Predicting Distress (and Identifying Interdependencies) among European Banks

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31 May 2013

Fed Cleveland & OFR conference on

“Financial Stability Analysis: Using the Tools, Finding the Data”

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Motivation

- The global financial crisis brought the banking systems in several EU countries to the verge of collapse

- By the end of 2011, the total financial crisis related state aid by the EU Member States had exceeded more than € 1.6 trl (around 13% of EU GDP)

- The costs in terms of lost output are probably even higher (e.g. in Dell Arriccia et al. (2010), Laeven and Valencia (2010) estimate the average cost of a banking crisis to be 20-25% of GDP)

This Project…

- Presents one of the first early-warning models for (a large set of individual) *European* banks based on individual bank balance sheets combined with macro-financial vulnerabilities

- It aims at predicting *vulnerable states* of banks (pre-distress periods), where a suitable trigger could lead the bank to be in distress

- Uses a state-of-the-art *evaluation framework* of early-warning signals (including taking into account the importance of individual banks)

- (Extension: include estimated bank *interdependences* (network effects) to the early-warning model)

Measuring bank distress

1) <u>Bankruptcies, liquidations and defaults</u> (sources: Moody's, Fitch and Bankscope)
   - Captures direct bank failures

2) <u>State aid</u> (Sources: EC, Bloomberg and Reuters)
   - A bank is defined to be in distress if

   a) it receives a capital injection from the state or

   b) it participates in an asset relief programme (asset protection or asset guarantees). It does not capture central bank liquidity support or guarantees on banks' liabilities

3) <u>Mergers in distress</u> (Sources: Bloomberg and Bankscope)
   - Merged entities are defined to be in distress if

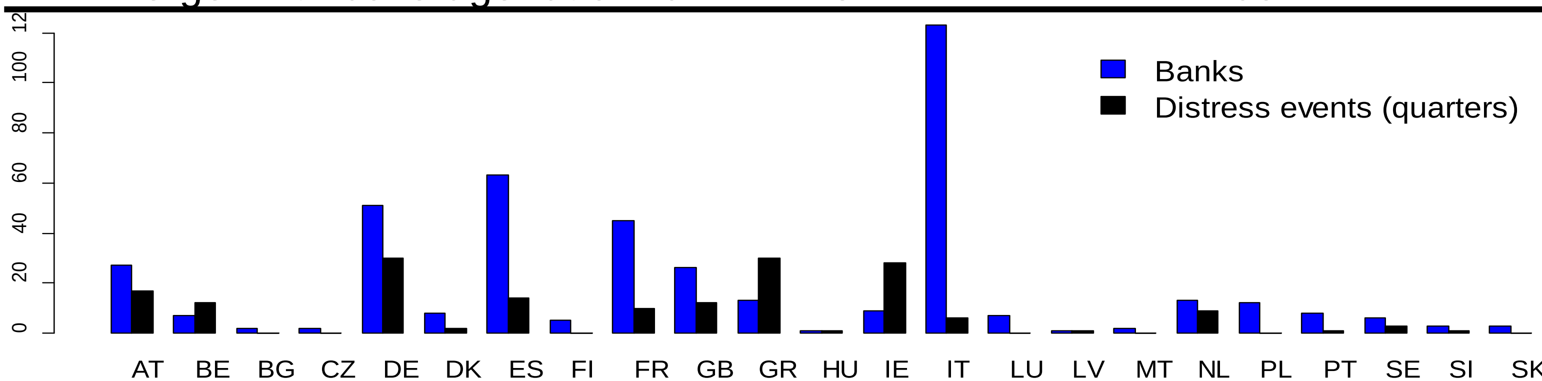
   a) a parent receives state aid within 12 months after merger or

   b) 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)

Sample & distress events

- 546 EU banks with at least € 1 bln in assets (potential sample selection bias)
- Quarterly data from 2000Q1-2011Q4
- 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

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

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

3) Country-specific macro-financial indicators
   - Structural internal and external imbalance indicators based on the EU Macroeconomic Imbalance Procedure (MIP) variables,
   - Asset prices (house and stock prices, government bond spread),
   - Business cycle variables (real GDP and inflation)

