Network Linkages to Predict Bank Distress

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Research Focus

Question: Does the predictive performance of bank early-warning models improve by augmenting them with estimated bank interdependencies?

Motivation:

- Banking systems are highly interconnected: vulnerability of one bank is also impacted by the vulnerability of its neighbors.
- Existing early-warning models have focused solely on individual bank distress.

This project incorporates pass-through effects via estimated networks into an early-warning model for European banks.

Implementation:

1. Estimate standard bank-level early-warning models
2. Estimate tail-dependence networks using banks' return innovations to account for contagion risk
    - markets' view accounts also for indirect sources of interdependence (e.g. common/correlated exposures and behavioral aspects.)
    - markets are forward-looking.
3. Provide a two-step approach to augment early-warning models with contagion variables that account for pass-through of distress.
4. Evaluate and compare the out-of-sample performance of early-warning models.

Related literature

1. Various approaches for deriving early-warning models:
   - *Frankel and Rose (1996)* - 'Logit analysis'
   - *Kaminsky and Reinhart (1999)* - 'Signaling approach'
   - *Demirguc-Kunt and Detragiache (2000)* - 'Logit analysis & loss function'
   - *Holopainen and Sarlin (2014)* - 'Horse race of 14 techniques'
   - *Lang, Peltonen, Sarlin (2015)* - 'LASSO approach for variable selection'

2. Bank-level models of interbank contagion and network effects:
   - *Upper and Worms (2004), Elsinger et al. (2006), Degryse and Nguyen (2007) , surveyed by Upper (2011)* - 'Interbank contagion'
   - *Poon, Rockinger, Tawn (2004); Hartmann, Straetmans and De Vries (2005)* - "Extreme value theory and contagion risk'

3. Country-level early-warning models with network effects:
   - *Rose and Spiegel (2009)* - 'MIMIC'
   - *Minoiu, Kang, Subrahmanian, Berea (2013)* - 'Cross-border connectedness'
   - *Rancan, Sarlin, Peltonen (2014)* - 'Domestic and cross-border connectedness'
   - *Hale, Kapan, Minoiu (2014)* - 'Crisis Transmission in the Global Banking Network'

4. To our knowledge, no work on pass-through effects in early-warning models: Extend the work of *Betz, Opricã, Peltonen and Sarlin (2014)*

Measuring bank distress

1. Bankruptcies, liquidations and defaults that capture direct bank failures (sources: Moody's, Fitch and Bankscope)

2. State aid (sources: European Commission, Bloomberg and Reuters)

   A bank is defined to be in distress if :

   - it receives a capital injection from the state or
   - 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. Mergers in distress (sources: Bloomberg and Bankscope)

   - a parent receives state aid within 12 months after merger or
   - if a merged entity has a negative coverage ratio within 12 months before the merger

The dependent variable will be equal to 1 eight quarters prior to distress events and 0 otherwise.

Data Samples

The analysis is based on two separate datasets, one for listed European banks used to construct the banking network and another used in the initial early-warning model for individual banks:

1. Network dataset
   - daily frequency, from 01/01/1999 to 15/04/2014
   - stock prices for 243 listed European banks (Bloomberg)
   - country-specific equity price index from Datastream
   - aggregate European banking sector equity price index from Datastream

2. Early-warning model dataset
   - quarterly frequency, from Q1/1999 to Q3/2014
   - balance sheet data for 469 European banks with more than 1bln euros in assets, from Bloomberg
   - country-specific banking sector indicators from ECB MFI Statistics
   - country-specific macro-financial indicators from Bloomberg, Eurostat, Alert Mechanism Report

Explanatory variables in the benchmark EWS

- **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 banking system leverage, non-core liabilities, loans to deposits, debt securities to liabilities, mortgages to loans, etc.
- **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)

Tail dependence network

Use extreme value theory techniques to measure the tail dependence between banks i and j, based on the innovations of their filtered equity returns pair (u_i, u_j).

