Paper discussion

Network Linkages to predict bank distress

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*) Views expressed herein are those of the presenter and do not necessarily reflect the official opinion of the OeNB or the Eurosystem.
Agenda

Literature Discussion

Model Discussion

Conclusion
The paper connects two strands of literature

Systemic risk / Inference from public data

Early warning / Crisis prediction models

The article incorporates network / systemic risk measures into a crisis prediction model
Some literature examples on systemic risk / network inference from public data

Causal links
Model Horse race of interbank link estimation: Anand et al. 2015
Literature survey on interbank exposure contagion: Upper 2011

Co-Movement-based systemic risk and linkage measures
Tail risks based on Quantile Regression:
• CoVaR (Adrian, Brunnermeier 2011)
• Network construction (using LASSO): Hautsch et al. (2014)

Tail risks based on capital shortfalls:
• SRISK (Brownlees, Engle 2012)
• Systemic expected shortfall (Acharya et al. 2010)

Others: e.g. principal components, linear and non-linear Granger causalities (Billio et al. 2012)
The article combines co-movement estimation with extreme value theory to construct networks

Measurement of co-movement
Most closely related to SRISK:
• Dynamic conditional beta estimation
• Accounts for shocks from common factors and heteroscedasticity

Network construction via multivariate EVT
SRISK is not a network measure – network construction:
• Extremal dependency of error terms (Poon et al. 2004)
• Asymptotic probability of receiving a shock when partner has received shock
• Network link = result of hypothesis test (null hypothesis: probability = 1)
The network is used as an additional explanatory variable in an early warning model

Model setup
Early warning model taken from Betz et al. 2014:
• Pooled logit regression, dependent = crisis time series
• Signaling thresholds based on utility f. accounting for Type I and II errors

Other early warning models with linkages
Minoiu et al. (2013): causal links (exposures) between countries (BIS data)
Peltonen et al. (2013): causal links between countries (BIS data) and sectors (estimated from national accounts)
Oet et al. (2013): CoVaR as connectivity measure (linkage bank → system)

The innovation of the article is to introduce a bank-level network into an early-warning model
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The article builds a comprehensive framework to address highly topical questions

Rationale and contributions of the article
• Why did we miss the crisis? How to make sure we don’t miss the next?
  → Build a comprehensive model framework for predicting financial crises
• Financial linkages are suspected to be at the heart of the last crisis
  → Integrate financial networks into crisis-prediction model

Usefulness for policy analysis (and limitations)
• Can we predict failures such as Lehman, Landsbanki, Anglo-Irish?
• Model works (for selected cases)! Would have predicted Dexia, CoBa
• What about others? Case study Austria: Hypo Group Alpe Adria
  • Largest crisis bank failure in Austria
  • Model cannot be applied (bank was not publicly traded)
• Would the model have worked if it had been traded? Problems:
  • Funding prices were distorted by state guarantees
  • Markets were misinformed (accounting fraud)
Technical Remarks

Network measure

- Two types of network measures used:
  - Sum of links to banks in distress or existence of link
  - Both measures only take into account network paths of length 1:

\[ l \in \mathbb{R}^n = (I - \beta A)^{-1} \alpha - \alpha \]

- Alternative: take all paths, decrease weight for more distant nodes

\[ l \in \mathbb{R}^n = (I - \beta B)^{-1} \mathbf{1} - \mathbf{1} \]

Where \( A \) is the matrix of estimated linkages, \( \alpha \in \mathbb{R}^n, \alpha_i = \mathbb{I}_{\text{crisis}} \), \( B_{ij} = A_{ij} a_j \) and \( \beta \in [0,1] \) could be set by assumption or optimized using the utility function.
Technical Remarks

Transformation of dependent variable
• Dependent = 1 during 8 quarters prior to crisis
→ Model calibration for 2015Q2? Wait for 2017Q2!
→ Serial correlation

Model benchmarking
• 2est benchmark: includes generated signals as additional explanatory to compare models of equal size
→ Interpretation?
• Alternatives: likelihood ratio test, information criteria, model selection (advantage: additional quality check, does variable get selected?)

Link estimation
• Why is the null hypothesis existence of a link?

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<th>Dependent</th>
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<td>0</td>
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</tbody>
</table>
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The paper makes an innovative contribution to the literature:
• General and customizable framework for predicting banking crises
• Crisis prediction model with financial network information

We learn that:
• Network linkages are important for explaining the financial crisis
• The crises at Dexia, Commerzbank, National Bank of Greece could have been predicted (!)

Potential extensions:
• Methodology for non-traded banks
• Explore causal links
Literature I


Literature II


Peltonen, T., Rancan M., and Sarlin P., Interconnectedness of the banking sector as a vulnerability to crises. mimeo, 2014
