Banking Network and Systemic Risk via Forward-Looking Partial Default Correlations

Jorge A. Chan-Lau, Chienmin Chuang, Jin-Chuan Duan, and Wei Sun

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Chan-Lau: International Monetary Fund
Chuang and Sun: Credit Research Initiative Team of the NUS Risk Management Institute
Duan: NUS Business School and Credit Research Initiative Team of the NUS Risk Management Institute

The views expressed are those of the authors and do not necessarily represent those of the IMF or IMF policy.

Motivation

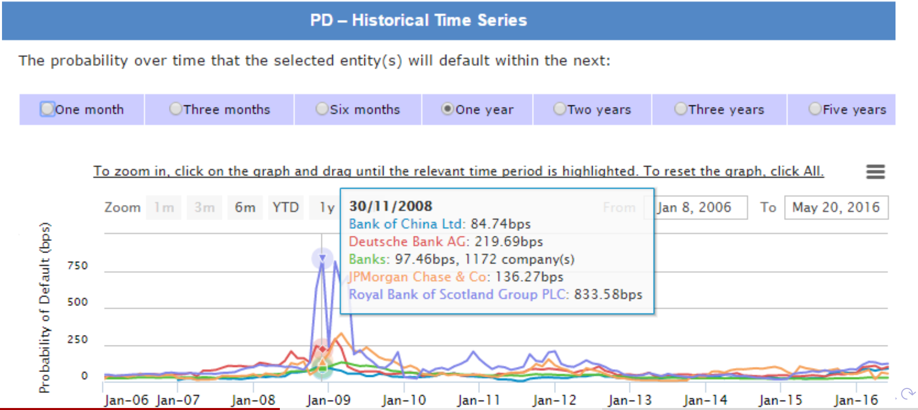
- The recent financial crisis has highlighted the interconnected nature of the global financial system and the need to identify the systemic risk in the global financial network and to design policy measures capable of assessing and thus perhaps containing system-wide distress.
- The current banking network literature typically relies on indirect measurements (stock returns, stock return volatilities, etc). We contend that systemic risk analysis should focus on interconnected default risks.
- Ideally, the analysis should cover the entire global banking system, which also allows for narrowly focussed interest.

The contribution

- **Data**: a global network of 1000+ banks.
- **Measurement**
  - **Probability of default (PD)** is a direct measure of financial distress.
  - **Forward-looking** default correlations are specific to a horizon of interest and dynamically respond to the state of the economy.
- **Methodology**
  - **Partial correlations** are deployed to disentangle the direct connection between two parties not via third parties.
  - **Group-centric** local banking communities allowing for overlapping.
  - Network centrality measures and systemic importance ranking: degree centrality; connection-strength centrality; eigenvector centralities; **weighted eigenvector centralities with node and edge characteristics**

The CRI Probability of Default (PD)

The Credit Research Initiative's (CRI) Probability of Default (PD) measures the likelihood that an individual obligor is unable to fulfill its financial obligations (Duan et al., *Journal of Econometrics*, 2012). The CRI PD has term structures from 1 to 60 months, and it is now available for over 60,000 exchange-listed firms in 119 economies.



Forward-looking default correlations

Duan and Miao (*Journal of Business & Economic Statistics*, 2016) propose a method to model default correlations:

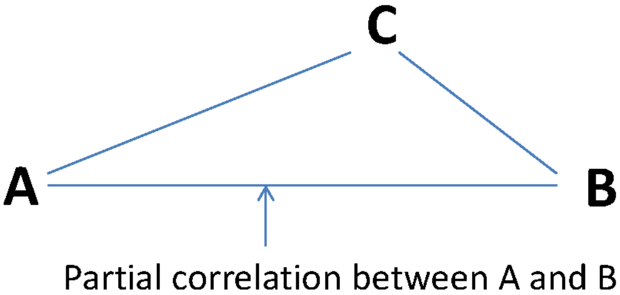
- 1 global and 10 sectoral credit cycle indices are generated from the individual 1-month PDs in the CRI database. Another set of 11 credit cycle indices based on 1-month POEs are also generated.
- The individual PDs and POEs are connected to the credit cycle indices through a factor model while allowing for sparse local correlations among residuals.
- The credit cycle indices follow a VAR(1) model on monthly.
- The individual PDs are mainly correlated through the common credit cycle drivers and their evolution over time.
- With this model in place, one can simulate future 1-month PDs and POEs from one point in time over any specified horizons, and then deduce future PDs of any duration of interest.

