sector indicators
  - Variables such as system leverage, asset growth, loans/deposits, etc.

- Country-specfic macro-financial indicators
  - EU Macroeconomic Imbalance Procedure (MIP) variables (internal and external), asset prices (house and stock prices, government bond spread) and business cycle variables (GDP, inflation)

Evaluation criterion

- Apply extended Alessi and Detken (2011) usefulness criterion as in Sarlin (2012):

		Actual class	
		1	-1
Predicted class	1	True positive (TP)	False positive (FP)
	-1	False negative (FN)	True negative (TN)

- Find the threshold that minimizes a loss function that depends on policymakers' preferences μ between Type I ($T_1 = FN \,/\, (FN + TP)$) errors (missing crises) and Type II errors ($T_2 = FP \,/\, (TN + FP)$) (false alarms) and unconditional probabilities of the events P_c and $1 - P_c$

$$L(\mu) = \mu P_c T_1 + (1 - \mu)(1 - P_c)\ T_2$$

- Define absolute usefulness U_a as the difference between the loss of disregarding the model (available usefulness) and the loss of the model

$$U_a = \min[\mu P_c, (1 - \mu)(1 - P_c)] - L(\mu)$$

Evaluation & estimation

- Relative usefulness U_r is the ratio of absolute usefulness to available usefulness given preferences and unconditional probabilities

$$U_r = U_a \,/\, \min[\mu\, P_c, (1-\mu)(1-P_c)]$$

- Also, we compute the Usefulness when including observation-specific misclassification costs by letting the policymaker define the importance w_j of each bank-year observation, e.g.

$$T_{w1} \in [0,1] = \sum_{j=1}^{N} w_j FN_j \,/\left(\sum_{j=1}^{N} w_j TP_j + \sum_{j=1}^{N} w_j FN_j\right)$$

Estimation

- Use pooled logit to predict vulnerable states, i.e. periods that preceed bank distress by up to 8 quarters (pre-distress)
- Recursive estimations:
  - Estimation sample: increasing window starting from 2000Q1-2006Q4
  - Out-of-sample prediction: for 2007Q1-2011Q4, predict each quarter *t* with data up to *t-1*

Predictive performance

- Out-of-sample prediction from 2007Q1-2011Q4

	(1) Benchmark	(2) BS Model	(3) BSI Model	(4) MF Model
μ	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$
0.6	0.02	0.00	0.00	0.00
0.7	0.12	0.02	-0.01	-0.01
0.8	0.23	0.05	0.01	0.10
0.9	**0.37**	**0.16**	**0.02**	**0.24**
R^2	0.32	0.17	0.06	0.14
N	10898	10898	10898	10898

The benchmark model in column (1) includes bank-specific balance sheet variables (BS), banking sector balance sheet items (BSI), and macro-financial indicators (MF). The models in columns (2) - (4) only include the variable group in the header. The frequency of pre-distress events in the sample is 7%. R^2 and N refer to the whole sample 2000Q1-2011Q4.

