Bank Credit Risk Networks: Evidence from the Eurozone

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Introduction

Why Care About Credit Risk of Financial Firms?

- Several systemic risk definitions associate systemic risk with the joint default of a large number of financial institutions.
  (cf. Hartmann, Straetmans, de Vries (2007))
- Measuring accurately the degree of credit risk interdependence can be crucial for effective systemic risk oversight
- Over the last years, large number of contributions that estimate credit risk interdependence, also thanks to the availability of CDS
  Contributions include research by Ang & Longstaff (2013), Patton and D'Oh (2014), Hautsch *et al.* (2014)

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Credit Risk Dependence in Large Panels

- Focus of this work in credit risk interdependence in large systems (say, hundreds of institutions)

- Leading approach for curse of dimensionality is factor modeling
  cf Ang & Longstaff (2013), Patton and D'Oh (2014)

- Factor approach in line with view where credit risk dependence is driven by common exposures to systematic shocks
  e.g. system wide macro and/or financial shocks
  Calomiris and Mason (2003), Stein (2012)

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- The network channel is a set of pairwise dependence relations among the individual firms in the panel (conditional on factors)
- Network approach consistent with the view that credit risk interdependence is driven by pairwise dependence between individual banks

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Network Modeling in a Nutshell

- **Network** is defined as the conditional dependence graph associated with the firms' shocks in the panel
- Network Estimation consist of detecting the underlying network structure from the data. This is typically carried out using sparse estimation techniques that exploit the relation between the network and the covariance matrix of the shocks.
- Highlights. Network modeling has advantages in terms of:
  1. Interpretation. Network representation can provide a parsimonious representation of large multivariate systems.
  2. Estimation. Network estimation can be interpreted as covariance regularization, which can deliver large accuracy gains in large systems.
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Roadmap

1. We introduce a model for the risk neutral default intensity of a panel of European financial institutions
   - Default intensity is decomposed in a systematic (global+country) and idiosyncratic components
   - Idiosyncratic shocks have a network structure called Bank Credit Risk Network.
2. Estimation strategy based on
   - extracting risk neutral default intensity from CDS data
   - and using LASSO–type estimation to recover the network structure of the system from the data.
3. We apply our methodology to study dependence structure in a panel of 72 banks from 10 Eurozone countries in 2006 - 2013.

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Empirical Findings

Empirical analysis shows that:

1. Factors do not capture the majority of the interdependence
2. For core European countries (non GIIPS) network channels accounts for most of the interdependence while for the periphery countries (GIIPS) factor channel matters the most
3. The most interconnected institutions are typically large banks from core European countries or distressed banks from periphery countries
4. Forecasting exercise shows that network provides more precise predictions of future bank interdependence

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Related Literature

Related literature includes:

1. **Credit Risk Modelling via CDS** in finance and financial econometrics
   Lando (1998), Ang and Longstaff (2013), Zhang, Schwaab, Lucas (2012), Oh and Patton (2012), Diebold and Yilmaz (2014), Betz, Hautsch, Peltonen and Schienle (2014), Cont and Kan (2013), Abbassi, Brownlees, Hans, Podlich (2014), Billio, Getmansky, Gray, Lo (2015)

2. **Network Literature** in statistics and econometrics
   Billio *et* al. (2012), Diebold and Yilmaz (2013), Dungey, Luciani, Veredas (2012), Barigozzi and Brownlees (2013), Hautsch, Schaumburg and Schienle (2014), Brownlees and Frison (2014), ...