Explanatory variables

		Variable	Definition and transformation	Source
Bank-specific balance sheet variables	C	Equity to assets	Total Equity / Total Assets	Bloomberg
		Tier 1 ratio	*Tier 1 Capital Ratio*	*Bloomberg*
	A	*Impaired assets*	*Non Performing Assets / Total Assets*	*Bloomberg*
		Reserves to impaired assets	*Reserves for Loan Losses / Non Performing Assets*	*Bloomberg*
		Loan loss provisions	*Provisions for Loan Losses / Total Average Loans*	*Bloomberg*
		Total assets (growth rate)	Growth rate of total assets	Bloomberg
		Debt to equity	Total Liabilities / Total Equity	Bloomberg
	M	Cost to income	Operating Costs / Operating Income	Bloomberg
		ROA	Return on Assets	Bloomberg
	E	ROE	Return on Equity	Bloomberg
		Net interest margin	*Net Interest Margin*	*Bloomberg*
	L	Interest expenses to liabilities	Interest Expenses / Total Liabilities	Bloomberg
		Deposits to funding	Deposits / Funding	Bloomberg
		Loans to deposits	*Total Loans / Customer Deposits*	*Bloomberg*
	S	Share of trading income	Trading Income / Operating Income	Bloomberg
		Loans to assets	*Total Loans / Total Assets*	*Bloomberg*
Country-specific banking sector variables		Financial liabilities (annual growth rate)	Growth rate of (Total Assets - Capital and Reserves)	ECB MFI statistics
		Non-core liabilities (annual growth rate)	Growth rate of (Total Liabilities - Capital and Reserves - Deposits)	ECB MFI statistics
		Debt securities to liabilities	Debt securities to liabilities	ECB MFI statistics
		Mortgages to loans	Mortgages to Total Loans	ECB MFI statistics
		Debt to equity	(Total Liabilities - Capital and Reserves) / Capital and Reserves	ECB MFI statistics
		Loans to deposits	Total Loans / Deposits	ECB MFI statistics
		Gross derivatives to capital and reserves (annual growth rate)	Growth rate of ((Positive Derivatives + Negative Derivatives) / Capital an	ECB MFI statistics
Country-specific macro-financial variables		GDP (annual growth rate)	Growth rate of real GDP	Eurostat
		Inflation (annual growth rate)	Growth rate of HICP index	Eurostat
		House price	Growth rate of house price index	ECB
		Stock price	Growth rate of stock price index	Bloomberg
		10-year bond spread	Long-term government bond yield - German long-term government	Bloomberg
		Government debt to GDP	General government debt as % of GDP	Eurostat / Alert Mechanism Report
		Private sector credit flow to GDP	Private sector credit flow as % of GDP	Eurostat / Alert Mechanism Report
		Private sector credit to GDP gap	Moving sum of 4 quarters of private sector credit / GDP - HP filtered	Haver Analytics / IMF IFS
		Unemployment rate (3-year average)	3 year average of unemployment rate	Eurostat / Alert Mechanism Report
		Current account balance to GDP (3-year average)	3 year average of current account balance as a % of GDP	Eurostat / Alert Mechanism Report
		International investment position to GDP	Net International Investment Position as a % of GDP	Eurostat / Alert Mechanism Report
		Real effective exchange rate (3-year % change)	% change (3 years) of Real Effective Exchange Rate, HICP deflators	Eurostat / Alert Mechanism Report
		Export market share (3-year % change)	% change (5 years) in export market shares	Eurostat / Alert Mechanism Report
		Unit labour cost (3-year % change)	% change (3 years) in nominal unit labour cost	Eurostat / Alert Mechanism Report

Note: Variables in italics are not included in the benchmark model due to data availability. Including them reduces the number of banks for which data can be retrieved by about 65%.

Evaluation framework

- Apply extended evaluation framework of Demirgüc-Kunt and Detragiache (2000) and Alessi and Detken (2011) usefulness criterion as 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 t 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

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

Evaluation framework (continues)

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

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

- Define the relative usefulness U_r as the ratio of absolute usefulness to available usefulness (i.e. ratio relative to a "perfect" model with L(μ)=0):

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

- 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. (systemic importance, size, etc.):

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

Estimation and calibration

- Use pooled logit model to predict vulnerable states of banks, i.e. periods that precede bank distress by up to 8 quarters (pre-distress periods)

- Recursive estimation:
  - Estimation sample: increasing window starting from first in-sample 2000Q1-2006Q4
  - Out-of-sample prediction: for 2007Q1-2011Q4, predict each quarter *t* with data up to *t-1*
  - Time-varying optimal threshold for evaluation of the model signal