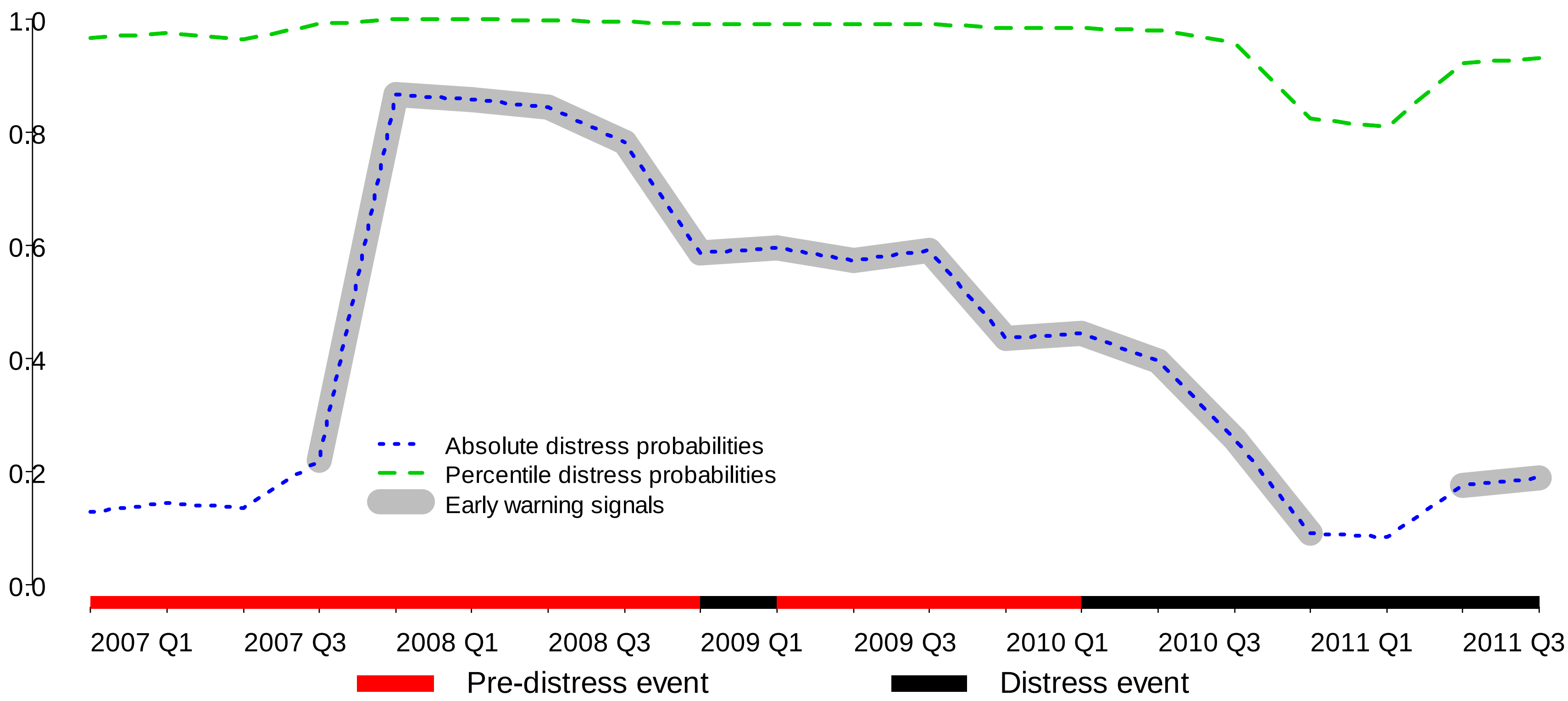
Policymakers' preferences

- Out-of-sample prediction from 2007Q1-2011Q4

		Benchmark model			
μ	Predicted distress	Missed distress	False alarms	$U_r(\mu)$	$U_r(w_j, \mu)$
0.0	0	605	0	NA	NA
0.1	0	605	0	0.00	0.00
0.2	0	605	0	0.00	0.00
0.3	0	605	0	0.00	0.01
0.4	20	585	26	-0.03	0.06
0.5	78	527	91	-0.02	0.11
0.6	119	486	161	0.02	0.19
0.7	187	418	262	0.12	0.32
0.8	243	362	414	0.23	0.26
0.9	**336**	**269**	**746**	**0.37**	**0.16**
1.0	605	0	5025	NA	NA