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Methodology

Credit Risk Modeling

- Several contributions in the financial econometrics literature typically take CDS spreads as a measure of default risk and focus on modelling directly an appropriate transformation of the spreads (typically, log–differences of the 5 year CDS spread)
- However, this approach has a number of limitations:
  - Does not make efficient use of data
  - Ignores interest rate dynamics
  - Economists are typically interested in default intensities
- Instead, we introduce a modification of the standard reduced form credit risk model which allows for correlation in idiosyncratic shocks,
- Specifically, we extend a credit risk model for systemic risk analysis introduced by Ang & Longstaff (2013)

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Credit Risk Model

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- Credit risk model for a panel of m financial entities
- Default of "bank" i can be triggered by different types of shocks
- Shocks are modelled as jumps of underlying Poisson processes with time varying intensity
  - Global-wide systematic shocks with intensity $\lambda_G(t)$
  - Country-wide systematic shocks with intensity $\lambda_\ell(t)$
    Following a county shock, cond. default probability of i is $\gamma_{i\ell}$.
  - Bank-specific idiosyncratic shock with intensity $\lambda_i(t)$
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Default Intensities

- The default intensities follow a square root process

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\begin{aligned}
d\lambda_G(t) &= a_G(m_G - \lambda_G(t))dt + b_G\sqrt{\lambda_G(t)}dB_G(t) \\
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d\xi_i(t) &= \alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t)
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- Focus is on the Brownian motion of the idiosyncratic intensity
  - $B_i(t)$ is independent of $B_G(t)$ and $B_\ell(t)$ $\forall i, \ell$
  - We assume that $\mathbf{B}(t) = (B_1(t), ..., B_n(t))$ is a correlated Brownian motion with covariance matrix $\mathbf{\Sigma}$
  - $\mathbf{\Sigma}$ is constrained to allow for network dependence. The network structure implied by $\mathbf{\Sigma}$ is what we call the Bank Credit Risk Network

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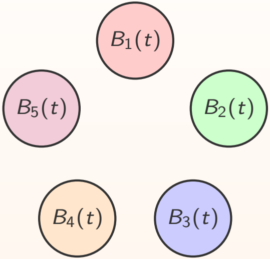
What is Network Dependence?

- The network associated with the $\mathbf{B}(t)$ is an undirected graph where



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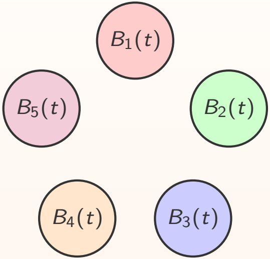

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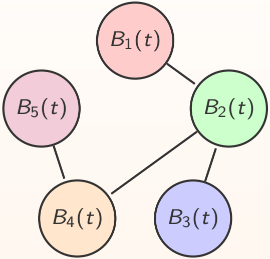

1. the components of $\mathbf{B}(t)$ denote vertices
2. the presence of an edge between i and j denotes that i and j are partially correlated

$$\rho^{ij} \neq 0$$

Refresher on Partial Correlation

- Partial Correlation measures (cross-sect.) linear conditional dependence between $B_i(t)$ and $B_j(t)$ given on all other variables:

$$\rho^{ij} = \mathrm{Cor}(B_i(t), B_j(t) | \{B_k(t) : k \neq i, j\}).$$

- Partial Correlation is related to Linear Regression:
For instance, consider the model

$$B_1(t) = c + \beta_{1\,2} B_2(t) + \beta_{1\,3} B_3(t) + \beta_{1\,4} B_4(t) + \beta_{1\,5} B_5(t) + u_{1\,t}$$

β_{13} is different from 0 $\Leftrightarrow$ 1 and 3 are partially correlated

- Partial Correlation is related to Correlation:
If there is exist a partial correlation path between nodes i and j, then i and j are correlated (and vice versa).

- Partial Correlation is related to Independence:
If $\mathbf{B}(t)$ is Gaussian, then $\rho^{ij} = 0$ implies conditional independence

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Bank Credit Risk Network

- We can equivalently characterize the network between idiosyncratic default shocks using the concentration matrix $\mathbf{K} = \mathbf{\Sigma}^{-1}$ with entries k_{ij}

- Then two banks are have zero partial correlation if $k_{ij} \neq 0$. This follows from the fact that

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in other words $\mathcal{E} = \{(i,j) | k_{ij} \neq 0\}$

- Implication: The structure of the network is encoded in the sparsity structure of the concentration matrix!

