SPECIAL FEATURES

A PREDICTING BANK DISTRESS AND IDENTIFYING INTERDEPENDENCIES AMONG EUROPEAN BANKS

Financial institutions have played a central role in the ongoing financial crisis. The bank bailout costs associated with the current global financial crisis and the large output losses experienced in several countries clearly motivate the attempts to develop early warning models for predicting banking crises and individual bank failures.

This special feature presents an early warning model based on publicly available bank-specific and country-level indicators for predicting vulnerable European banks that could potentially experience distress given suitable triggers. A novel model extension incorporates an estimated tail dependence network of European banks to the early warning model in order to take into account vulnerabilities arising from estimated interdependencies.

INTRODUCTION

The global financial crisis has brought a large number of banks to the brink of collapse – including several European banks. Data from the European Commission show that the amount of aid granted by EU states to stabilise the EU banking sector that had been used by the end of 2010 had exceeded $\notin 1.6$ trillion, more than 13% of EU GDP.¹ Though large, the immediate bailout costs account only for a moderate share of the total cost of a banking crisis. Output losses of previous banking crises have averaged around 20-25% of GDP.² In addition, the interplay of fiscally strained sovereigns and weak banking systems that characterise the ongoing sovereign debt crisis in Europe underscore the need for a means of providing robust predictions of banking sector distress to facilitate timely policy action.

The outbreak of financial and banking crises or corporate failures is however difficult to predict, not least in situations where market prices do not reflect systemic risk. That said, detecting underlying vulnerabilities and finding common patterns preceding financial crises *is* possible. Hence, the aim is to predict *vulnerable states* of banks, where one or multiple triggers could lead to bank distress, rather than trying to predict the exact timings of bank failures per se. As outright bank failures are rare events, particularly in Europe, the definition of bank distress used here also takes into account state intervention and mergers in distress.

This special feature presents an early warning model that uses publicly available indicators of vulnerabilities calculated from bank and country-level variables.³ The approach contains four basic building blocks. First, it defines "bank distress events". In addition to bankruptcies, liquidations and defaults, state interventions and forced mergers are also taken into account to represent bank distress. Second, it draws from bank-specific and banking-sector vulnerability indicators, as well as incorporating measures of macroeconomic and financial imbalances from the EU Alert Mechanism Report of the EU Macroeconomic Imbalance Procedure (MIP). Third, it includes an estimated tail dependence network in order to model vulnerabilities arising from interdependencies. Lastly, it takes into account policy-maker preferences between missing distress events versus issuing false

An early warning model to predict bank distress

Four building blocks of an early warning system for banks



¹ At the time of writing, the data for state aid in the context of the financial and economic crisis was available only for 2007-10. An update of the data is expected to become available towards the end of the year.

² See, for example, G. Dell'Ariccia, E. Detragiache and R. Rajan, "The Real Effects of Banking Crises", *Journal of Financial Intermediation*, 17, 2008, pp. 89-112, and L. Laeven and F. Valencia, "Systemic Banking Crises: A New Database", *IMF Working Papers*, No 08/224, 2008.

³ For more details of the methodology, see F. Betz, S. Oprica, T. Peltonen and P. Sarlin, "Predicting distress in European banks", *ECB Working Paper Series*, forthcoming, and F. Betz, T. Peltonen and P. Sarlin, "Measures of tail dependence to predict distress in European banks", *ECB Working Paper Series*, forthcoming.

alarms. The methodology is applied to a sample of 439 large and medium-sized banks from 23 EU countries with more than €1 billion in total assets.

IDENTIFYING BANK DISTRESS EVENTS

Identifying bank distress events Identifying bank distress events is challenging, given that outright bank failures have been rather rare in Europe. To account for this, the definition of bank failure is widened beyond bankruptcies, liquidations and defaults to capture a broader notion of distress that also incorporates cases where financial institutions have been subject to public or private intervention. To that end, three different criteria are applied in order to capture different aspects of bank distress. First, data on *bankruptcies, liquidations and defaults* capture actual bank failures. Second, data on *state support* are also used to detect distressed banks. A bank is defined as being in distress if it receives a capital injection by the state or participates in asset relief programmes (asset protection or asset guarantees). It should be noted that this definition does not include liquidity support or guarantees on banks' liabilities. Third, *mergers in distress* capture private sector solutions to bank distress – either in the form of state aid or represented by a low coverage ratio prior to the merger.⁴

This methodology identifies 194 quarters at which banks are in distress during the period from 2000 to 2011 (see Table A.1). This figure is smaller than the sum of events across the three above categories as they are not mutually exclusive. Chart A.1 shows the number of banks and distress events (distress quarters) by country. Within the available sample, Italy is the country with the largest number of banks, followed by Spain, Germany and France. In the case of Greece, Ireland and Belgium, the number of distress events exceeds the number of banks, which is feasible as a bank can experience multiple distress periods.

