Tail event driven networks of SIFIs

Cathy Yi-Hsuan Chen
Wolfgang Härdle
Yarema Okhrin

C.A.S.E. – Center for Applied Statistics
and Economics
Humboldt–Universität zu Berlin
Chung-Hua University
University of Augsburg
http://lvb.wiwi.hu-berlin.de

Motivation

- Systemic risk threatens financial stability
- Interconnectedness of financial institutions is key to understanding systemic risk
- Important research questions
  - Quantify systemic risk
  - Identify important contributors to systemic risk

Outline

Characteristics of SIFIs

Systemically important financial institution (SIFI)
Financial institution whose failure might trigger a financial crisis

- List of 28 SIFIs published 2011 by FSB
- too-big-too-fail principle
- Characteristic factors
  - size
  - global activity
  - interconnectedness
  - lack of substitutes for its provided financial infrastructure

Index	Name of SIFI	Firm Size	Debt Ratio	Bucket	Country
1	JP MORGAN CHASE	21.506	0.261	4	U.S.
2	BANK OF AMERICA	21.446	0.302	2	U.S.
3	BANK OF NEW YORK MELLON	19.499	0.095	1	U.S.
4	CITIGROUP	21.359	0.300	3	U.S.
5	GOLDMAN SACHS	20.624	0.509	2	U.S.
6	MORGAN STANLEY	20.501	0.417	2	U.S.
7	STATE STREET	19.106	0.153	1	U.S.
8	WELLS FARGO	20.980	0.183	1	U.S.
9	ROYAL BANK OF SCTL	21.588	0.252	1	U.K.
10	BARCLAYS	21.604	0.286	3	U.K.
11	HSBC	21.682	0.127	4	U.K.
12	STANDARD CHARTERED	20.136	0.187	1	U.K.
13	BNP PARIBAS	21.684	0.136	3	France
14	CREDIT AGRICOLE	21.489	0.211	1	France
15	SOCIETE GENERALE	21.184	0.139	1	France
16	DEUTSCHE BANK	21.630	0.200	3	Germany
17	UNICREDIT	20.929	0.360	1	Italy
18	ING GROEP	21.156	0.103	1	Netherlands
19	SANTANDER	21.158	0.368	1	Spain
20	NORDEA BANK	20.476	0.326	1	Sweden
21	CREDIT SUISSE GROUP N	20.744	0.339	2	Switzerland
22	UBS GROUP	21.008	0.251	1	Switzerland
23	BANK OF CHINA	21.200	0.160	1	China
24	ICBC	21.508	0.089	1	China
25	CHINA CON.BANK	21.281	0.092	1	China
26	MITSUBISHI UFJ	21.533	0.159	2	Japan
27	MIZUHO	21.247	0.233	1	Japan
28	SUMITOMO.MITSUI	21.044	0.125	1	Japan

Table 1: Overview of SIFIs

Note: Buckets assigned by BCBS, required level of additional common equity loss absorbency

Similarity Matrix

- SIFIs are connected if they share certain degree of similarity
- Risk profile similarity

$$\rho_{ij,t} = \frac{X_{i,t}^\top X_{j,t}}{\|X_{i,t}\|\|X_{j,t}\|} \quad \text{for } j \neq i,\ i = 1, \ldots, N,\ t = 1, \ldots, T,$$

with $X_{i,t} = [\mathrm{VaR}_{i,t}, \mathrm{ES}_{i,t}, \mathrm{IV}_{i,t}]^\top$

  - Value-at-risk at 95 % level
  - Expected shortfall at 95 % level
  - Implied volatility