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Remarks

- Model formulation induces factor type structure of the default intensity of a firm. In fact, the instantenous default intensity of firm i is:

$$\lambda_i(s) = \gamma_{iG}\lambda_G(s) + \gamma_{i\ell}\lambda_\ell(s) + \xi_i(s)$$

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Empirical Application

The European Bank Credit Risk Network

- We use the proposed methodology to analyse the bank credit risk network of top European financial institutions between 08 and 13
- We carry out static and rolling analysis:
  - Static: Network estimated using the full sample
  - Rolling: Network estimated recursively using 2 year window

  Empirically, there is strong evidence of time variation in the network. Static analysis is mainly used to illustrate in more detail network model fitting and network analysis
- We also carry out a predictive exercise to assess if the estimation methodology provides more accurate estimates of the covariance matrix of idiosyncratic intensities

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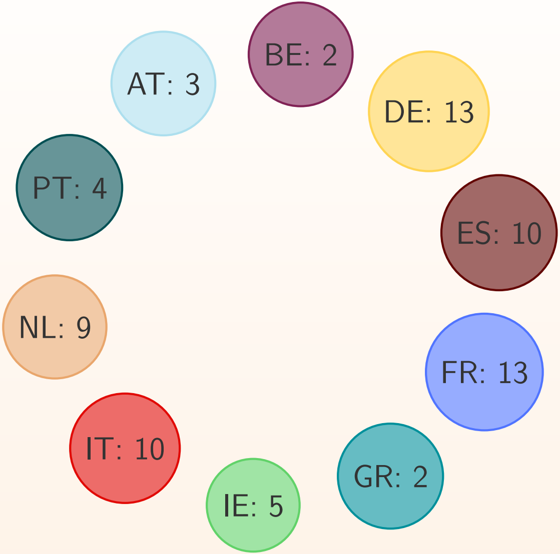
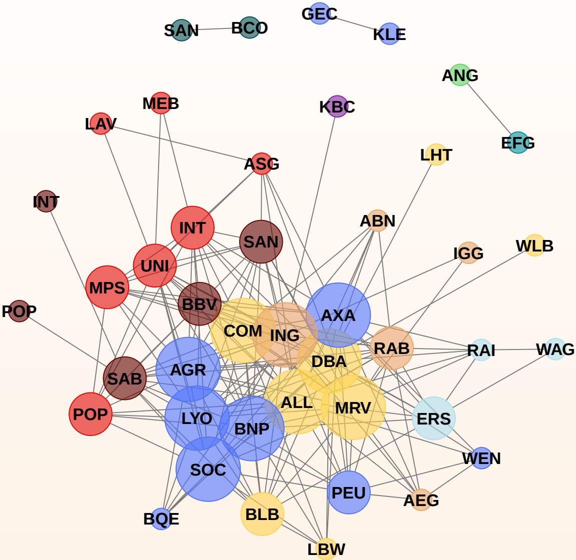
Country Colormap and Number of Banks



Static Network Analysis

Bank Credit Risk Network



Bank Credit Risk Network: Remarks

- Sparsity – 210 links (approx 10%)
- Giant Component - BCRN contains a giant component linking 41 out of 71 banks
- Country Clustering – more links among banks in same country
- Core/Periphery – Core Periphery Network Structure
- Centrality – most central banks are large core entities and vulnerable periphery entities

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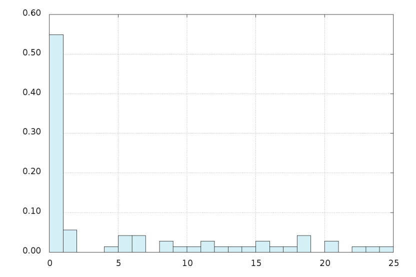
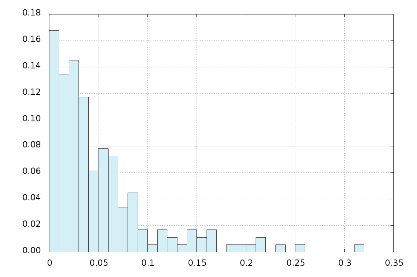
Degree and Partial Correlation Distribution



