Industry Interdependency Dynamics in a Network Context

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Interdependency Literature

- financial contagion:
  Rodriguez(2007), May and Arinaminpathy(2010), Hasman (2013), Georg (2013), Acemoglu et al. (2015)

- interdependency among financial sector and real economy sectors:
  Baur (2012), Chiu et al. (2015), Claessens et al. (2012)

Industry Interdependency

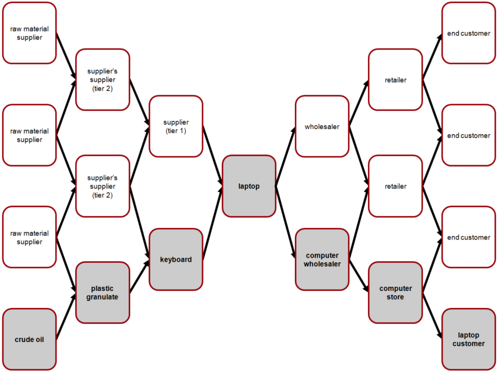
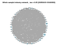


Figure 1: Supply chain

Challenges

- not just dyadic relationship
- high dimensional data
- whether extreme markets matter?



Literature on Interdependency under Network Framework

- real networks:
  Schweitzer et al.(2009), Zhu et al. (2016), Zhu, Wang, Wang & Härdle (2016), Gençay et al.(2015)

- artificial networks:
  Diebold & Yilmaz (2014), Billio et al. (2011), Chan-Lau et al. (2016), Härdle et al. (2016), Rapach et al. (2016)

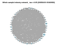
Outline

1. Motivation ✓
2. Model Setup
3. Empirical Analysis
4. Appendix
5. References

Network Structure

Network structure $(\mathcal{N}_g, \mathcal{E}_g)$ to explain industry interdependencies

- nodes $\mathcal{N}_g$: each industry portfolio
- edges $\mathcal{E}_g$: linkages between every pair of nodes

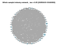


Linear Predictive Model

(Rapach et al., 2016)

$$r_{i,t+1} = \beta_{0,i} + \sum_{j=1}^{N} \beta_{i,j} r_{j,t} + \varepsilon_{i,t+1}, t = 1, \ldots, T-1 \tag{1}$$

- $r_{i,t}$: log-return of industry i at time t
- N: total number of industries
- $\varepsilon_{i,t}$: zero-mean disturbance term



Generalized Quantile Regression

Let $\{X_i, Y_i\}_{i=1}^n$ be r.v., $X \in \mathbb{R}^p$, $\tau \in (0,1)$.

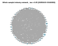
$$Y_i = X_i^\top \theta + \varepsilon_i \tag{2}$$

$$\hat{\theta} = \arg \min_{\theta \in \mathbb{R}^p} \sum_{i=1}^n \rho_\tau (Y_i - X_i^\top \theta) \tag{3}$$

(1) is a special case of the generalized quantile regression (2), if we set $y_i = r_{i,t+1}, x_i = (1, r_t), \alpha = 1, \tau = 0.5$, where $r_t = \{r_{j,t}\}_{j=1}^N$. where $\rho_\tau(\cdot)$ is an asymmetric loss function

$$\rho_\tau(u) = |u|^\alpha |\mathbf{I}(u \leq 0) - \tau|$$

with $\alpha = 1$ and $\alpha = 2$ corresponding to a quantile and expectile regression respectively.



Asymmetric Loss Functions

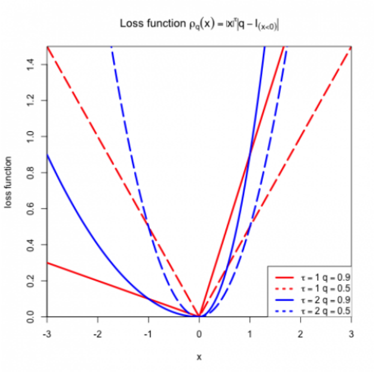


Figure 2: Asymmetric Loss Functions for Quantile and Expectile, solid lines: $\tau = 0.9$, dashed lines: $\tau = 0.5$

LQRcheck

LASSO

$$\hat{\beta}(lasso) = \arg\min_{\beta} \sum_{i=1}^{n} (y_i - x_i^\top \beta)^2 + \lambda \sum_{i=1}^{p} |\beta_i| \tag{4}$$

- λ: nonnegative regularization parameter
- $\lambda \sum_{j=1}^{p} |\beta_j|$: l_1 penalty