- Analogous to Pearson correlation coefficient

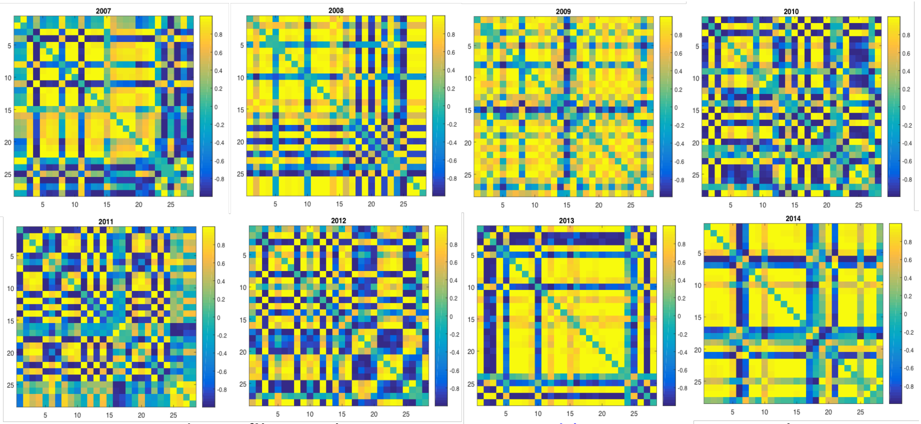


Figure 1: Risk profile similarity 2007 - 2014, blue: negative correlation, yellow: positive correlation

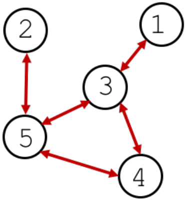
Adjacency matrix

Each network is characterized by the adjacency matrix $\mathbf{A} = \{a_{ij}\}$, for i, j = 1, ... N.

$$a_{ij} = \begin{cases} 1 & \text{, if } i \text{ is directly connected to } j \\ 0 & \text{, if } i \text{ is not directly connected to } j \end{cases}$$

If $a_{ij} = a_{ji}$ for all i and j then the network is an undirected network

	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	1	.	.	.	.
[2,]	0	1	.	.	.
[3,]	1	0	1	.	.
[4,]	0	0	1	1	.
[5,]	0	1	1	1	1



Adjacency matrix

- Need for three groups to disentangle asymmetric correlations

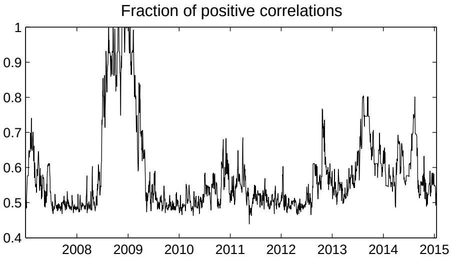


Figure 2: Fractions of positive correlations in the similarity matrix

Adjacency matrix

- Ordered Fisher's Z transformed correlations $\rho^* = (\rho^*_1, \rho^*_2, ..., \rho^*_n)^\top$

Appendix: Transformation

- Edges are constructed based on large spacings between ρ^*_j and ρ^*_{j-1}, h equals sample size

$$\Delta_j = \Phi\left(\sqrt{h-3}\rho^*_j\right) - \Phi\left(\sqrt{h-3}\rho^*_{j-1}\right)$$

- Split spacing sequence Δ_j into three homogeneous groups

Appendix: Classification approach

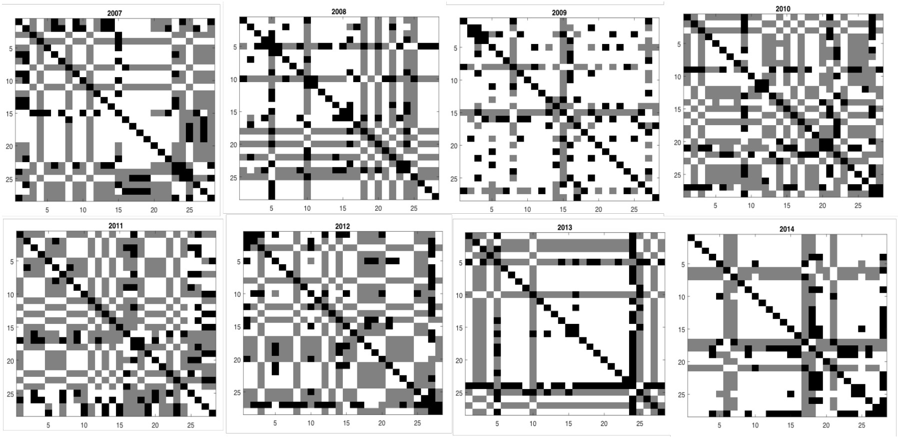


Figure 3: Positive (white), negative (gray) and weak correlation (black) for 2007 - 2014.