VULNERABILITY INDICATORS

Bank-specific indicators...

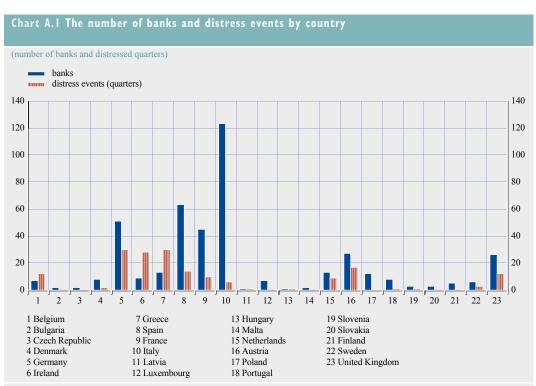
Three different categories of indicators represent various aspects of a bank's vulnerability to distress. First, *bank-specific vulnerabilities* are captured by indicators from banks' income statements and balance sheets. As common in the literature, indicators from the CAMELS rating system are proxied as follows.⁵ The equity-to-assets and Tier 1 capital ratio represent capital adequacy (C).

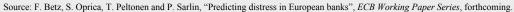
4 The coverage ratio is defined as the ratio of capital equity and loan reserves minus non-performing loans to total assets.

5 The Uniform Financial Rating System, informally known as the CAMEL ratings system, was introduced by US regulators in 1979, where the letters refer to Capital adequacy, Asset quality, Management quality, Earnings and Liquidity. Since 1996 the rating system also includes Sensitivity to market risk (i.e. CAMELS).

Event	Definition	Incidence	Source
 Bankruptcies, liquidations and defaults 	Actual bank failures	13	Bureau van Dijk Bankscope (bankruptcie and liquidations), Moody's and Fitch (annual compendiums of corporate defaults)
2. State support	Entity receives a capital injection by the state or participates in asset relief programmes	153	European Commission and data collected from market sources (Reuters and Bloomberg)
3. Mergers in distress	If (i) a parent receives state aid within 12 months after the merger or (ii) a merged entity has a coverage ratio smaller than 0 during the 12 months prior to the merger	35	Bureau van Dijk Bankscope (mergers) and Bloomberg (coverage ratio computed using banks' balance sheet items)







Asset quality (A) is measured by return on assets (ROA), size of total assets, the debt-to-equity ratio, impaired assets and loan loss provisions. The cost-to-income ratio represents management quality (M), while return on equity (ROE) and the net interest margin measure earnings (E). Liquidity (L) is represented by the share of interest expenses to total liabilities, the deposits-to-funding ratio and the ratio of loans to deposits. Finally, the share of trading income proxies sensitivity to market risk (S).

Second, *country-specific banking sector indicators* represent imbalances at the level of banking systems. These indicators are often cited as important early warning indicators for banking crises.⁶ The indicators proxy the following types of imbalances: booms and rapid increases in banks' balance sheets, e.g. growth in financial liabilities and non-core liabilities; securitisation, e.g. debt securities to liabilities; property booms, e.g. mortgage-to-loans ratios; banking system leverage, e.g. debt-to-equity and loans-to-deposits ratios; and banking system exposures to derivatives contracts, e.g. gross derivatives to capital and reserves.

Third, *country-specific macro-financial indicators* identify macroeconomic imbalances and control for conjunctural variation in asset prices and business cycles. Regarding macroeconomic imbalances, this special feature uses most of the internal and external variables from the EU MIP, such as current account imbalances, unit labour costs, the unemployment rate and general government debt. Moreover, asset prices (stock and house price gaps) and business cycle variables (real GDP growth and consumer price inflation) capture conjunctural variation.