Quantile LASSO

$$\hat{\beta}(qlasso) = \arg \min_{\beta_0, \beta} \sum_{t=1}^{T-1} \rho_\tau (r_{i,t+1} - \beta_0 - r_t^\top \beta) + \lambda \|\beta\|_1 \tag{5}$$

- r_t: return vector of all industries at time t
- β: vector of intercept and coefficients

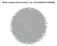
Adjacency Matrix

Network structure $(\mathcal{N}_g, \mathcal{E}_g)$ corresponding to a unique adjacency matrix A

A can be unweighted $0-1$ matrix or weighted matrix

$A = \{a_{ij}\}_{i,j=1}^{N}$

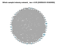
- a_{ij}: the measure of the linkage between node i and j
- N: total number of nodes in network $(\mathcal{N}_g, \mathcal{E}_g)$



Network Centrality

Answers to "what characterizes the important nodes?"

- Degree centrality
- Closeness centrality
- Betweenness centrality
- **Eigenvector centrality**
- Katz centrality
- PageRank centrality
- Percolation centrality
- Cross-clique centrality
- Freeman Centrality

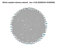


Eigenvector Centrality

A node is important if it is connected to other important nodes!

$$C_E(v) = \frac{1}{\lambda} \sum_{t \in M(v)} C_E(t)$$
$$= \frac{1}{\lambda} \sum_{t \in \mathcal{G}} a_{v,t} C_E(t)$$

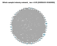
- λ: the maximum eigenvalue of adjacency matrix A
- $M(v)$: the set of neighbors of node v
- $a_{v,t}$: the vt_{th} element of adjacency matrix A



Data

- data source: Kenneth R. French data library
- 49 industry portfolios
- Data frequency: daily
- Time span: 20050103-20160930
- window size: 252 days, step: 126 days

details



Summary Statistics

- Average daily returns $\in (0.0001, 0.0005)$
- Left-skewed
- Fatter tail than normal distributions
- Agriculture, petroleum and natural gas, utilities, communications, banking, insurance, financial trading and others are the most leptokurtotic

▸ summary statistics

Whole Sample Industry Network ($\tau = 0.5$)

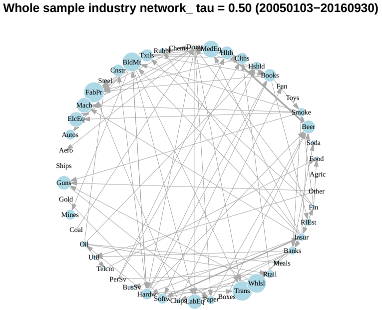
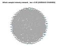


Figure 3: Whole sample network of industry portfolios with size denoting the eigenvector centrality - $\tau = 0.5$

totalnet



Whole Sample Industry Network ($\tau = 0.05$)

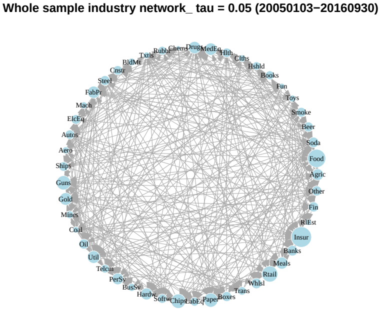


Figure 4: Whole sample network of industry portfolios with size denoting the eigenvector centrality - $\tau = 0.05$

totalnet

Whole Sample Industry Network ($\tau = 0.95$)

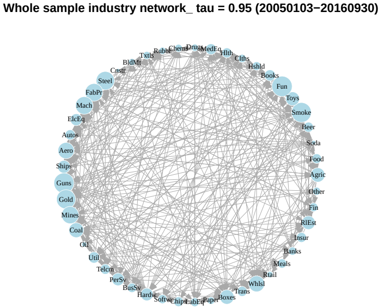


Figure 5: Whole sample network of industry portfolios with size denoting the eigenvector centrality - $\tau = 0.95$

totalnet

Top 10 Leading Industries

τ	Leading industries
0.5	FabPr, Trans, BldMt, Whlsl, MedEq Mach, ElcEq, LabEq, Guns, Beer
0.05	Insur, Food, Rtail, Chips, Guns Paper, Gold, Util, MedEq, Drugs
0.95	Fun, Guns, Smoke, Gold, Steel FabPr, Mach, Mines, Aero, Whlsl