- Banks' demeaned equity return series are regressed on their lag, country equity return index, and the European banking sector return index:

$$r_{i,t} = \beta_i r_{i,t-1} + \beta_{C_i} r_{C_i,t} + \beta_S r_{S,t} + e_{i,t}$$

- The residuals are filtered using an asymmetric GARCH model and return innovations (u_i, u_j) are extracted:

$$e_{i,t} = \sigma_{i,t} + u_{i,t}$$

where $\sigma_{I,j}$ follows an asymmetric GARCH(1,1) process

Tail dependence network

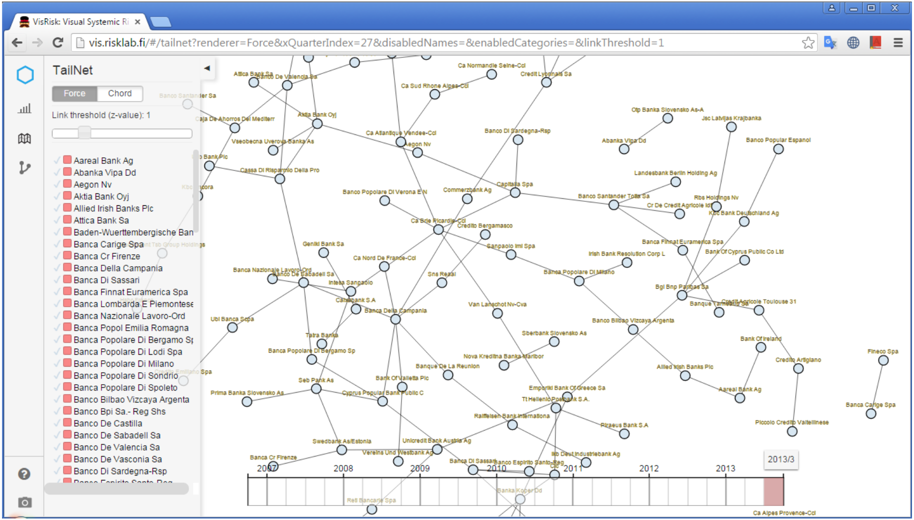
- We remove the influence of marginal aspects by transforming the pair of innovations (u_i, u_j) to common unit Fréchet marginals (S, T), which keep the same dependence structure as the innovations.
- The degree of extremal/asymptotic dependence $\bar{\chi}$ for the bivariate case (S, T) is computed using the following representation (*Ledford and Tawn (1996)*):

$$\bar{\chi} = 2\eta - 1,$$
$$var(\hat{\bar{\chi}}) = (\hat{\bar{\chi}} + 1)^2 / k.$$

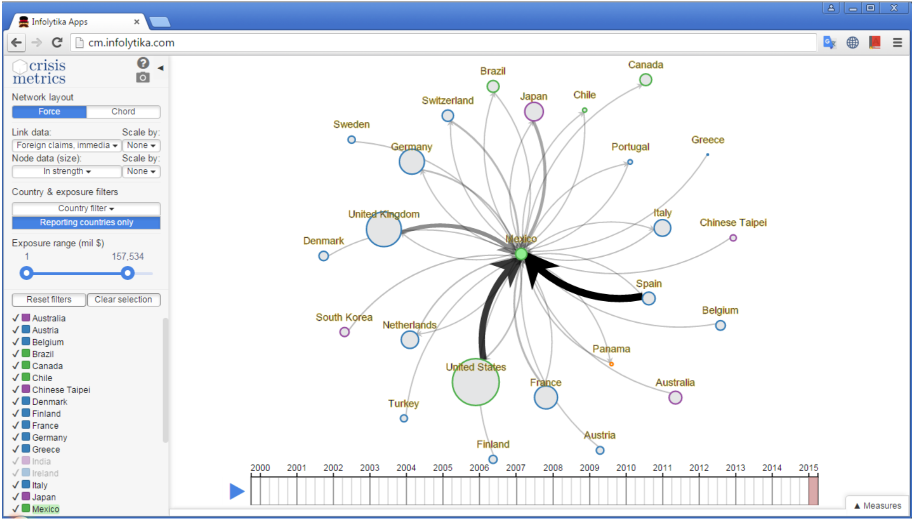
  where η is the tail index of the variable $Z = min(S, T)$ and k is the tail threshold.
- η is estimated using the modified Hill estimator proposed by *Huisman et. al (2001)*.