Systemic risk score

- Quantifies degree of systemic risk in financial system
- Systemic risk score S is function of compromise level of all nodes

$$S(C, A) = C^\top A C$$

  - A, adjacency matrix
  - $C = (C_1, ..., C_N)^\top$, compromise vector
  - Level of compromise defined as nodal market capitalization (Basel III, "too-big-to-fail"-consideration)

Risk decomposition

- Decomposes aggregate risk S into individual risk score S_i
- Euler's equation to decompose first-order functions

$$S = \sum_{i=1}^{N} S_i = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + ... + \frac{\partial S}{\partial C_N} C_N$$

- Enables to identify source of systemic vulnerabilities

	SIFI	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	JP MORGAN	150	217	221	153	158	150	205	225	205
2	BANK OF AMERICA	135	193	207	172	186	172	140	223	149
3	BANK OF NEW YORK MELLON	171	187	149	138	149	138	121	206	64
4	CITIGROUP	158	193	210	171	175	189	207	199	202
5	GOLDMAN SACHS	182	83	168	178	161	152	87	192	187
6	MORGAN STANLEY	175	197	202	160	164	182	200	130	191
7	STATE STREET	164	176	190	160	138	171	188	132	180
8	WELLS FARGO	159	207	149	181	182	156	206	221	193
9	ROYAL BANK OF SCTL	191	201	204	109	168	190	211	198	198
10	BARCLAYS	190	107	219	182	173	160	131	214	204
11	HSBC	171	212	220	187	173	192	210	226	211
12	STANDARD CHARTERED	179	196	208	152	167	141	193	200	121
13	BNP PARIBAS	178	200	211	160	161	190	209	211	155
14	CREDIT AGRICOLE	181	194	183	171	182	142	207	214	130
15	SOCIETE GENERALE	146	188	115	151	162	168	205	193	202
16	DEUTSCHE BANK	202	160	155	169	142	192	182	202	150
17	UNICREDIT	199	199	189	167	110	159	208	119	202
18	ING GROEP	196	125	221	169	156	147	202	85	197
19	SANTANDER	202	216	183	183	174	155	204	155	194
20	NORDEA BANK	191	125	215	154	163	150	202	217	93
21	CREDIT SUISSE GROUP N	193	206	218	117	179	170	205	133	193
22	UBS GROUP	182	129	199	134	156	184	201	198	147
23	BANK OF CHINA	143	185	209	172	166	183	200	193	173
24	ICBC	131	105	212	148	162	188	43	185	197
25	CHINA CON.BANK	151	139	198	149	161	151	114	203	196
26	MITSUBISHI UFJ	148	206	216	163	142	160	206	201	209
27	MIZUHO	146	204	147	103	153	69	140	211	205
28	SUMITOMO.MITSUI	131	201	215	168	148	189	202	111	196
	Systemic Risk Score	4746	4938	5430	4419	4514	4588	5032	5193	4942
	Average score (US)	162	182	187	164	164	164	169	191	172
	Average score (Europe)	186	175	196	157	162	167	198	183	171
	Average score (Asia)	142	173	200	150	155	157	151	184	196

Table 2: Systemic risk score and decomposition, red: maximum value per column

Tail event driven network quantile regression

Three issues on network dynamics

- Current nodal response is related to connectedness at previous time point
- SIFIs respond stronger to negative than positive network effect
- Returns are subject to geographical proximity