Table 1: Top 10 central industries under stress situations

Network Evolution of USA Industries - $\tau = 0.5$

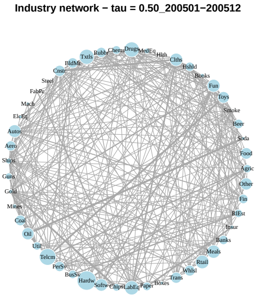
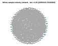


Figure 6: Evolution of USA industry network - $\tau = 0.5$



Network Evolution of USA Industries - $\tau = 0.05$

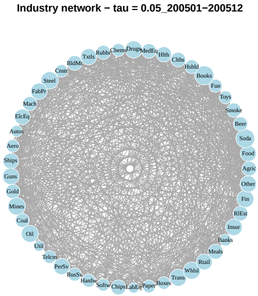
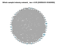


Figure 7: Evolution of USA industry network - $\tau = 0.05$



Network Evolution of USA Industries - $\tau = 0.95$

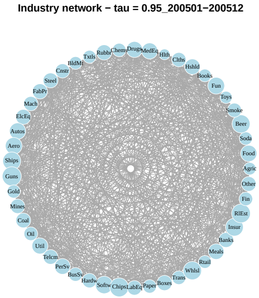
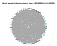


Figure 8: Evolution of USA industry network - $\tau = 0.95$

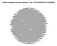


Structure Change of Networks

Distance between two matrices $A = \{a_{ij}\}_{i,j=1}^{n}$ and $B = \{b_{ij}\}_{i,j=1}^{n}$

- l_1 distance: $d_1(A, B) = \sum_{i=1}^{n} \sum_{j=1}^{n} |a_{ij} - b_{ij}|$
- l_2 distance: $d_2(A, B) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_{ij} - b_{ij})^2}$
- l_∞ distance: $d_\infty(A, B) = \max_{1 \le i \le n} \max_{1 \le j \le n} |a_{ij} - b_{ij}|$

▸ data results



Matrix Distance

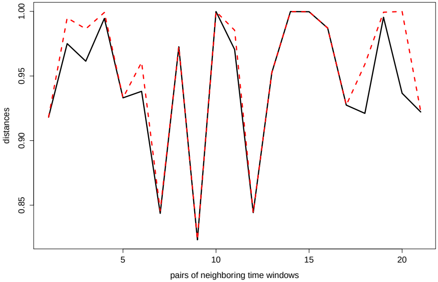


Figure 9: l_∞ distance (black) vs the maximum value of neighboring adjacency matrices (red) - $\tau = 0.5$

distance

Matrix Distance

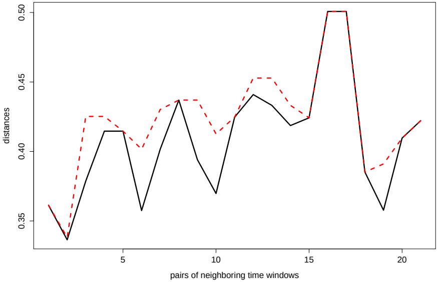


Figure 10: l_∞ distance (black) vs the maximum value of neighboring adjacency matrices (red) - $\tau = 0.05$

distance

Matrix Distance

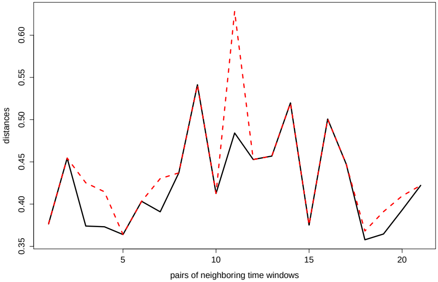


Figure 11: l_∞ distance (black) vs the maximum value of neighboring adjacency matrices (red) - $\tau = 0.95$

distance

Basic Conclusions

For American industry portfolio data,

- Tail dependency is higher than median dependency
- Leading industries vary in median and tail cases
- Dynamic network structure changes across time

Possible Extensions

- network effect (based on known network structure information)
- use individual stocks in each industry
- nonlinear function

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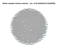
French's 49 industry portfolios

Code	Full name
Agric	Agriculture
Food	Food Products
Soda	Candy & Soda
Beer	Beer & Liquor
Smoke	Tobacco Products
Toys	Recreation
Fun	Entertainment
Books	Printing and Publishing
Hshld	Consumer Goods
Clths	Apparel
Hlth	Healthcare
MedEq	Medical Equipment

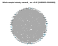
Table 2: 49 industry portfolios from French's data library