Finally, we assign a link between banks i and j if $\bar{\chi} = 1$ (or $\eta = 1$) at conventional levels of statistical significance.

Network of EU banks, 2013Q3, vis.risklab.fi/#/tailnet



CrisisMetrics, http://cm.infolytika.com/



CrisisModeler, http://cm.infolytika.com/

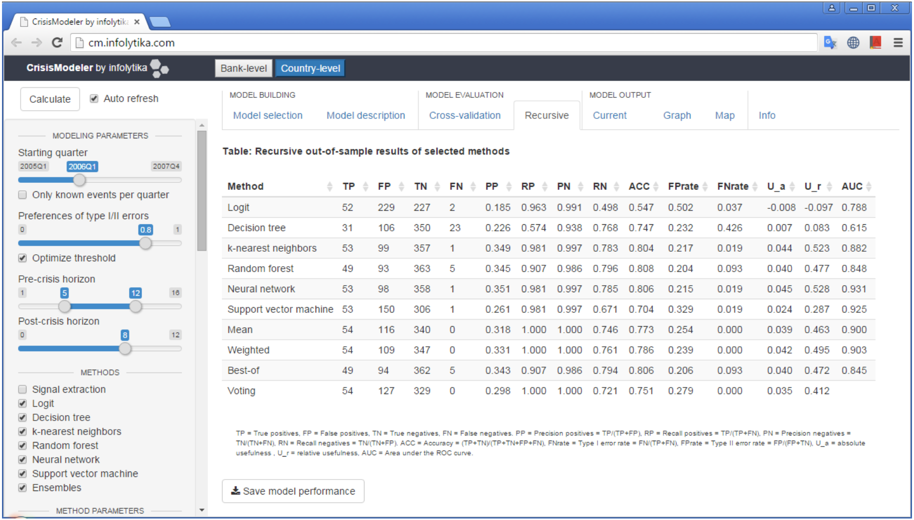
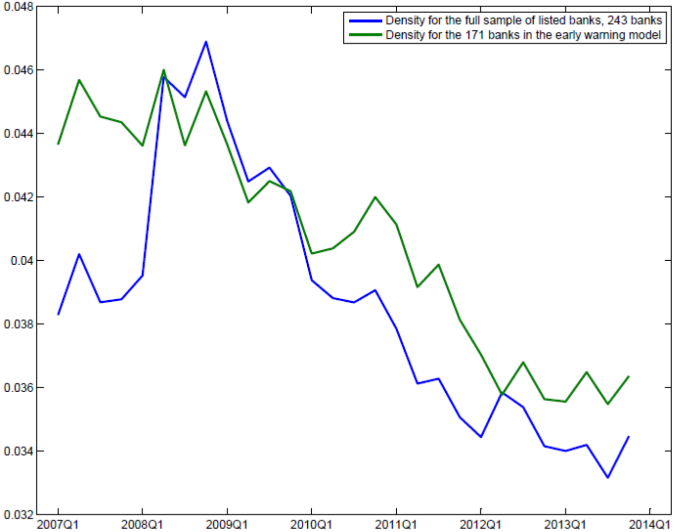


Table: Recursive out-of-sample results of selected methods

Method	TP	FP	TN	FN	PP	RP	PN	RN	ACC	FPrate	FNrate	U_a	U_r	AUC
Logit	52	229	227	2	0.185	0.963	0.991	0.498	0.547	0.502	0.037	-0.008	-0.097	0.788
Decision tree	31	106	350	23	0.226	0.574	0.938	0.768	0.747	0.232	0.426	0.007	0.083	0.615
k-nearest neighbors	53	99	357	1	0.349	0.981	0.997	0.783	0.804	0.217	0.019	0.044	0.523	0.882
Random forest	49	93	363	5	0.345	0.907	0.986	0.796	0.808	0.204	0.093	0.040	0.477	0.848
Neural network	53	98	358	1	0.351	0.981	0.997	0.785	0.806	0.215	0.019	0.045	0.528	0.931
Support vector machine	53	150	306	1	0.261	0.981	0.997	0.671	0.704	0.329	0.019	0.024	0.287	0.925
Mean	54	116	340	0	0.318	1.000	1.000	0.746	0.773	0.254	0.000	0.039	0.463	0.900
Weighted	54	109	347	0	0.331	1.000	1.000	0.761	0.786	0.239	0.000	0.042	0.495	0.903
Best-of	49	94	362	5	0.343	0.907	0.986	0.794	0.806	0.206	0.093	0.040	0.472	0.845
Voting	54	127	329	0	0.298	1.000	1.000	0.721	0.751	0.279	0.000	0.035	0.412	