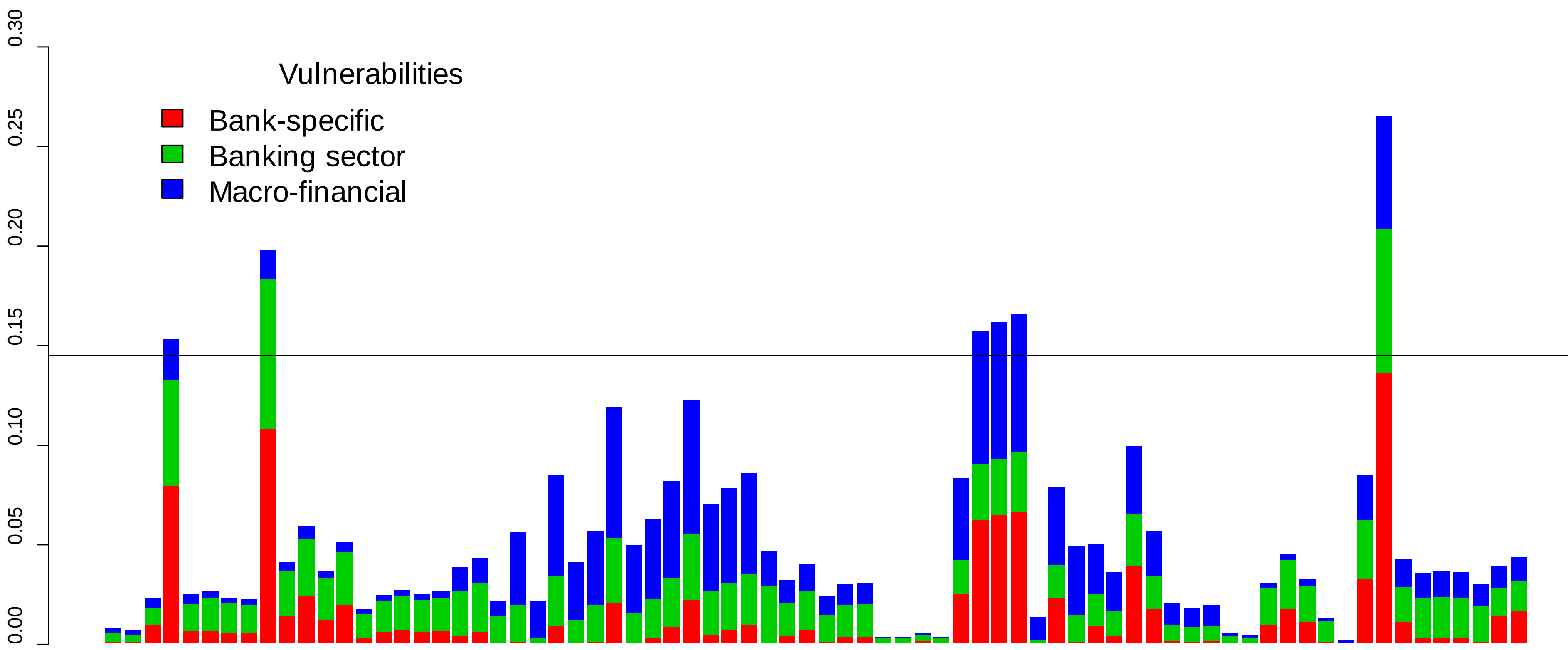
A case study – Bank of Ireland

- Out-of-sample prediction from 2007Q1-2011Q4



EBA sample

- Out-of-sample prediction in 2012Q2



The main findings are. . .