French's 49 industry portfolios

Code	Full name
Drugs	Pharmaceutical Products
Chems	Chemicals
Rubbr	Rubber & Plastic Products
Txtls	Textiles
BldMt	Construction Materials
Cnstr	Construction
Steel	Steel Works Etc
FabPr	Fabricated Products
Mach	Machinery
ElcEq	Electrical Equipment
Autos	Automobiles and Trucks
Aero	Aircraft

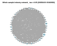
Table 3: 49 industry portfolios from French's data library



French's 49 industry portfolios

Code	Full name
Ships	Shipbuilding, Railroad Equipment
Guns	Defense
Gold	Precious Metals
Mines	Non-Metallic & Industrial Metal Mining
Coal	Coal
Oil	Petroleum and Natural Gas
Util	Utilities
Telcm	Communication
PerSv	Personal Services
BusSv	Business Services
Hardw	Computers
Softw	Computer Software
Chips	Electronic Equipment

Table 4: 49 industry portfolios from French's data library

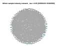


French's 49 industry portfolios

Code	Full name
LabEq	Measuring and Control Equipment
Paper	Business Supplies
Boxes	Shipping Containers
Trans	Transportation
Whlsl	Wholesale
Rtail	Retail
Meals	Restaurants, Hotels, Motels
Banks	Banking
Insur	Insurance
RlEst	Real Estate
Fin	Trading
Other	Almost Nothing

Table 5: 49 industry portfolios from French's data library

back



Summary statistics

Industry	Mean($*10^{-4}$)	SD	Median	Min	Max	Skew	Kurtosis
Agric	3.1062	0.0190	0.0003	-0.1657	0.1675	-0.0554	10.6799
Food	3.8923	0.0096	0.0007	-0.0753	0.0714	-0.2852	6.6862
Soda	4.7142	0.0130	0.0006	-0.0836	0.1105	0.0953	8.6942
Beer	4.7780	0.0096	0.0006	-0.0801	0.0964	0.1782	9.8727
Smoke	6.1863	0.0116	0.0008	-0.0769	0.1250	-0.0070	9.1658
Toys	1.6561	0.0155	0.0005	-0.1049	0.0885	-0.3122	5.0812
Fun	2.7690	0.0203	0.0006	-0.1298	0.1534	-0.2410	6.1780
Books	-0.4006	0.0164	0.0002	-0.1192	0.1060	-0.2653	7.3542
Hshld	2.7328	0.0102	0.0004	-0.0753	0.0902	-0.2119	7.6839
Clths	3.8065	0.0162	0.0005	-0.1224	0.1195	-0.1664	5.4622
Hlth	2.7768	0.0130	0.0008	-0.1065	0.0796	-0.9579	7.8605
MedEq	3.3065	0.0117	0.0007	-0.0748	0.1106	-0.3813	7.1696

Table 6: Descriptive statistics of the log daily return data of 49 industry portfolios. SD is standard deviation.

Summary statistics

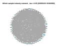
Industry	Mean($*10^{-4}$)	SD	Median	Min	Max	Skew	Kurtosis
Drugs	3.9174	0.0109	0.0007	-0.0675	0.1056	-0.1154	6.7057
Chems	3.7073	0.0162	0.0010	-0.1208	0.1227	-0.6025	7.4163
Rubbr	4.0918	0.0148	0.0007	-0.1069	0.0778	-0.3401	4.5921
Tstls	3.4916	0.0197	0.0006	-0.1305	0.1781	0.1610	7.4695
BldMt	2.8505	0.0170	0.0007	-0.1128	0.0918	-0.2653	4.5604
Cnstr	0.3539	0.0213	0.0005	-0.1324	0.1446	-0.2124	4.7104
Steel	0.3541	0.0234	0.0009	-0.1732	0.1845	-0.3953	7.2477
FabPr	0.1129	0.0207	0.0008	-0.1678	0.1000	-0.5072	4.7701
Mach	3.4442	0.0175	0.0010	-0.1308	0.1301	-0.4244	7.0357
ElcEq	2.6185	0.0164	0.0007	-0.1404	0.1317	-0.2585	7.5385
Autos	0.8108	0.0189	0.0008	-0.1191	0.1106	-0.2721	5.6895
Aero	4.0760	0.0144	0.0008	-0.0796	0.1272	-0.0438	7.0038

Table 7: Descriptive statistics of the log daily return data of 49 industry portfolios. SD is standard deviation.