6 See, for example, A. Demirgüc-Kunt and E. Detragiache, "The determinants of banking crises in developed and developing countries", *IMF Staff Papers*, No 45(1), 1998, and A. Demirgüc-Kunt and E. Detragiache, "Monitoring Banking Sector Fragility. A Multivariate Logit", *World Bank Economic Review*, No 14(2), 2000, or G. Kaminsky and C.M. Reinhart, "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems", *American Economic Review*, No 89(3), 1999. ... country-specific macro-financial indicators...

SPECIAL FEATURES

... and banking sector indicators

INTERPRETING THE EARLY WARNING SIGNALS: MISSED DISTRESS EVENTS VERSUS FALSE ALARMS

Interpreting early warning signals Early warning models require evaluation criteria that account for the nature of the underlying problem. Distress events are often outliers in three respects: the dynamics of the economy differ significantly from tranquil times, they are often costly, and they occur rarely. Given these properties, an evaluation framework that resembles the decision problem faced by a policy-maker is of central importance.

Designing a comprehensive evaluation framework for early warning signals is challenging as there are several political economy aspects to be taken into account. For instance, the frequency and optimal timing of when the policy-maker should signal a distress event might be different depending on whether the policy-maker maximises his/her own utility or social welfare. While important, these considerations are beyond the scope of this special feature. Thus, the signal evaluation framework focuses only on a policy-maker with relative preferences between Type I errors (missing distress events) and Type II errors (false alarms), and the usefulness of using the early warning model versus not using it. However, the model evaluation can also be extended to account for the potential systemic relevance of each individual financial institution, e.g. proxied by its size.⁷

A MODEL FOR PREDICTING DISTRESS IN EUROPEAN BANKS

As common in the literature,⁸ a pooled logit model is used for estimating distress probabilities. The indicator capturing a bank's vulnerability to distress (pre-distress period) is defined as a specified number of quarters prior to the actual distress event (e.g. eight quarters in the benchmark case). The model is recursive – predicting the probability of pre-distress one quarter ahead at each quarter. In practice, the model is estimated at each quarter *t* with all available information up to that point. The model is then used to calculate the probability of a bank being distressed. Then, the signals of the model are evaluated with respect to the optimal threshold for given preferences between missing distress events and issuing false alarms.

The estimates of a logit model for factors with an impact on bank distress are reported in Table A.2 and are based on data from the first quarter of 2000 until the last quarter of 2009 (full estimation sample).⁹ The benchmark model (column 1) contains vulnerability indicators that are drawn from the three groups introduced earlier: bank-level balance sheet indicators, country-specific banking sector indicators and country-level macro-financial indicators. The benchmark model is chosen based on two considerations. On the one hand, it should be encompassing and contain a wide-range of potential vulnerabilities. On the other hand, a relatively short publicly available time series of bank balance sheet items from market sources limits the number of observations.

Combining a broad set of indicators is important in predicting bank distress Most of the estimated coefficients in the benchmark model have the expected signs and are statistically significant. Among the bank-specific variables, a high capital ratio and a high return on assets are associated with lower distress probabilities. High interest expenses and a high deposits-to-funding ratio, on the other hand, increase the probability of bank distress.

Of the country-level banking-sector indicators, almost all are statistically significant. As expected, rapid growth in both financial liabilities and non-core liabilities is associated with higher

7 For the technical details on the evaluation framework, see P. Sarlin, "On policymakers' loss functions and the evaluation of early warning systems", *TUCS Technical Report*, No 1054, Turku Centre for Computer Science, 2012.

B See, for example, E.P. Davis and D. Karim, "Comparing Early Warning Systems for Banking Crisis", Journal of Financial Stability, No 4(2), 2008.

9 The sample Q1 2000-Q4 2009 is the full estimation sample in the benchmark case, where a bank distress event is predicted eight quarters ahead and where full information on bank distress events is available until the fourth quarter of 2011.