- Highly imbalanced sample: the share of pre-distress periods in the out-of-sample prediction sample is 11% (whole sample 7%).
  - Thus, set the benchmark preference parameter $\mu=0.9$ as an attempt to build an EWS with imbalanced data implicitly necessitates a policymaker to be more concerned about the rare class

Policymakers' preferences

- *Out-of-sample* prediction for 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

Predictive performance

- *Out-of-sample* prediction for 2007Q1-2011Q4

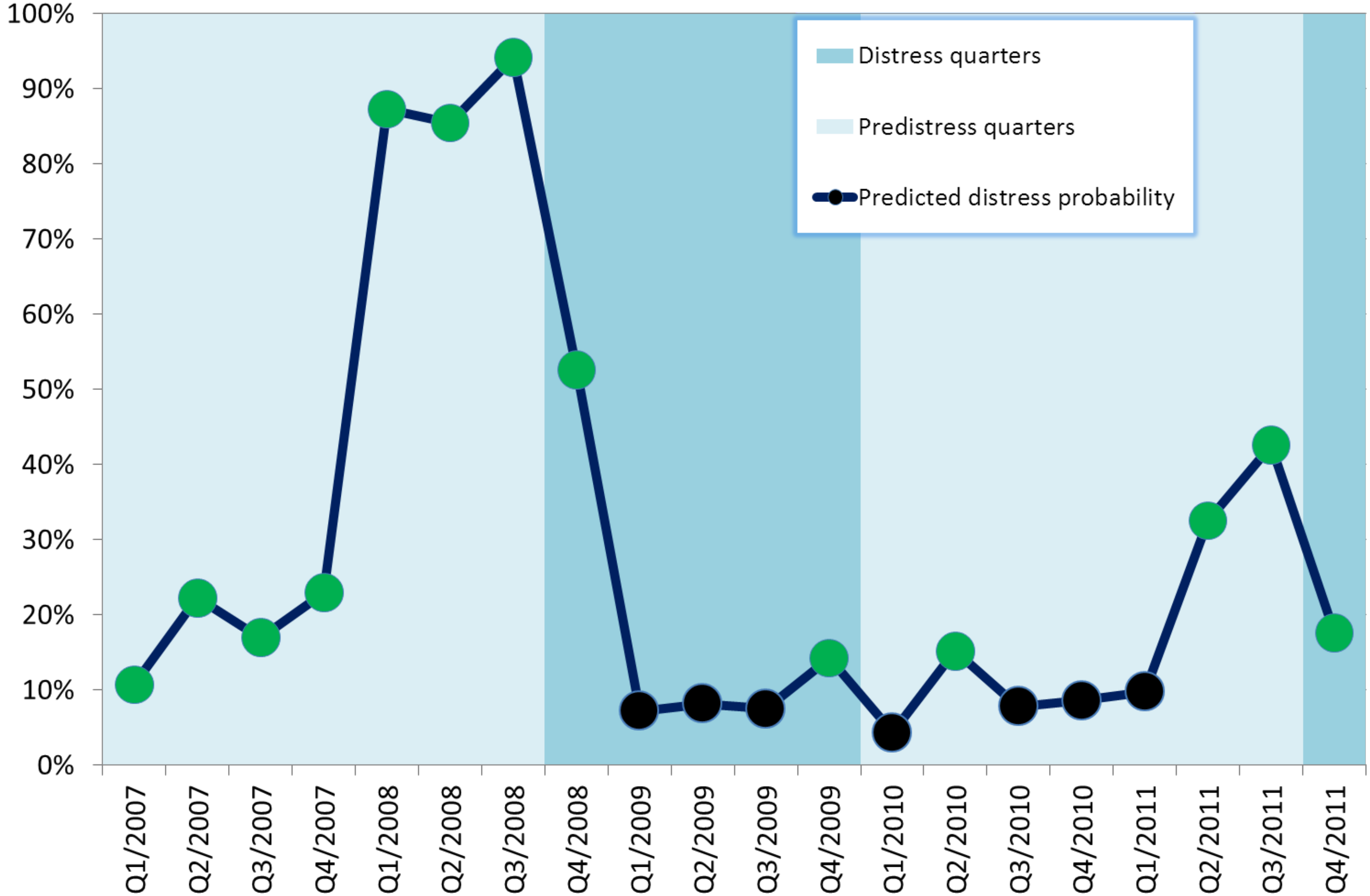
	(1) Benchmark	(2) Bank	(3) Banking sector	(4) Macro-financial
μ	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$
0.6	0.02	0.00	0.00	0.00
0.7	0.12	0.02	-0.01	-0.01
0.8	0.23	0.05	0.01	0.10
0.9	**0.37**	**0.16**	**0.02**	**0.24**
R^2	0.32	0.17	0.06	0.14
N	10898	10898	10898	10898