Summary statistics

Industry	Mean*(10^{-4})	SD	Median	Min	Max	Skew	Kurtosis
Ships	6.1252	0.0179	0.0012	-0.0987	0.1009	-0.1781	2.9731
Guns	5.5976	0.0133	0.0006	-0.0943	0.0973	-0.4653	6.6345
Gold	0.0029	0.0262	-0.0007	-0.1527	0.2276	0.2098	5.2919
Mines	3.0516	0.0247	0.0007	-0.1862	0.1811	-0.2448	5.7195
Coal	-4.3598	0.0348	-0.0002	-0.2149	0.1936	-0.3968	4.6325
Oil	2.6547	0.0181	0.0007	-0.1670	0.1762	-0.3443	10.5703
Util	3.5080	0.0117	0.0009	-0.0934	0.1348	0.1648	14.2488
Telcm	3.4180	0.0127	0.0007	-0.1017	0.1355	0.0783	14.1894
PerSv	0.1920	0.0150	0.0004	-0.0987	0.0857	-0.4612	4.1734
BusSv	3.2767	0.0128	0.0008	-0.0923	0.0803	-0.4072	6.2750
Hardw	2.9138	0.0150	0.0010	-0.1077	0.1149	-0.1310	5.1693
Softw	3.5987	0.0132	0.0007	-0.0859	0.1192	-0.0656	6.9920
Chips	2.9089	0.0149	0.0009	-0.0932	0.1017	-0.1971	4.6437

Table 8: Descriptive statistics of the log daily return data of 49 industry portfolios. SD is standard deviation.



Summary statistics

Industry	Mean($*10^{-4}$)	SD	Median	Min	Max	Skew	Kurtosis
LabEq	4.3703	0.0143	0.0010	-0.0943	0.1196	-0.2862	5.6984
Paper	3.0339	0.0130	0.0008	-0.1010	0.0828	-0.3754	5.9790
Boxes	4.0762	0.0150	0.0009	-0.0948	0.1036	-0.3045	4.6428
Trans	3.6277	0.0150	0.0010	-0.0917	0.0892	-0.2654	4.2135
Whlsl	3.4948	0.0122	0.0008	-0.0888	0.0929	-0.3444	6.5364
Rtail	3.6609	0.0120	0.0008	-0.0868	0.1111	-0.0107	6.9020
Meals	4.6596	0.0124	0.0008	-0.0865	0.0854	-0.1524	4.4038
Banks	-0.0951	0.0214	0.0003	-0.1861	0.1567	-0.0491	14.2028
Insur	2.2736	0.0161	0.0009	-0.1225	0.1642	-0.2770	13.2337
RlEst	0.3347	0.0214	0.0005	-0.1684	0.1710	-0.1991	8.1153
Fin	1.6841	0.0203	0.0009	-0.1776	0.1650	-0.1289	11.4964
Other	1.5905	0.0134	0.0004	-0.1040	0.1417	0.0190	11.4981

Table 9: Descriptive statistics of the log daily return data of 49 industry portfolios. SD is standard deviation.

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Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.5$

pair of time windows	d_1	d_2	d_∞
200501-200512 v.s. 200507-200606	146.7288	2.8066	0.9215
200507-200606 v.s. 200601-200612	160.5246	3.0205	0.8506
200601-200612 v.s. 200607-200706	143.6747	18.5443	0.9992
200607-200706 v.s. 200701-200712	128.9033	5.1225	0.9771
200701-200712 v.s. 200707-200806	133.2289	11.8568	0.9606
200707-200806 v.s. 200801-200812	135.4467	7.6565	0.9606
200801-200812 v.s. 200807-200906	148.6320	1.0243	0.9726
200807-200906 v.s. 200901-200912	144.9802	5.0967	0.9726
200901-200912 v.s. 200907-201006	126.9965	0.3589	0.9200
200907-201006 v.s. 201001-201012	120.0651	34.4157	0.9999
201001-201012 v.s. 201007-201106	115.3484	29.3195	0.9459

Table 10: Adjacency matrix distance of neighboring time windows - $\tau = 0.5$

Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.5$

pair of time window	d_1	d_2	d_∞
201007-201106 v.s. 201101-201112	129.4392	0.1265	0.9527
201101-201112 v.s. 201107-201206	135.3363	17.0319	0.9466
201107-201206 v.s. 201201-201212	140.9679	26.9248	0.9999
201201-201212 v.s. 201207-201306	139.4486	20.4433	0.9997
201207-201306 v.s. 201301-201312	127.5499	23.6689	0.9871
201301-201312 v.s. 201307-201406	106.7012	4.4477	0.9591
201307-201406 v.s. 201401-201412	134.4348	28.5986	0.9994
201401-201512 v.s. 201407-201506	150.4417	3.3981	0.9999
201407-201506 v.s. 201501-201512	134.7607	7.3711	0.9226
201501-201512 v.s. 201507-201606	149.5438	13.7838	0.9740