TP = True positives, FP = False positives, TN = True negatives, FN = False negatives. PP = Precision positives = TP/(TP+FP), RP = Recall positives = TP/(TP+FN), PN = Precision negatives = TN/(TN+FN), RN = Recall negatives = TN/(TN+FP). ACC = Accuracy = (TP+TN)/(TP+TN+FP+FN), FNrate = Type I error rate = FN/(TP+FN), FPrate = Type II error rate = FP/(FP+TN), U_a = absolute usefulness , U_r = relative usefulness, AUC = Area under the ROC curve.

Network density for European banks



Signal evaluation framework

- Use the evaluation framework of *Demirgüc-Kunt and Detragiache (2000)*, *Alessi and Detken (2011)* and *Sarlin (2012)*

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

- Find the probability threshold that minimizes the loss function that depends on:
  - policymaker's preference μ between $T1$ (missing crises) and $T2$ errors (false alarms)
  - unconditional probabilities of the events P_C:

$$L_\mu = \mu P_C T_1 + (1-\mu)(1-P_C)T_2$$

- Absolute usefulness U_a: the extent to which a model performs better than no model at all.

- Relative usefulness U_r: the proportion of usefulness that a policymaker would obtain compared to a perfectly performing model

$$U_r = \frac{min[\mu P_C, (1-\mu)(1-P_C)] - L(\mu)}{min(\mu P_C, (1-\mu)(1-P_C))}$$

EWS estimation and calibration

- We use a pooled logit model with country fixed effects to predict vulnerable states of banks, i.e. pre-distress periods, for in-sample data.
- We construct the following contagion variables:
  - *Network Dummy*: indicates for each bank whether there are any vulnerable banks to which it is estimated to be connected.
  - *Network Sum*: counts how many vulnerable neighboring banks the bank has in its estimated tail dependency network.
  - *Country Dummy*: indicates for each bank whether there are other banks being signaled as vulnerable in the same country.
  - *Country Share*: the share of vulnerable banks of total banks in the respective country.
- Highly imbalanced sample: the share of pre-distress periods in the out-of-sample prediction sample is 18.8% (in the whole sample 7.9%).
- Set the benchmark preference parameter $\mu = 0.85$; building an EWS with imbalanced data implicitly necessitates a policymaker to be more concerned about the rare class (need to have a preference to predict distress.)

EWS estimation and calibration

Iterative estimation of out-of-sample distress probabilities, for each quarter q from 2007Q1-2012Q3:

1. Estimate the benchmark early-warning model on the in-sample period:
$$p_i = Pr(y_{it} = 1) = \Lambda(\beta X_{it}),$$
2. Choose the probability thresholds λ that maximizes in-sample Usefulness:
$$y_{it} = \begin{cases} 1 & \text{if } \hat{p}_i > \lambda \\ 0 & \text{otherwise} \end{cases}$$
3. Collect signals y_{it} from the previous estimation and signal the neighbours of vulnerable banks. Introduce contagion variable back in the benchmark model:
$$p_i^* = Pr(y_{it} = 1) = \Lambda(\beta X_{it} + \gamma NC_{it}),$$
4. Choose the new optimal threshold λ^* with respect to in-sample Usefulness and use it to signal out-of-sample vulnerable banks :
$$y_{it}^* = \begin{cases} 1 & \text{if } \hat{p}_i^* > \lambda^* \\ 0 & \text{otherwise} \end{cases}$$