Model for SIFI returns

$$Y_{it} = \alpha_0 + \alpha_{i1} Y_{i,t-1} + \alpha_{i2}^\top W_t + \alpha_{i3} S_{it} + \nu_{it}, \text{ for i = 1, ..., N, t = 1, ..., T,}$$

with

- Y_{it}, $Y_{i,t-1}$: return and autoregressive term of SIFI i
- W_t: market influence (VIX, TED spread)
- S_{it}: node-specific variables (log firm size, total debt to asset ratio)
- Estimation by OLS: for individual nodes or stacked groups of SIFIs

Random coefficient model

'Residual returns' may contain network information

$$\hat{\nu}_{it} = \beta_{r0}(U_t) + \beta_{r1}(U_t) \sum_{j \in B_i} m_i(Y_{j,t-1}), \qquad \text{for } i \in \mathcal{R}_r$$

- β_{r1} represents network effect
- $\mathcal{R}_r$, with $r = 1, 2, 3$ all SIFIs from US, Europe, Asia
- $m_i(Y_{j,t-1})$ connectedness, B_i neighbors of node i
- $\{U_t\} \sim$ U(0,1) iid sequence

Conditional quantile function

$$Q_{\hat{\nu}_{it}}(\tau|\mathcal{I}_{t-1}) = \beta_{r0}(\tau) + \beta_{r1}(\tau) \sum_{j \in B_j} m_i(Y_{j,t-1})$$

- $m_i(Y_{j,t-1})$, connectedness of nodes within network
- Network factor, average impact from i-th node neighbors

$$\sum_{j \in B_j} m_i(Y_{j,t-1}) = \frac{1}{|B_i|} \sum_{j=1}^{N} a_{ij,t-1} Y_{j,t-1}$$

- Significance of network factor can be statistically tested

TENQR: Estimation

Minimize objective function (Koenker and Xiao, 2006)

$$\hat{V}_r(\tau) = \min_{\theta_r(\tau)\in\mathbb{R}^2} \sum_{t=1}^{T} \sum_{i\in\mathcal{R}_r} \rho_\tau \left\{ \hat{v}_{it} - \mathbf{x}_{i,t-1}^\top \theta_r(\tau) \right\} \qquad \text{for} \quad \tau \in (0,1)$$

- $\rho_\tau(u) = u \cdot \{\tau - I(u<0)\}$ is asymmetric loss function
- $\mathbf{x}_{i,t-1}^\top$ contains all relevant explanatory variables
- $\theta_r(\tau) = \{\beta_{r0}(\tau), \beta_{r1}(\tau)\}$

Estimation result pooled return model

	const	Y_{t-1}	VIX	TEDrate	assets	debt ratio
US	-0.0267	-0.0626***	-0.0221***	0.0485**	0.0030	-0.1108
Europe	1.2054	0.0485***	-0.0183***	0.0080	-0.0564	-0.0595
Asia	1.9158	0.0145	0.0023	-0.0973***	-0.0861	-0.2937

Table 3: Estimation of returns on lagged returns, market- and node-specific covariates for each geographic region (daily data on SIFI returns 01.01.2007 - 31.12.2015)

Distribution of residuals

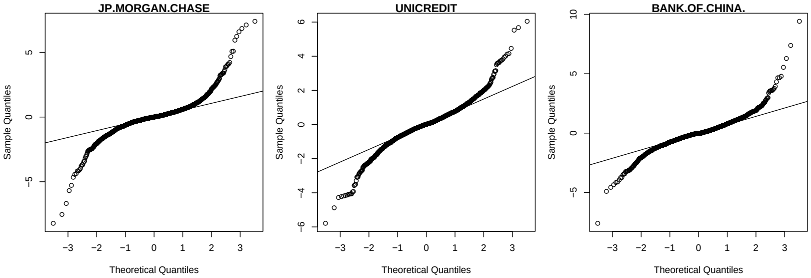


Figure 4: QQ plots of the absolute residuals from the individual regressions for JP Morgan, Unicredit and Bank of China and the Gaussian distribution (full sample estimation)