SPECIAL FEATURES

Table A.2 Logit model estimates on factors with an impact on bank distress

(estimated coef	ficients)				
		(1)	(2)	(3)	(4
	Estimates	Benchmark	Bank-specific	Banking	Macro
		model	model	sector model	financial mod
Bank-specific	Intercept	-10.76***	-4.65***	-5.35***	-3.36**
balance sheet	C Equity to assets	-13.32***	-15.47***		
variables	Size (total assets)	0.47***	0.38***		
	A Debt to equity	0.00	-0.01		
	ROA	-36.07**	-16.34		
	M Cost to income	0.00	-0.01		
	E ROE	-1.03	-2.53***		
	Interest expenses to liabilities	1.86***	2.61***		
	L Deposits to funding	24.43***	21.14***		
	S Share of trading income	-0.05	-0.07		
	Financial liabilities (annual growth rate)	8.50***		0.62	
	Non-core liabilities (annual growth rate)	10.07*		14.40***	
Country-	Debt securities to liabilities	2.49*		-3.62***	
specific	Mortgages to loans	2.51*		7.56***	
banking sector	Debt to equity	0.07***		0.08***	
ariables	Loans to deposits	0.34***		0.26***	
	Gross derivatives to capital and reserves				
	(annual growth rate)	-0.56		-0.51	
	GDP (annual growth rate)	-5.94			-7.82*
	Inflation (annual growth rate)	19.58***			24.51*
	House price gap	0.13***			0.10*
	Stock price gap	0.00**			0.00*
	10-year Bund spread	12.77			3.92
	Government debt to GDP	1.13***			-0.61*
	Private sector credit flow to GDP	-3.79***			-1.63*
Country-	Private sector credit to GDP gap	6.98***			10.92*
pecific	Unemployment rate (3-year average)	9.45***			2.74
nacro-	Current account balance to GDP				
inancial	(3-year average)	5.79**			5.33*
variables	International investment position				
	to GDP	-2.59***			-1.41*
	Real effective exchange rate				
	(3-year percentage change)	4.80***			4.99*
	Export market share (3-year percentage				
	change)	-1.90***			-3.23*
	Unit labour cost (3-year percentage	0.12			4.574
	change)	0.13			-4.57*
	R ²	0.32	0.17	0.06	0.14
	No of observations	10,898	10,898	10,898	10,898
	Evaluation of the predictive performance				
	of the models	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$	$U_r(\mu)$
	μ=0.6	0.02	0.00	0.00	0.00
Jsefulness	μ=0.7	0.12	0.02	-0.01	-0.01
measures	μ=0.8	0.23	0.05	0.01	0.10
	µ=0.9	0.37	0.16	0.02	0.24

Source: F. Betz, S. Oprica, T. Peltonen and P. Sarlin, "Predicting distress in European banks", *ECB Working Paper Series*, forthcoming. Note: Statistical significance : "***" = 0.001; "**" = 0.01; "*" = 0.10. The estimation sample is from the first quarter of 2000 to the fourth quarter of 2009. The usefulness for a policy-maker is computed with relative usefulness $U_t(\mu)$. The relative $U_t(\mu)$ summarises the gain the policy-maker gets by using the model versus ignoring it in terms of making Type I and Type II errors.

probabilities of distress. The same applies to the ratio of debt securities to liabilities, a measure of securitisation, and the share of mortgages among loans, a proxy for property booms. Likewise, high banking system leverage and a high loans-to-deposits ratio increase bank vulnerability.

Table A.3 The predictive performance of the early warning model for different policy-maker preferences (μ) between missing bank distress events and issuing false alarms

Preferences	Predicted pre-distress observations	Missed pre-distress observations	Predicted tranquil observations	False alarm observations	U _r (μ)	$U_r(\mu, w_j)$
$\mu = 0.0$	0	605	5,025	0	NA	NA
$\mu = 0.1$	0	605	5,025	0	0.00	0.00
$\mu = 0.2$	0	605	5,025	0	0.00	0.00
$\mu = 0.3$	0	605	5,025	0	0.00	0.01
$\mu = 0.4$	20	585	4,999	26	-0.03	0.06
$\mu = 0.5$	78	527	4,934	91	-0.02	0.11
$\mu = 0.6$	119	486	4,864	161	0.02	0.19
$\mu = 0.7$	187	418	4,763	262	0.12	0.32
$\mu = 0.8$	243	362	4,611	414	0.23	0.26
$\mu = 0.9$	336	269	4,279	746	0.37	0.16
$\mu = 1.0$	605	0	0	5,025	NA	NA