Degree



Partial Correlation

Bank Credit Risk Network: Link Summary

	AT	BE	GE	ES	FR	GR	IR	IT	NE	PT	TOTAL
AT	33.3	0.0	33.3	0.0	16.7	0.0	0.0	0.0	16.7	0.0	18
BE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	1
GE	5.7	0.0	28.6	11.4	31.4	0.0	0.0	8.6	14.3	0.0	105
ES	0.0	0.0	27.9	18.6	25.6	0.0	0.0	18.6	9.3	0.0	43
FR	2.5	0.0	27.3	9.1	34.7	0.0	0.0	13.2	13.2	0.0	121
GR	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	1
IR	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	1
IT	0.0	0.0	15.0	13.3	26.7	0.0	0.0	40.0	5.0	0.0	60
NE	5.6	1.9	27.8	7.4	29.6	0.0	0.0	5.6	22.2	0.0	54
PT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	2

Bank Credit Risk Network: Link Summary

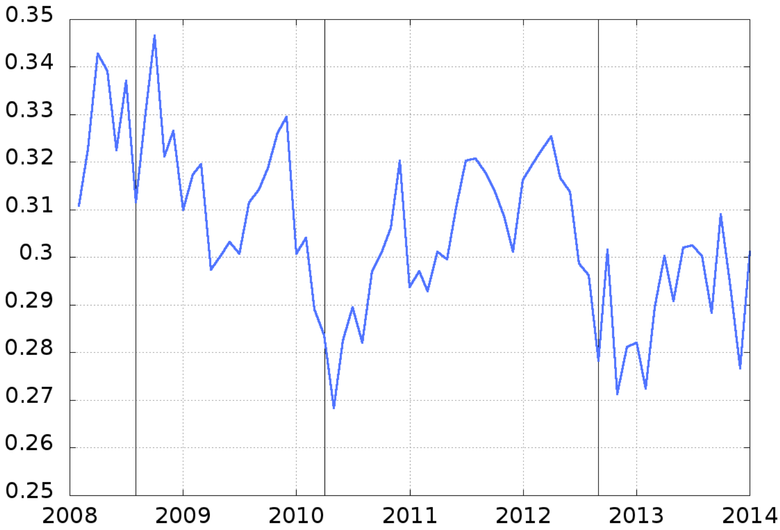
Number of Links			BIS cons. foreign claims	
1	France	121	France	1.210.000 $
2	Germany	105	Germany	1.078.974 $
3	Italy	60	Netherlands	647.027 $
4	Netherlands	54	Italy	486.706 $
5	Spain	43	Belgium	345.309 $
6	Austria	18	Spain	263.312 $
7	Portugal	2	Ireland	138.154 $
8	Belgium	1	Austria	113.529 $
9	Ireland	1	Portugal	688.888 $
10	Greece	1	Greece	9.108 $

Centrality – Page Rank Algorithm

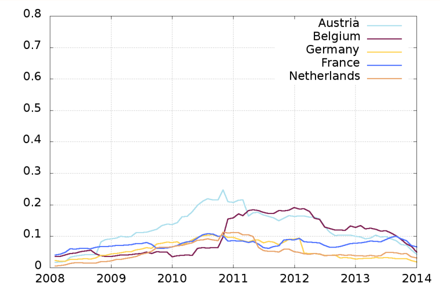
Rank	Company	Country
1	ING	Netherlands
2	DBA	Germany
3	ALL	Germany
4	BNP	France
5	AGR	France
6	LYO	France
7	COM	Germany
8	AXA	France
9	MRV	Germany
10	BBV	Spain