Quantilogram

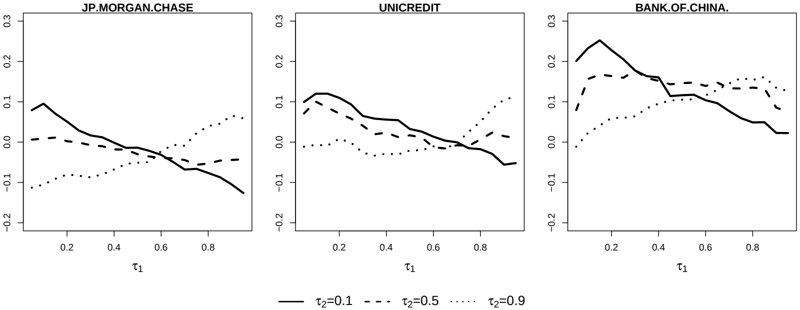


Figure 5: Quantilograms of residuals from the individual regressions for JP Morgan, Unicredit and Bank of China with the 10%, 50% and 90% quantiles of network factor (full sample estimation)

Appendix: cross-quantilogram

Coefficient curve based on geographic regions

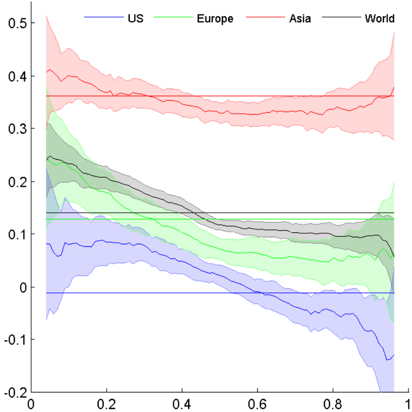


Figure 6: Slopes from quantile regressions of residuals grouped by geographic regions on network factor (full sample). Colored area shows 95% confidence band, horizontal lines depict OLS parameters

Time variation of network effect

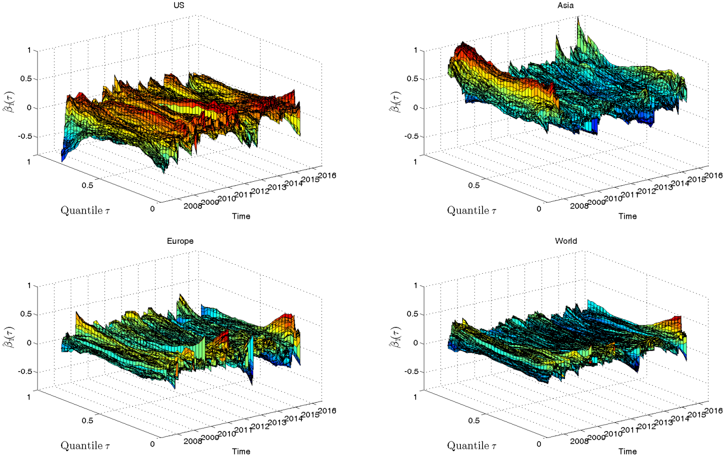


Figure 7: Moving window estimation (90 days) of $\beta_1(\tau)$ in quantile regression aggregate for geographic regions

Conclusion

- Systemic risk depends on interdependence of SIFIs in stress situations
- TENQR method allows to isolate network factor and to study joint dynamics
- Network topology allows precise insight into management of systemic risk
- Supervisors may identify high risk contributors and predict their impact in an interconnected financial system

Tail event driven networks of SIFIs

Cathy Yi-Hsuan Chen
Wolfgang Härdle
Yarema Okhrin

C.A.S.E. – Center for Applied Statistics
and Economics
Humboldt–Universität zu Berlin
Chung-Hua University
University of Augsburg
http://lvb.wiwi.hu-berlin.de