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

A case study

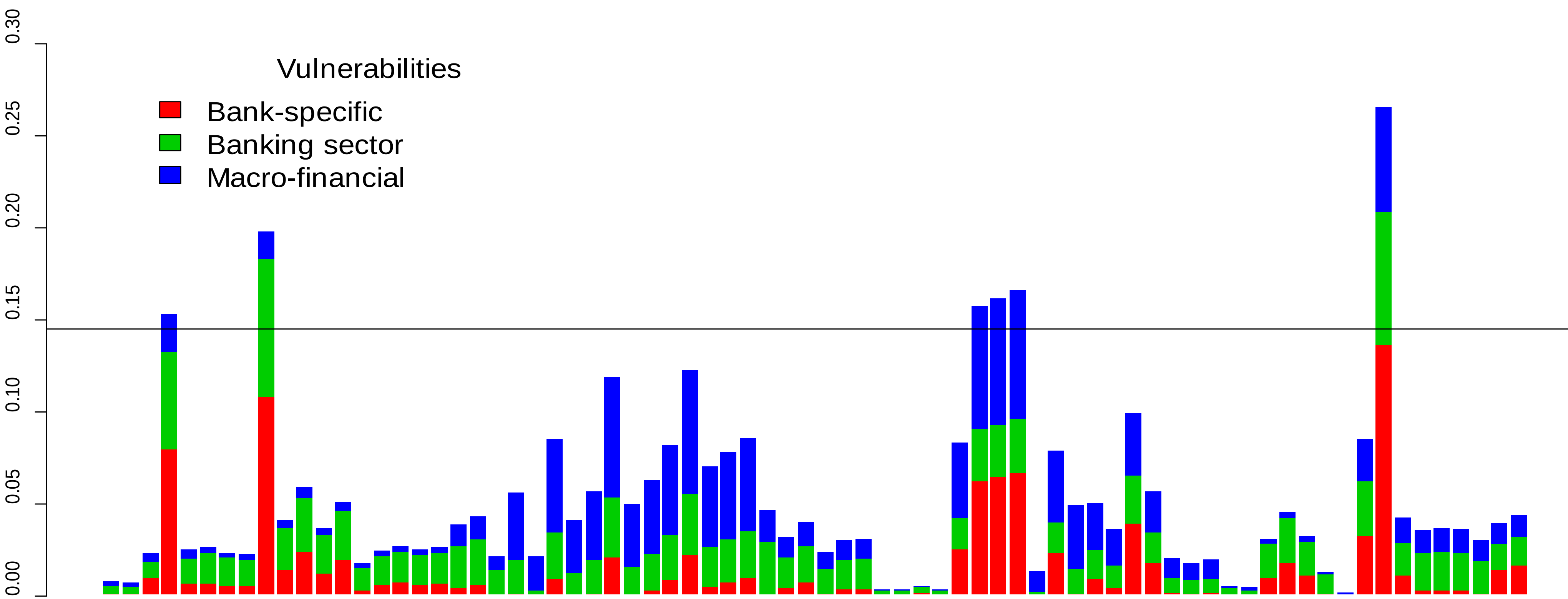
- Out-of-sample prediction of distress probability from 2007Q1-2011Q4

Note: Green dots denote ‘correct’ signals, while black dots denote ‘missed’ signals



