Lecture 11: Application of network theory in finance, technology, biology and social science

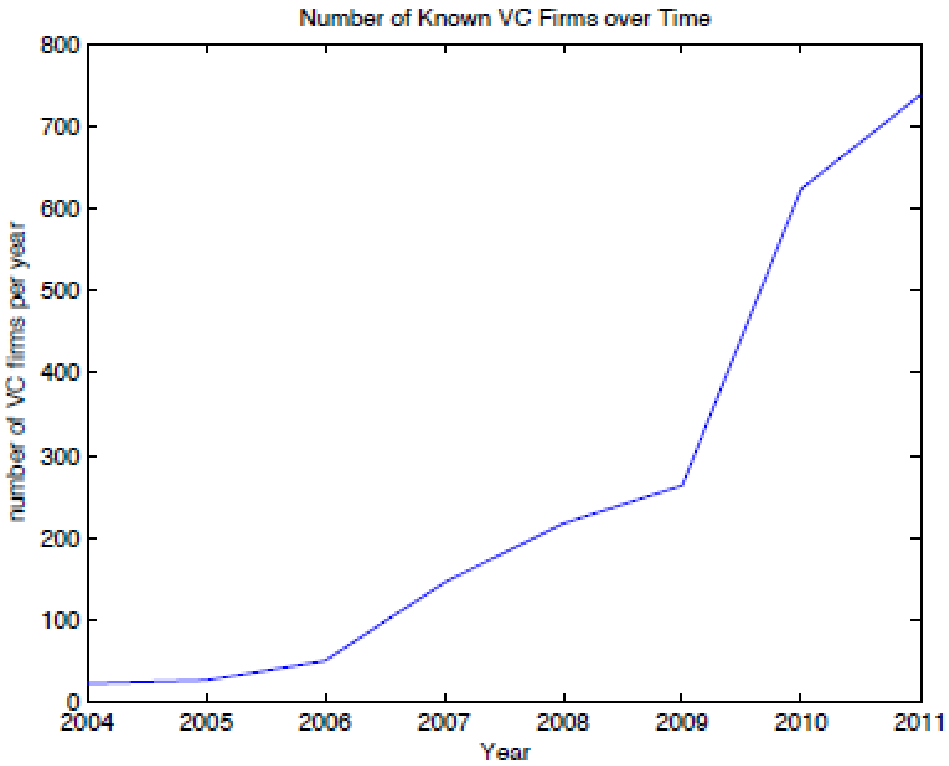
Examples of Complex Networks in Finance, Technology, Biology and Social Science

Example: The Chinese Venture Capital Industry revisited

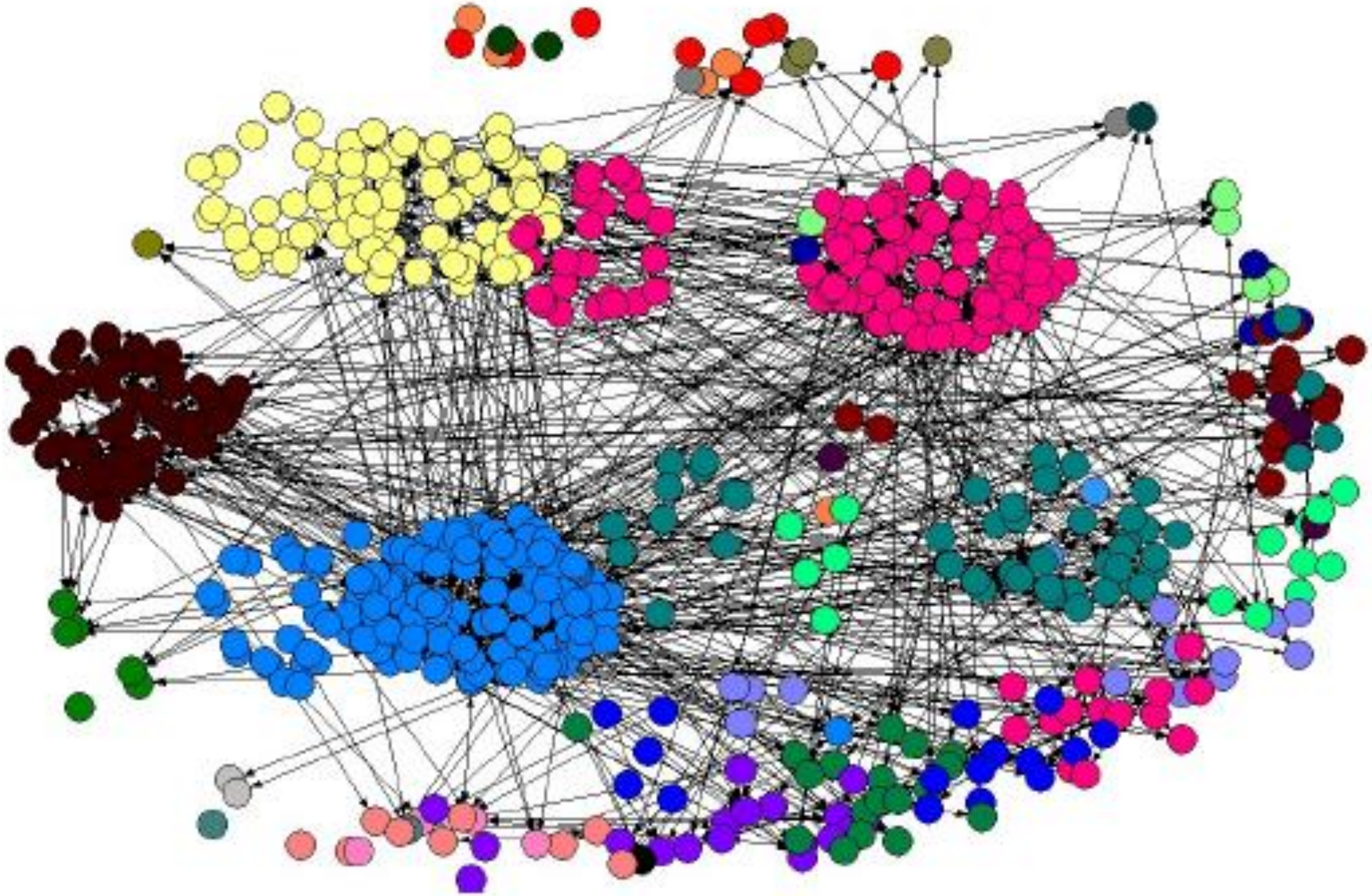
Since 2011, China has become the second largest economy in the world.