Bibliography

Adrian, T. and Brunnermeier, M. K.
CoVaR
American Economic Review, 2016

Das, S. R.
Matrix metrics: Network-based systemic risk scoring
Journal of Alternative Investments: Special Issue on Systemic Risk, 2016

Fan, Y., Härdle, W. K., Wang, W. and Zhu, L.
Single index based CoVaR with very high dimensional covariates
Journal of Business Economics and Statistics, 2016

Bibliography

Han, H., Linton, O., Okac, T. and Whang, Y.-J.
The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series
Journal of Econometrics, 2016

Härdle, W. K., Wang, W. and Yu, L.
TENET: Tail-Event driven NETwork risk
Journal of Econometrics , 2016

Koenker, R. and Xiao, Z.
Quantile autoregression
Journal of the American Statistical Association, 2006

Bibliography

Ng, S
Testing cross-section correlation in panel data using spacings
Journal of Business and Economic Statistics, 2006

Zhu, X., Pan, R., Li, G., Liu, Y. and Wang, H.
Network vector autoregression
Annals of Statistics, 2017

Zhu, X., Wang, W., Wang, H. and Härdle, W.
Network quantile autoregression
Journal of American Statistical Association, 2016

Fisher's Z transformation

- Transformation:

$$\rho_j^* = \frac{1}{2}\log\left(\frac{1+\rho_j}{1-\rho_j}\right)$$

- Transformed correlations are approximately normal with constant $\mathrm{Var}(\rho^*) = \frac{1}{(h-3)}$ (h = sample size)

Back

Estimation of break fractions $\hat{\theta}_1,\hat{\theta}_2$

Minimize the total sum of squared residuals

$$(\hat{\theta}_1, \hat{\theta}_2) = \underset{\theta_{1,2}\in[\underline{\theta},\bar{\theta}]}{\operatorname{argmin}} \sum_{j=1}^{[\theta_1 n]} (\Delta_{(j)} - \bar{\Delta}_S)^2 + \sum_{j=[\theta_1 n]+1}^{[\theta_2 n]} (\Delta_{(j)} - \bar{\Delta}_M)^2 + \sum_{j=[\theta_2 n]+1}^{n} (\Delta_{(j)} - \bar{\Delta}_L)^2$$

with

$$\Delta_S = \frac{1}{[\theta_1 n]} \sum_{j=1}^{[\theta_1 n]} \Delta_{(j)},$$

$$\Delta_M = \frac{1}{[\theta_2 n] - [\theta_1 n]} \sum_{j=[\theta_1 n]+1}^{[\theta_2 n]} \Delta_{(j)},$$

$$\Delta_L = \frac{1}{n - [\theta_2 n]} \sum_{j=[\theta_2 n]+1}^{n} \Delta_{(j)}.$$

- $\Delta_{(j)}$ ordered spacings, $[\theta n]$ integer part of θn and $\underline{\theta} = 0.1 = 1 - \bar{\theta}$
- θ_1: fraction of highly negative correlations
- θ_2: fraction of highly positive correlations

Back

Cross-quantilogram , Han et al. (2016)

Capture of serial dependence between the two series at different conditional quantile levels

$$\varrho_{(\tau_1\tau_2)(k)} = \frac{\sum_{t=k+1}^{T} \varphi_{\tau_1}(y_{1t} - \tilde{y}_{1,\tau_1})\varphi_{\tau_2}(y_{2,t-k} - \tilde{y}_{2,\tau_2})}{\sqrt{\sum_{t=k+1}^{T} \varphi_{\tau_1}^2(y_{1t} - \tilde{y}_{1,\tau_1}) \sum_{t=k+1}^{T} \varphi_{\tau_2}^2(y_{2,t-k} - \tilde{y}_{2,\tau_2})}}$$

where $\varphi_\tau(u) = I(u < 0) - \tau$, with $\tau \in (0,1)$

Back