Sample of large European banks

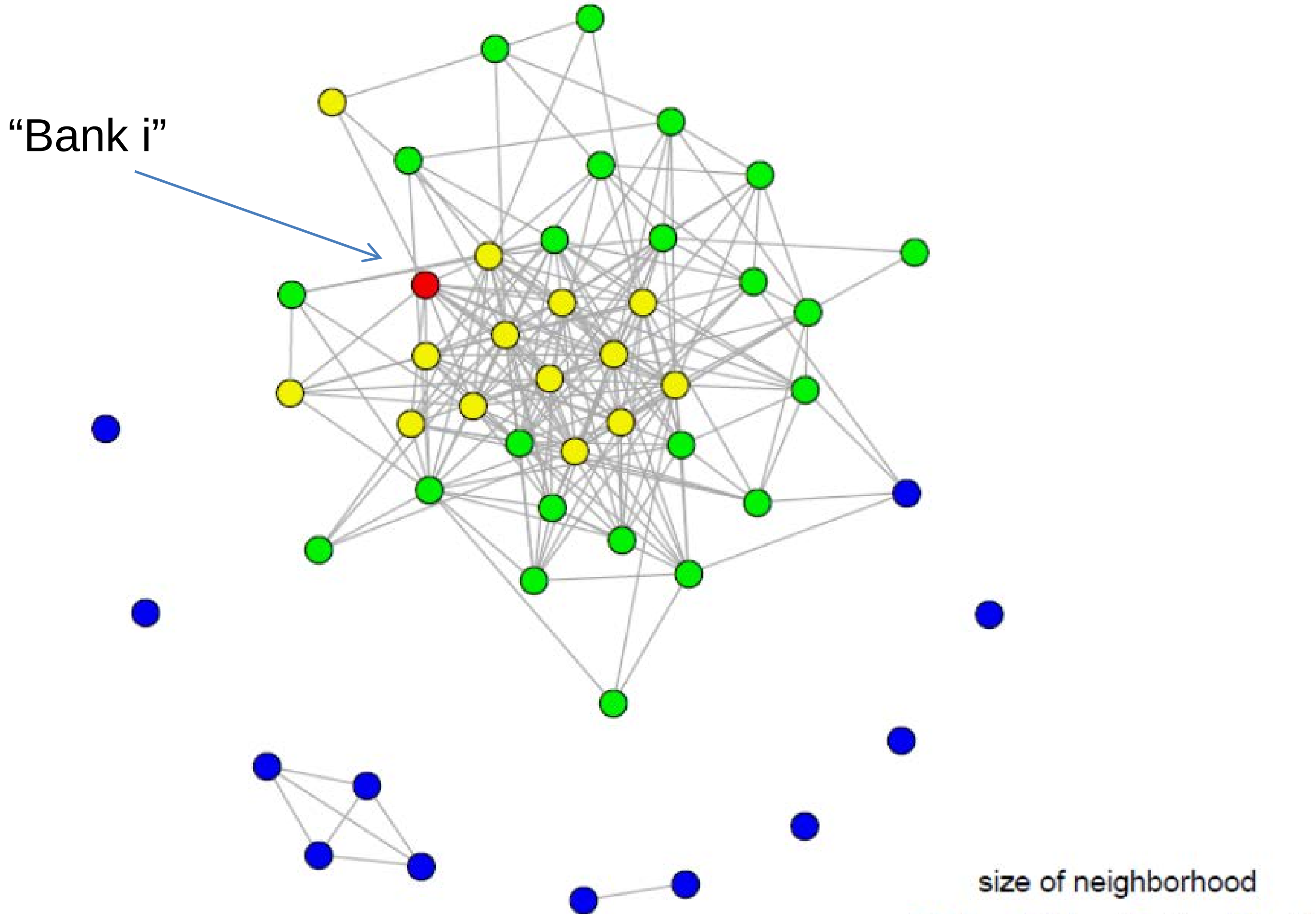
- Out-of-sample prediction of distress probabilities (in 2012Q2)



Research in progress

- **Does the predictive performance improve if the bank early-warning model is augmented with <u>*estimated* bank interdependencies</u>?**
- <u>Motivation</u>: Banking systems are highly <u>interconnected</u>. Existing early-warning models have focused solely on individual bank distress
- <u>Idea:</u> To take into account estimated interconnectedness among banks in an early-warning model
- <u>Implementation:</u>
  - 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 (as in Hautsch et al., 2012) and construct a tail-dependence network
  - Predict bank distress focusing on individual bank distress
  - Use an indicator of signals in a bank's neighbourhood to predict distress in the interconnected banking system

Estimated tail dependence network for large European banks



Network estimation 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%.