Estimation Results for in-sample data

Full sample, country fixed effects	Benchmark		Country dummy		Country share		Network dummy		Network sum	
Intercept	-6.07	***	-5.9	***	-5.58	***	-6.11	***	-6.65	***
Total leverage ratio	-4.55	***	-4.47	***	-4.41	***	-4.38	***	-3.95	***
ROA	0.71	***	0.69	***	0.41		0.66	**	0.54	*
Cost to Income	-4.03	***	-3.87	***	-3.39	***	-3.89	***	-3.51	***
Net short-trem borrowing to Liabilities	0.51	***	0.51	***	0.49	***	0.48	***	0.41	***
Share of trading income to Revenue	-2.57	***	-2.49	***	-2.23	***	-2.44	***	-2.09	***
Total assets to GDP	13.73	***	12.45	***	9.49	***	13.15	***	10.63	***
Debt to equity	-1.07	***	-1.06	***	-1.09	***	-1.05	***	-0.86	**
Loans to deposits	0.82	*	0.75		0.83	*	0.79	*	0.82	*
Debt securities to liabilities	1.03	**	0.82		0.38		0.99	*	1.16	**
Real GDP	0.21	*	0.19		0.14		0.18		0.11	
Long-term government bond yield	0.51	***	0.49	***	0.23	*	0.49	***	0.37	**
Government debt to GDP	-1.86	***	-1.66	***	-1.82	***	-1.82	***	-1.53	***
Private sector credit flow to GDP	0.33	**	0.3	*	0.12		0.31	*	0.19	
Country contagion dummy			8.51	***						
Country contagion share					5.93	**				
Network contagion dummy							9.26	***		
Network contagion sum									8.79	***
N	3150		3150		3150		3150		3150	
R squared	0.05		0.06		0.07		0.05		0.05	

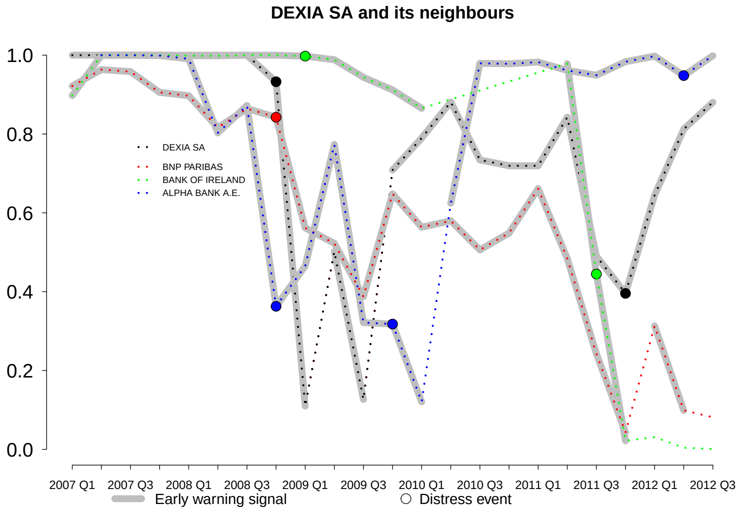
Model Evaluation

Estimation period 1999Q1-2007Q1, out-of-sample prediction 2007Q1 - 2012Q3.

Contagion based on estimated vulnerabilities only, $\mu = 0.85$.

Full model, country fixed effects, μ = 0.85	AUC	U_r	FN rate	FP rate	TN rate	TP rate
1-estimation Benchmark	0.8941	0.5800	0.1799	0.2095	0.7905	0.8201
2-estimation Benchmark	0.8944	0.5770	0.1799	0.2125	0.7875	0.8201
Country Dummy	0.8933	0.5807	0.1691	0.2214	0.7786	0.8309
Country Share	0.8959	0.5904	0.1799	0.1991	0.8009	0.8201
Network Dummy	0.8992	0.6060	0.1367	0.2340	0.7660	0.8633
Network Sum	0.8986	0.6444	0.1655	0.1620	0.8380	0.8345