Forward-looking vs historical default correlations

- Historical default correlations will certainly face the missing data problem, but forward-looking correlations won't because they are generated by simulation according to a model.
- Historical default correlations are hard to match with the horizon of interest, but forward-looking correlations can be computed for any horizon of interest.
- Historical default correlations are average co-movements which don't reflect the current market condition well, but forward-looking correlations do reflect the current market condition via the credit cycle indices.

Partial default correlations

Partial correlation measures the direct connectedness between two parties not via third parties.



Partial default correlations

We use the CONCORD algorithm (Khare et al., 2015; Oh et al., 2014) to regularize the partial correlation matrix to achieve sparsity.

We allow no 'orphan' banks to appear.

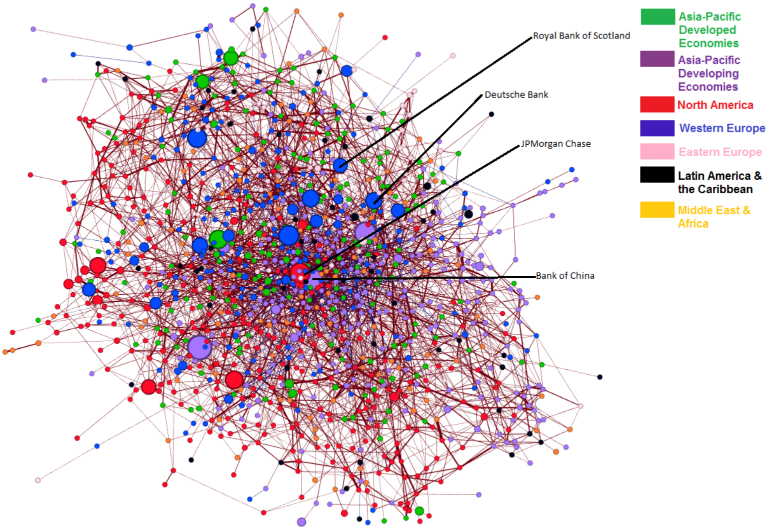
The CONCORD objective function is:

$$Q_{con}(\Omega) = \frac{N}{2}\left\{-ln[det(\Omega_D^2)] + tr(S_N\Omega^2) + \lambda\|\Omega_X\|_1\right\}$$

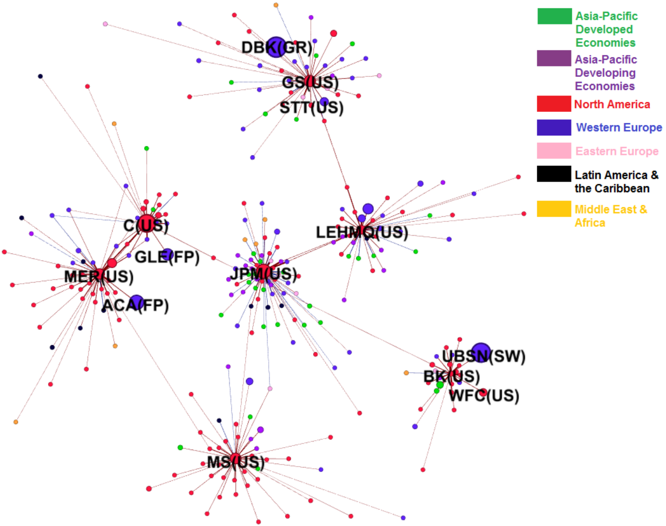
where Ω is the inverse of the correlation matrix to be solved, S_N is the sample correlation matrix, $\Omega = \Omega_D + \Omega_X$ where Ω_D and Ω_X are matrices containing Ω's diagonal and off-diagonal elements.