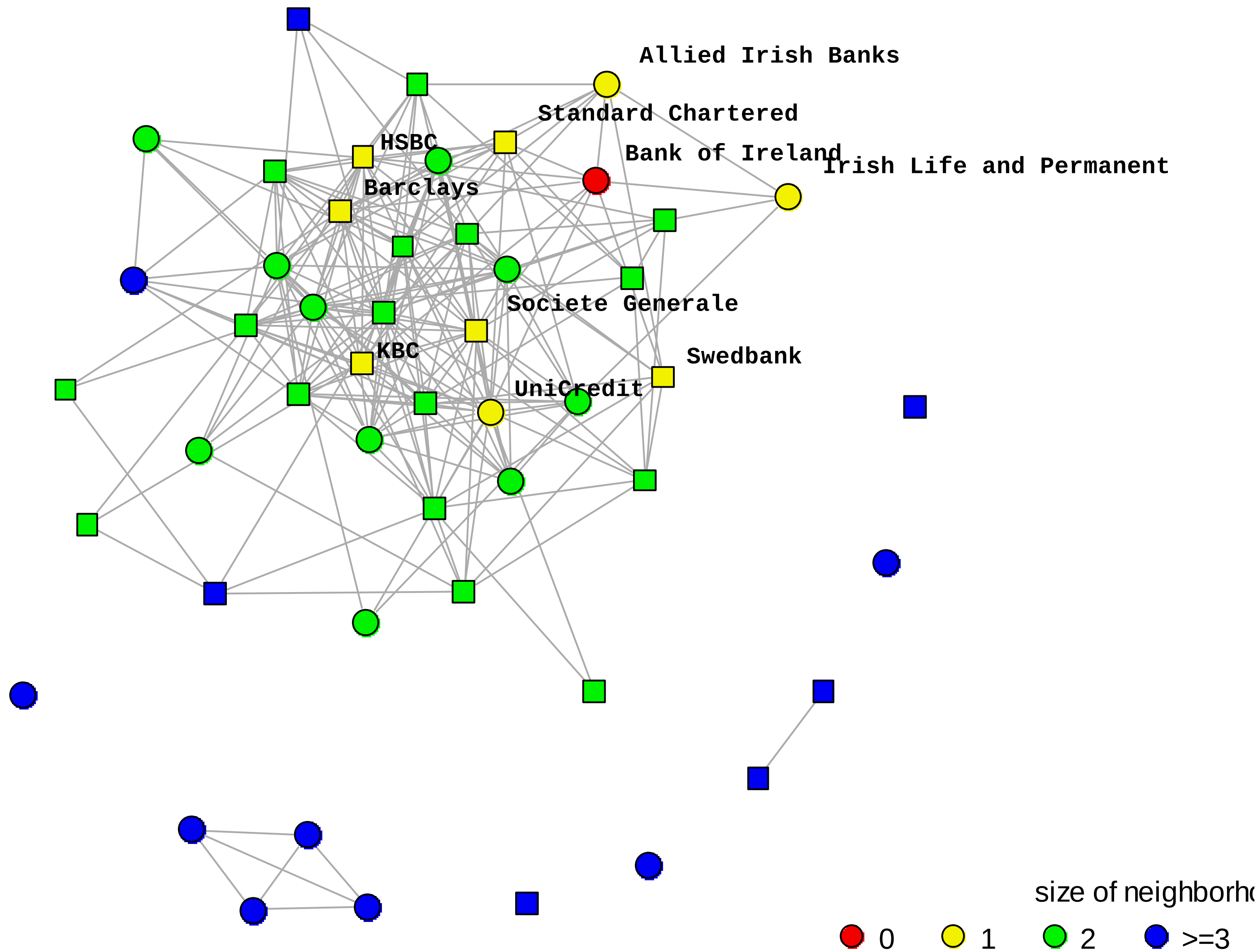
- One of the first early-warning models for European banks and a new dataset of bank distress in Europe
- A micro-macro perspective to predict bank distress with results that highlight the importance to complement bank-specific vulnerabilities with indicators for macro-financial imbalances.
- The early-warning model based on publicly available data would have been useful to predict individual bank distress related to the ongoing global financial crisis.
- For a policymaker, it is important to be more concerned of misclassifying bank distress events and to signals related to systemically important (large vs. small) banks.

Research in progress

- Does predictive performance improve if an early-warning model is augmented with bank interdependencies?

- **Motivation**: Banking systems are highly interconnected. Early-warning models have in the past focused on individual bank distress
- **Idea**: To take into account estimated interconnectedness among banks (as in Hautsch *et al.*, 2012) in an early-warning model
- **Implementation**:
  - Estimate a tail-dependence network using quantile regression of stock returns of bank *i* on the unconditional VaR exceedances of all other banks in the sample (10^{th} percentile). Use LASSO to obtain the set of relevant tail-risk drivers
  - Use an indicator of signals in a bank's neighbourhood to predict distress

Bank of Ireland in the tail dependence network



Preliminary results

- Out-of-sample prediction from 2007Q1-2011Q4

	(1) Benchmark	(2) Network	(3) Country	(4) EU
Network		3.91***		
Country			0.22***	
EU				0.03***
R^2	0.32	0.41	0.39	0.43
N	5783	5783	5783	5783
μ	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$
0.9	0.14	0.30	0.18	0.22

The performance of the benchmark model on this sample is shown in column (1). The models in columns (2) - (4) also include the signals through the neighborhood relation in the header. The frequency of pre-distress events in the sample is 13%.

Thank you for your attention!