Dynamic Network Analysis

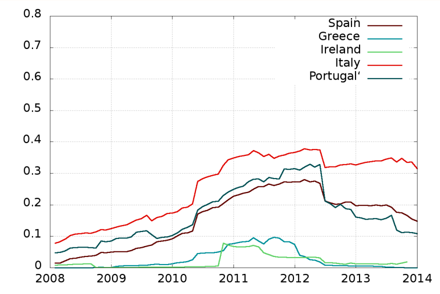
Network Density



Factor R^2

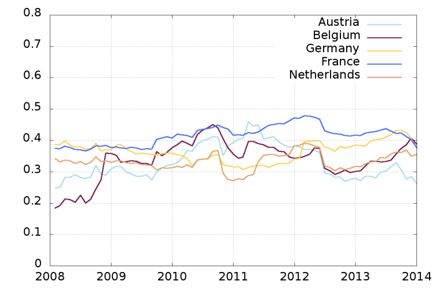


Core



Periphery

(Additional) Network R^2



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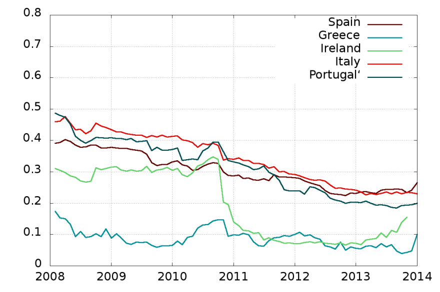

Periphery

Predictive Analysis

Predictive Analysis

- The network estimation procedure boils down to covariance regularization based on assumimg sparsity of the concentration
- It is interesting to assess if this regularization provides more precise estimates of the covariance matrix.
- We address this question by recursively estimating the network implied covariance and assessing how well it predicts the future covariance of idiosyncratic intensity computed over one year.

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\widehat{\boldsymbol{\Sigma}}_N &= \text{Network} \\
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\end{aligned}
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$$L(\widehat{\boldsymbol{\Sigma}}_{\mathrm{OUT}}, \widehat{\boldsymbol{\Sigma}}_X) = \mathrm{tr}(\widehat{\boldsymbol{\Sigma}}_{\mathrm{OUT}} \widehat{\boldsymbol{\Sigma}}_X^{-1}) - \log |\widehat{\boldsymbol{\Sigma}}_{\mathrm{OUT}} \widehat{\boldsymbol{\Sigma}}_X^{-1}|$$

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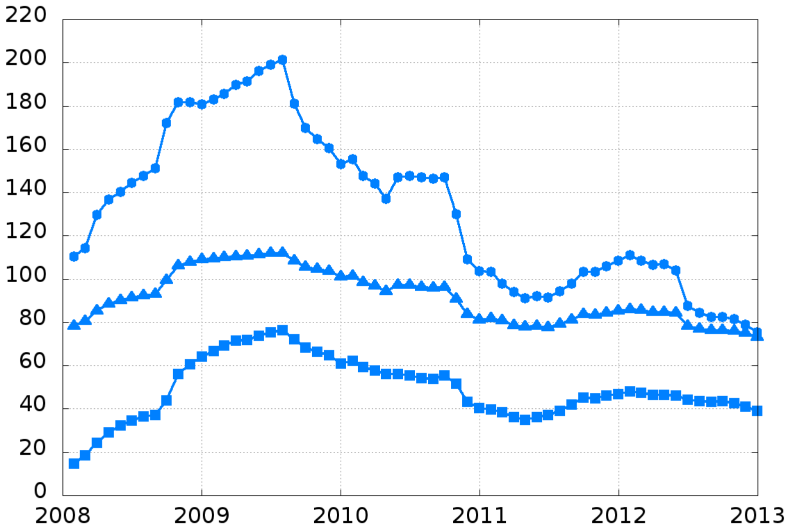
Out–of–Sample Likelihood



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