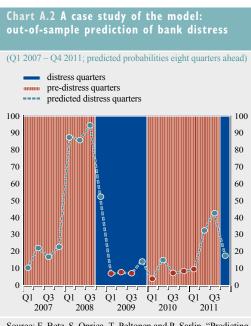
Source: F. Betz, S. Oprica, T. Peltonen and P. Sarlin, "Predicting distress in European banks", *ECB Working Paper Series*, forthcoming. Notes: The table reports results for out-of-sample predictions of a logit model for different policy-maker preferences (μ) between missing distress events (Type I error) and issuing false alarms (Type II error). The sample period is Q1 2007-Q4 2011 and the forecast horizon is eight quarters. Relative usefulness $U_r(\mu)$ summarises the gain the policy-maker gets by using the model versus ignoring it in terms of making Type I and Type II errors, while $U_r(\mu, w)$ denotes the relative usefulness taking into account bank size measured using total assets. See Betz et al., op. cit., or Sarlin, op. cit. for more details.

Among the country-specific macro-financial indicators, all estimates have the expected signs. High inflation and low real GDP growth increase bank vulnerability. Likewise, positive stock and house price gaps that proxy for an overvaluation of assets increase distress probabilities. Regarding indicators of internal imbalances, the estimated coefficient for government debt is positive, whereas the estimated coefficient for private sector credit flow is negative and the coefficient for the private sector credit-to-GDP gap is positive. Higher levels of unemployment increase bank vulnerability.

Finally, regarding external competitiveness, high net external borrowing by a country increases bank vulnerability, whereas a higher current account balance lowers bank vulnerability. An increase in the real effective exchange rate and a decrease in export market share positively affect bank vulnerability through a loss of competitiveness.

The importance of macro-financial variables in bank distress

Regarding the predictive power of the three variable groups, when focusing on the relative usefulness measure $U_r(\mu)$, the model based on macro-financial variables (model presented in column 4 of Table A.2) clearly outperforms the other models presented in columns 2-4 of Table A.2. The specification that includes only bank balance sheet items (column 2 of Table A.2) performs nearly as well. By contrast, the model including only banking sector variables (column 3 of Table A.2) performs the worst. Interestingly, macrofinancial variables turn out to be more useful for predicting distress at the bank level than bank-specific variables. However, combining bank-level balance sheet indicators with both



Source: F. Betz, S. Oprica, T. Peltonen and P. Sarlin, "Predicting distress in European banks", *ECB Working Paper Series*, forthcoming. Notes: The green dots are "correct" signals (i.e. signals above the threehold when there is either a pre dictress period or a dictress

threshold when there is either a pre-distress period or a distress period), while red dots are signals below the time-varying threshold for parameter μ =0.90.

macro-financial indicators and banking sector variables produces a model that outperforms the other models for out-of-sample forecasts.

The predictive performance of the benchmark model for different policy-maker preferences (parameter μ) between Type I (missing distress events) and Type II (false alarms) errors is presented in Table A.3. The table shows that, given the uneven distribution of tranquil and (pre-)distress periods, it is optimal to disregard the model for $\mu \leq 0.5$, i.e. when the policy-maker prefers to miss a distress event than to issue a false alarm. As discussed above, it is assumed that the policy-maker is substantially more interested in correctly calling bank distress events than tranquil periods. This is intuitive if it is assumed that an early warning signal triggers an internal review of a bank's fundamentals, business model and peers. Should the analysis reveal that the signal is false, there is no loss of credibility on behalf of the policy authority. Hence, in the benchmark case, preferences are set to $\mu=0.9$.

Chart A.2 shows a case study illustrating the predictive performance of the model. As shown in the chart, the model signals early on and consistently vulnerabilities in the bank prior to the distress events in 2008 and 2011.

IDENTIFICATION OF VULNERABILITIES THROUGH ESTIMATED BANK INTERDEPENDENCIES

A novel feature of the model is the introduction of estimated interdependencies among banks into an early warning model. In practice, this is done in two steps. First, in order to detect potential vulnerabilities arising from bank interdependencies, a tail dependence network for the European banking system is estimated. The aim is to identify co-movements in equity returns in the left – or distressed – tail of the distribution that could arise from either direct bilateral exposures or from exposures to common risk factors.