Table 11: Adjacency matrix distance of neighboring time windows - $\tau = 0.5$

Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.05$

pair of time window	d_1	d_2	d_∞
200501-200512 v.s. 200507-200606	95.1477	7.2065	0.3613
200507-200606 v.s. 200601-200612	92.6064	2.6973	0.3365
200601-200612 v.s. 200607-200706	103.1707	10.6360	0.3788
200607-200706 v.s. 200701-200712	107.8980	4.2199	0.4146
200701-200712 v.s. 200707-200806	104.8444	23.5002	0.4146
200707-200806 v.s. 200801-200812	92.4060	11.6163	0.3575
200801-200812 v.s. 200807-200906	97.5810	2.9557	0.4016
200807-200906 v.s. 200901-200912	110.3298	5.3947	0.4370
200901-200912 v.s. 200907-201006	116.1927	2.0440	0.3941
200907-201006 v.s. 201001-201012	104.8516	4.1334	0.3698
201001-201012 v.s. 201007-201106	126.4240	3.4539	0.4248

Table 12: Adjacency matrix distance of neighboring time windows - $\tau = 0.05$

Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.05$

pair of time window	d_1	d_2	d_∞
201007-201106 v.s. 201101-201112	121.4599	7.6940	0.4409
201101-201112 v.s. 201107-201206	115.6800	4.7839	0.4332
201107-201206 v.s. 201201-201212	108.9449	10.1360	0.4186
201201-201212 v.s. 201207-201306	104.2969	4.8781	0.4242
201207-201306 v.s. 201301-201312	117.5054	9.8534	0.5007
201301-201312 v.s. 201307-201406	115.0835	11.4502	0.5007
201307-201406 v.s. 201401-201412	105.6410	1.8460	0.3852
201401-201512 v.s. 201407-201506	107.1695	2.4965	0.3578
201407-201506 v.s. 201501-201512	106.9011	15.6671	0.4096
201501-201512 v.s. 201507-201606	96.1459	7.3254	0.4222

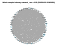
Table 13: Adjacency matrix distance of neighboring time windows - $\tau = 0.05$

Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.95$

pair of time window	d_1	d_2	d_∞
200501-200512 v.s. 200507-200606	102.2347	0.5891	0.4544
200507-200606 v.s. 200601-200612	101.0121	1.0296	0.3773
200601-200612 v.s. 200607-200706	97.6527	1.3343	0.3696
200607-200706 v.s. 200701-200712	94.6807	4.3154	0.3449
200701-200712 v.s. 200707-200806	94.8847	4.4401	0.4033
200707-200806 v.s. 200801-200812	99.7637	3.6284	0.4033
200801-200812 v.s. 200807-200906	105.0967	0.7088	0.3861
200807-200906 v.s. 200901-200912	97.5194	6.9120	0.5413
200901-200912 v.s. 200907-201006	94.2207	0.8623	0.3816
200907-201006 v.s. 201001-201012	98.2760	5.2769	0.4378
201001-201012 v.s. 201007-201106	101.6706	3.0913	0.6281

Table 14: Adjacency matrix distance of neighboring time windows - $\tau = 0.95$



Empirical Results of the 3 distances

Distance between any pair of matrices of the neighboring time window - $\tau = 0.95$

pair of time window	d_1	d_2	d_∞
201007-201106 v.s. 201101-201112	101.1624	5.1981	0.4188
201101-201112 v.s. 201107-201206	118.4790	12.5355	0.5198
201107-201206 v.s. 201201-201212	112.9983	1.1984	0.4558
201201-201212 v.s. 201207-201306	103.6998	8.2127	0.4159
201207-201306 v.s. 201301-201312	103.9175	4.3584	0.4472
201301-201312 v.s. 201307-201406	93.5120	5.3286	0.3409
201307-201406 v.s. 201401-201412	107.1948	1.0255	0.3443
201401-201512 v.s. 201407-201506	95.3437	2.0087	0.3929
201407-201506 v.s. 201501-201512	96.9354	0.0936	0.3929
201501-201512 v.s. 201507-201606	92.1470	3.5065	0.4776

Table 15: Adjacency matrix distance of neighboring time windows - $\tau = 0.95$

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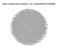

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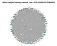

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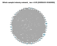

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