P is the partial correlation matrix and its entries can be computed using the elements of Ω with the formula: $-\frac{\omega_{ij}}{\sqrt{\omega_{ii}\omega_{jj}}}$.

The global network of 1275 banks based on partial default correlations (December 2014)



The NY-centered banking community based on partial default correlations (August 2008)



Network centrality measures

P_X: equal to the $n \times n$ partial correlation matrix P except that its diagonal elements are set to 0.

A: adjacency matrix with entries of 0 and 1, depending on whether their corresponding elements in P_X equal 0 or not.

- **Degree Centrality**: number of connected parties in the network.
- **Connection Strength Centrality**: $i-$th row sum of $|P_X|$ divided by n.
- **Eigenvector Centrality**: eigenvector of A that corresponds to the largest eigenvalue.
- **Connection-Strength Eigenvector Centrality**: eigenvector of $|P_X|$ that corresponds to the largest eigenvalue.

Network centrality measures

Eigenvector centrality:

$$\boldsymbol{A}x = \lambda x$$

According to the Perron-Frobenius theorem, the non-negative matrix $\boldsymbol{A}$ will have its largest eigenvalue being positive and its corresponding eigenvector is a non-negative vector. The values in this eigenvector are the centrality scores of the members of the network.

Connection-strength eigenvector centrality:

$$|\boldsymbol{P}_X|x = \lambda x$$

Network centrality measures

q_i: size of the bank, measured by total asset in USD, over the total size of the banking network.

$\boldsymbol{Q}$: diagonal matrix with q_i being its $i-$th diagonal element.

When taking node characteristics into account, we have two novel centrality measures:

- **Weighted Eigenvector Centrality**: eigenvector of $\boldsymbol{QAQ}$ that corresponds to the largest eigenvalue.
- **Weighted Connection-Strength Eigenvector Centrality**: eigenvector of $\boldsymbol{Q}|\boldsymbol{P}_X|\boldsymbol{Q}$ that corresponds to the largest eigenvalue.

Systemic importance rankings of the NY-centered banks (August 2008)

Systemic rankings and the total assets for New York City-based banks, August 2008

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Bank Asset Size (in billions of USD)
Citigroup	1,014	274	1,104	680	20	14	2,199,848
JPMorgan Chase	12	7	14	10	391	395	1,642,862
Goldman Sachs	287	967	464	848	152	66	1,189,006
Morgan Stanley	287	817	118	1,167	440	607	1,090,896
Merrill Lynch	209	157	448	525	10	8	1,042,054
Lehman Brothers	452	355	480	206	26	25	786,035
Bank of New York Mellon	1,080	247	1,180	634	18	24	204,935

Systemic importance rankings of FSB G-SIBs (December 2014)

FSB loss absorbency and systemic importance rankings for the 2014 G-SIBs (part 1)

Bank Name	FSB Loss Absorbency Requirement	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector
HSBC Holdings PLC	2.50%	432	309	288	205	1	2
JPMorgan Chase & Co	2.50%	95	58	118	22	3	7
Barclays PLC	2.00%	703	350	566	223	2	1
BNP Paribas SA	2.00%	473	548	649	574	19	104
Citigroup Inc	2.00%	1,014	833	1,126	1,100	25	59
Deutsche Bank AG	2.00%	255	656	238	541	22	33
Bank of America Corp	1.50%	703	663	792	772	60	186
Credit Suisse Group AG	1.50%	390	938	428	1,076	9	16
Goldman Sachs Group Inc	1.50%	338	975	589	1,113	31	48
Mitsubishi UFJ Financial Group Inc	1.50%	195	836	195	923	5	8
Morgan Stanley	1.50%	125	532	319	1,023	61	122
Royal Bank of Scotland Group PLC	1.50%	390	597	450	513	11	3
Rank correlations with FSB (1,275 banks)		0.01	0.01	0.01	0.04	0.59	0.36
Rank correlations with SRISK (453 banks)		0.10	0.13	0.14	0.14	0.25	0.23

* Groupe BPCE is not a listed firm. We use Natixis SA, the major listed entity in this banking group, to proxy for its systemic ranking.
Source: RMI-CRI (National University of Singapore) and authors' calculations.