The applied method follows Hautsch et al. in using the quantile-Lasso¹⁰ developed by Belloni and Chernozhukov¹¹. In a nutshell, the method identifies a set of banks whose stock returns move in parallel with those of any individual bank in the case of tail events. To obtain the set of tail risk drivers for an individual bank, the stock return of a bank is regressed using a quantile regression method on its own lagged return and the unconditional Value-at-Risk (VaR) exceedances of all other banks in the sample. The VaR exceedances are represented by binary indicators equal to one if a bank's stock return is in the tenth percentile of the unconditional distribution of stock returns. The Lasso procedure is then used to select the subset of relevant risk drivers for a pool of banks' VaR exceedances and macro-financial state variables. The size of this subset depends on a bank-specific penalty parameter that is obtained in a data-driven way, which governs how many banks survive the Lasso shrinkage.

As a second step, a simple binary indicator is created that equals one for all banks in the estimated neighbourhood of a bank that the model signals to be in distress and zero otherwise. Then, the indicator of signals in the bank's neighbourhood is used as an additional variable in the early warning model to predict the probability of distress for the individual banks.

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A 30% gain if a policy-maker uses the model

Bank-specific distress events are rarely independent

Estimating a tail dependence network for the European banking system

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¹⁰ Lasso stands for least absolute shrinkage and selection operator. See R. Tibshirani, "Regression Shrinkage and Selection via the Lasso", *Journal of the Royal Statistical Society*, Series B, Vol. 58, Issue 1, 1996.

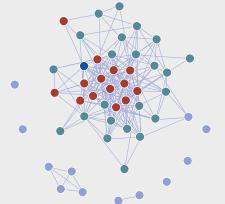
¹¹ See N. J. Hautsch, J. Schaumburg and M. Schienle, "Financial Network Systemic Risk Contributions", SFB 649 Discussion Paper, No 2011-072, Humboldt-Universität zu Berlin, 2011, and A. Belloni and V. Chernozhukov, "L1-penalized quantile regression in highdimensional sparse models", The Annals of Statistics, No 39, 2011.

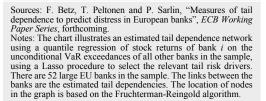
ESTIMATED BANK INTERDEPENDENCIES IN THE EARLY WARNING MODEL

Benefits of a model including estimated interdependency To evaluate the performance of the early warning model augmented with the estimated bank interdependencies, it is compared with the benchmark model and with two simpler ways of introducing proxies for potential contagion effects. estimation As the of bank interdependencies requires stock returns, the sample is restricted to a subset of listed banks. The results show that any specification including a proxy for estimated interdependencies and potential contagion effects in the model perform better than the benchmark model. In particular, in out-of-sample forecasting the model including the estimated interdependencies appears to outperform the two simpler approaches to control for potential contagion effects.

A further advantage of this method is the visualisation of the banks' interconnectedness and the identities of neighbouring banks provided by the tail dependence network. This type of information may be of importance to a policy-maker for assessing possible future financial stability risks. In order to focus on the interlinkages among major European banks, the illustration of

Chart A.3 A case study of an estimated tail dependence network for a bank *i* (estimated tail dependence network for bank *i*, for Q1 2000– Q4 2006) Size of neighbourhood $0 \qquad 0 \qquad 2$ $0 \qquad 1 \qquad 0 \qquad >=3$





the tail dependence network is based on a sub-sample of 52 banks, consisting of the European "global systemically important financial institutions" (G-SIFIs) as defined by the Financial Stability Board, complemented by the largest financial institutions in the 27 EU Member States.

Chart A.3 displays the estimated tail dependence network for bank *i* for a sample from the first quarter of 2000 to the fourth quarter of 2006. The colour coding represents bank *i*'s estimated neighbourhood: nodes marked red are bank *i*'s direct neighbours, while those in green represent the neighbours' neighbours. The links between the banks are the estimated tail dependencies, while the location of nodes in the graph is based on the Fruchterman-Reingold algorithm.¹²

CONCLUDING REMARKS

This special feature describes an early warning model for predicting bank distress in the EU banking sector. It builds upon both bank-level and country-level indicators of vulnerabilities, along with explicitly accounting for vulnerabilities arising from estimated bank interdependencies and evaluating model signals based on policy-makers' preferences. Examining EU banks over the last decade, it suggests that early warnings based on publicly available data would have yielded useful out-of-sample predictions of bank distress during the current global financial crisis.

12 See T. M. J. Fruchterman and E.M. Reingold, "Graph Drawing by Force-Directed Placement", *Software: Practice and Experience*, 21(11), 1991.

Visualising the estimated interconnectedness of the banks

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