The main findings are…

- One of the first early-warning models for European banks, including a signal evaluation framework for a policymaker, and a new dataset of bank distress in Europe

- Results highlight the importance to complement bank-specific vulnerabilities with indicators for <u>macro-financial imbalances as well as estimated interconnections between banks</u>
- The model allows the evaluation of the <u>sources of vulnerabilities, which is</u> particularly useful for policy purposes
- The model evaluation framework allows the calibration of the model signals according to <u>policymaker's preferences</u> between Type I and II errors. It also allows the policymaker to focus (and weigh more) on distress signals coming from e.g. systematically important banks

Thank you for your attention!

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Extra slides

Estimates - CAMELS

	(1) Benchmark	(2) BS Model	(3) BSI Model	(4) MF Model
Intercept	-3.85***	-3.09***		
Equity to assets	-0.62***	-0.72***		
Size (total assets)	0.83***	0.68***		
Debt to equity	-0.03	-0.14.		
ROA	-0.27**	-0.12		
Cost to income	-0.03	-0.05		
ROE	-0.12.	-0.30***		
Interest expenses to liabilities	0.43***	0.37***		
Deposits to funding	0.45***	0.63***		
Share of trading income	-0.05	-0.07.		
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.

Estimates - banking sector

	(1) Benchmark	(2) BS Model	(3) BSI Model	(4) MF Model
Financial liabilities	0.21***		0.02	
Non-core liabilities	0.13*		0.19***	
Debt securities to liabilities	0.22*		-0.32***	
Mortgages to loans	0.18*		0.54***	
Debt to equity	0.27***		0.34***	
Loans to deposits	0.26***		0.20***	
Gross derivatives to capital and reserves	-0.06		-0.05	
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.

Estimates - macro-financial

	(1) Benchmark	(2) BS Model	(3) BSI Model	(4) MF Model
GDP	-0.17.			-0.22**
Inflation	0.36***			0.46***
House price gap	0.48***			0.36***
Stock price gap	0.20**			0.13*
10-year bund spread	0.09			0.03
Government debt to GDP	0.31***			-0.17*
Private sector credit flow to GDP	-0.42***			-0.18*
Private sector credit to GDP gap	0.30***			0.47***
Unemployment rate	0.27***			0.08
Current account balance to GDP	0.26**			0.23**
International investment position to GDP	-0.85***			-0.46***
Real effective exchange rate	0.30***			0.31***
Export market share	-0.30***			-0.52***
Unit labour cost	0.01			-0.28**