Case study


DEXIA SA and its neighbours
1.0
0.8
0.6
0.4
0.2
0.0
DEXIA SA
BNP PARIBAS
BANK OF IRELAND
ALPHA BANK A.E.
2007 Q1
2007 Q3
2008 Q1
2008 Q3
2009 Q1
2009 Q3
2010 Q1
2010 Q3
2011 Q1
2011 Q3
2012 Q1
2012 Q3
Early warning signal
Distress event

Robustness

Change in μ

μ=0.80	AUC	U_r	FN	FP
1est Bm	0.8941	0.6295	0.2230	0.1218
2est Bm	0.8948	0.6286	0.2230	0.1226
CtryD	0.8951	0.6277	0.2158	0.1293
CtryS	0.8990***	0.6250	0.2194	0.1285
NtwD	0.8985	0.6214	0.1799	0.1642
NtwS	0.9009**	0.6610	0.1906	0.1226
NtwDL	0.8974	0.6259	0.1799	0.1605
NtwSL	0.9009**	0.6655	0.1978	0.1129

μ=0.90	AUC	U_r	FN	FP
1est Bm	0.8941	0.4978	0.1079	0.3016
2est Bm	0.8930	0.4933	0.1223	0.2793
CtryD	0.8936	0.4733	0.1259	0.2927
CtryS	0.8974**	0.4970	0.1187	0.2823
NtwD	0.8972**	0.5022	0.1043	0.3039
NtwS	0.8978	0.5208	0.1079	0.2786
NtwDL	0.8961*	0.5022	0.1079	0.2972
NtwSL	0.8969	0.5260	0.1151	0.2600

Include historical distresses and impose convergence of signals ($\mu = 0.85$)

hist. distress	AUC	U_r	FN	FP
NtwD	0.8973	0.6320	0.1475	0.1954
NtwS	0.8974	0.6454	0.1691	0.1568
NtwDL	0.8973	0.6169	0.1547	0.2021
NtwSL	0.8970	0.6399	0.1763	0.1538

convergence	AUC	U_r	FN	FP
NtwD	0.8980*	0.5998	0.1331	0.2444
NtwS	0.8985*	0.6308	0.1835	0.1545
NtwDL	0.8969	0.5830	0.1475	0.2444
NtwSL	0.8970	0.6230	0.1793	0.1838

Conclusion

- Objective: to incorporate pass-through effects into an early-warning model to proxy for the interconnected European banking system.
- This project...
  - ...provides a two-step approach to account for pass-through effects
  - ...empirically highlights the importance to complement standard early-warning indicators with measures of pass-through effects.
- The approach is general in nature
  - The framework for incorporating pass-through effects lends to various contexts, such as country-level models.
  - The approach is not dependent on how the network is obtained; it helps comparing the efficiency of different network estimations.

Thank you for your attention

Bank-specific balance sheet variables	C	Total leverage ratio	Bloomberg
	A	Reserves for NPLs to Non-performing Assets	Bloomberg
		ROA	Bloomberg
		Loan Loss Provisions to Total Loans	Bloomberg
	M	Cost to Income	Bloomberg
	E	ROE	Bloomberg
	L	Interest expenses to Liabilities	Bloomberg
		Deposits to Liabilities	Bloomberg
		Net short-term borrowing to Liabilities	Bloomberg
	S	Share of trading income to Revenue	Bloomberg
Counrty-specific banking sector variables		Total assets to GDP	ECB MFI Statistics
		Non-core liabilities	ECB MFI Statistics
		Debt to equity	ECB MFI Statistics
		Loans to deposits	ECB MFI Statistics
		Debt securities to liabilities	ECB MFI Statistics
		Mortgages to loans	ECB MFI Statistics
Country-specific macro-financial variables		Real GD	Eurostat
		Inflation	Eurostat
		Stock prices	Bloomberg
		House prices	ECB MFI Statistics
		Long-term government bond yield	Bloomberg
		International investment position to GDP	Eurostat / Alert Mechanism Report
		Government debt to GDP	Eurostat / Alert Mechanism Report
		Private sector credit flow to GDP	Eurostat / Alert Mechanism Report