FSB loss absorbency and systemic importance rankings for the 2014 G-SIBs (part 2)

Bank Name	FSB Loss Absorbency Requirement	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector
Agricultural Bank of China Ltd	1.00%	1,215	1,247	1,161	1,251	16	93
Bank of China Ltd	1.00%	2	1	3	2	42	108
Bank of New York Mellon Corp	1.00%	1,158	333	1,215	886	91	115
Banco Bilbao Vizcaya Argentaria SA	1.00%	296	813	237	880	73	235
Groupe BPCE*	1.00%	526	1,025	467	843	120	112
Credit Agricole SA	1.00%	526	544	526	615	13	15
Industrial & Commercial Bank of China Ltd	1.00%	125	762	169	699	14	100
ING Groep NV	1.00%	149	586	106	597	4	6
Mizuho Financial Group Inc	1.00%	223	154	424	272	189	185
Nordea Bank AB	1.00%	637	265	611	264	36	41
Banco Santander SA	1.00%	338	509	223	818	26	207
Societe Generale SA	1.00%	851	697	644	447	12	22
Standard Chartered PLC	1.00%	1,260	1,260	1,198	1,147	17	11
State Street Corp	1.00%	637	1,063	906	1,109	27	39
Sumitomo Mitsui Financial Group Inc	1.00%	851	366	868	510	319	243
UBS Group AG	1.00%	801	559	637	736	6	12
UniCredit SpA	1.00%	576	774	699	661	34	126
Wells Fargo & Co	1.00%	1,173	604	1,199	961	108	349
Rank correlations with FSB (1,275 banks)		0.01	0.01	0.01	0.04	0.59	0.36
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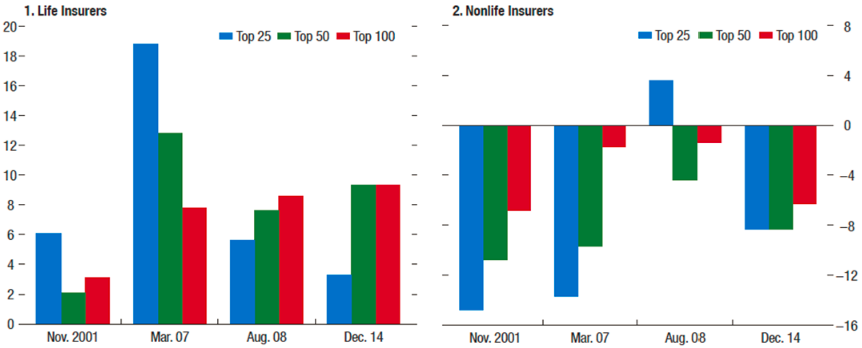
Application I: The systemic ranking methodology

IMF Global Financial Stability Report, April 2016

Figure 3.9. Forward-Looking Default Correlation Networks
(Percent; over- or underrepresentation of insurers)



Sources: Risk Management Institute 2015; and IMF staff calculations.
Note: Figure shows over- or underrepresentation of life and nonlife insurers, in the top 25, top 50, and top 100 firms included in the forward-looking default correlation network. For example, a 5 percent value for the top 100 indicates that there are 5 percent more insurance firms among the top 100 than justified by their sample share. Total sample size ranges between 1,263 and 1,679 firms, including 310 to 410 insurers. Owing to the large number of firms, a regularization adjustment was required to generate fully connected networks, where no firm is an orphan (Oh and others 2014).

Application II: CriSIFI

The CRI will release its systemic importance ranking CriSIFI (CRI Systemic Important Financial Institutions) for the world's exchange-listed banks and insurance companies (around 1,200 banks and 400 insurers) by the end of 2016.

Future Research

- Systemic risk and capital requirement: translating systemic risk rankings into dollar values.
- Banking network and individual systemic importance under ***what-if*** scenarios.