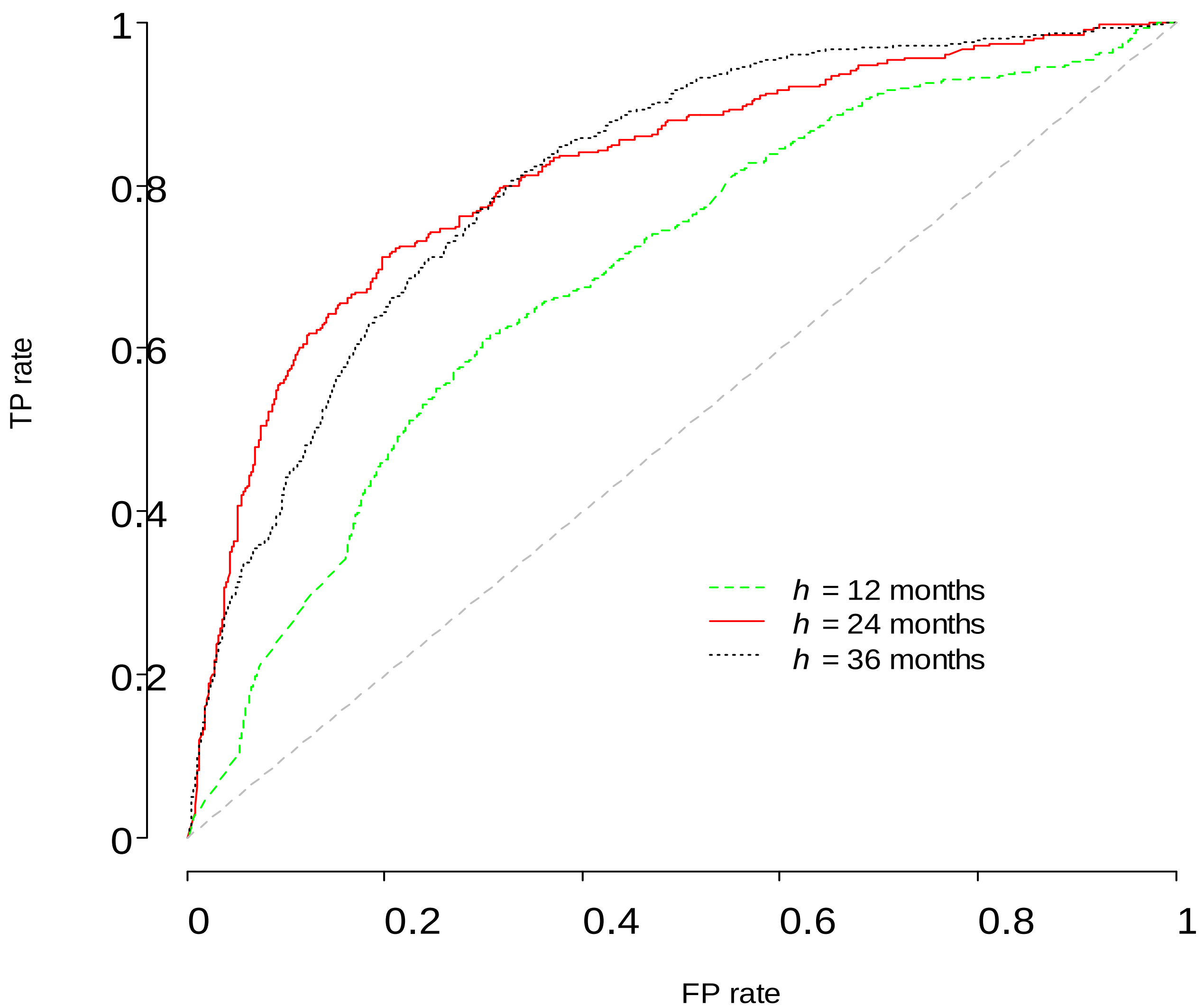
The benchmark model in column (1) includes bank-specific balance sheet variables (BS), banking sector balance sheet items (BSI), and macro-financial indicators (MF). The models in columns (2) - (4) only include the variable group in the header.

Predictive performance

Preferences	TP	FP	TN	FN	Positives Precision	Positives Recall	Negatives Precision	Negatives Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)$	$U_a(\mu, w_j$	$U_r(\mu, w_j$	AUC
μ=0.0	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	NA	0.00	NA	0.80
μ=0.1	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	0 %	0.80
μ=0.2	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	0 %	0.80
μ=0.3	0	0	5025	605	NA	0.00	0.89	1.00	0.89	0.00	1.00	0.00	0 %	0.00	1 %	0.80
μ=0.4	20	26	4999	585	0.43	0.03	0.90	0.99	0.89	0.01	0.97	0.00	-3 %	0.01	6 %	0.80
μ=0.5	78	91	4934	527	0.46	0.13	0.90	0.98	0.89	0.02	0.87	0.00	-2 %	0.01	11 %	0.80
μ=0.6	119	161	4864	486	0.43	0.20	0.91	0.97	0.89	0.03	0.80	0.00	2 %	0.03	19 %	0.80
μ=0.7	187	262	4763	418	0.42	0.31	0.92	0.95	0.88	0.05	0.69	0.01	12 %	0.06	32 %	0.80
μ=0.8	243	414	4611	362	0.37	0.40	0.93	0.92	0.86	0.08	0.60	0.02	23 %	0.04	26 %	0.80
μ=0.9	**336**	**746**	**4279**	**269**	**0.31**	**0.56**	**0.94**	**0.85**	**0.82**	**0.15**	**0.44**	**0.03**	**37 %**	**0.01**	**16 %**	**0.80**
μ=1.0	605	5025	0	0	0.11	1.00	NA	0.00	0.11	1.00	0.00	0.00	NA	0.00	NA	0.80

Notes: The table reports results for real-time out-of-sample predictions of a logit model with optimal thresholds w.r.t. Usefulness with given preferences. Bold entries correspond to the benchmark preferences. Thresholds are calculated for μ={0.0,0.1,...,1.0} and the forecast horizon is 8 quarters. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 4.1 for further details on the measures.

ROC curves



1
0.8
0.6
0.4
0.2
0
TP rate
0
0.2
0.4
0.6
0.8
1
FP rate
h = 12 months
h = 24 months
h = 36 months