Research showed that small and medium enterprise owners in China relied mainly on the financial support from their own savings and immediate family in the past due to the stringent listing requirements.

Chinese government attempted to promote venture capital to fill the SME finance gap from the 1980s, and the Chinese VC industry has grown significantly since the late 1990s.



Number of Chinese venture capital companies from 2004 to 2011.



The VC Network of China. Nodes of the same color belong to the same province or district.

Statistical and Topological Properties of the VC Network

(1) Mean Shortest Path

$$\bar{l} = \frac{2}{N(N-1)} \sum_{i \geq j} d_{ij}$$

where d_{ij} is the distance of the shortest path between nodes i and j.

(2) Degree

The degree of a node is the number of links that are associated with this node.

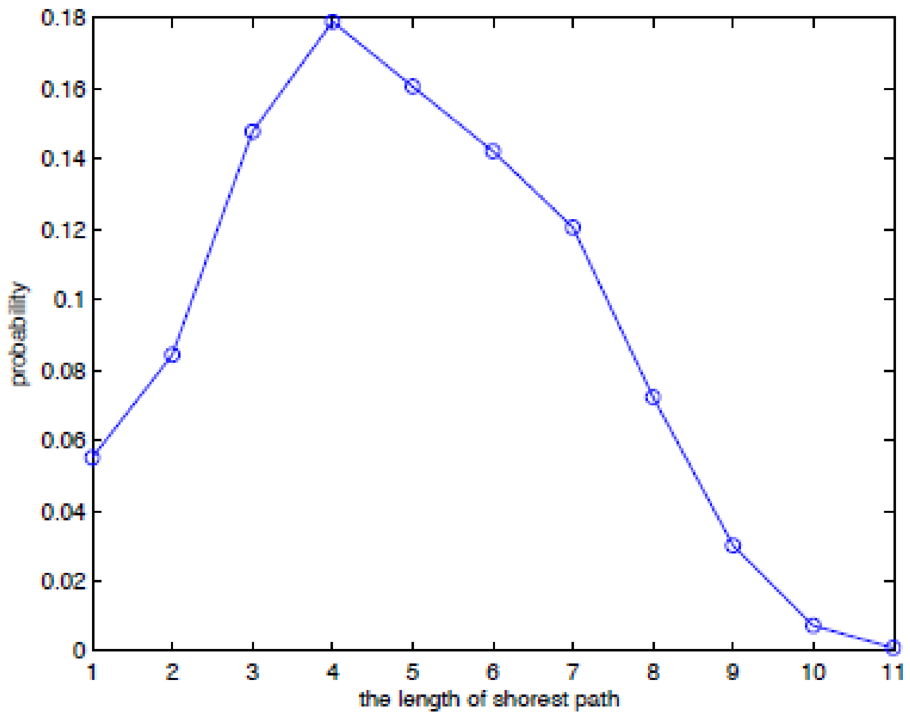
(3) Clustering Coefficients

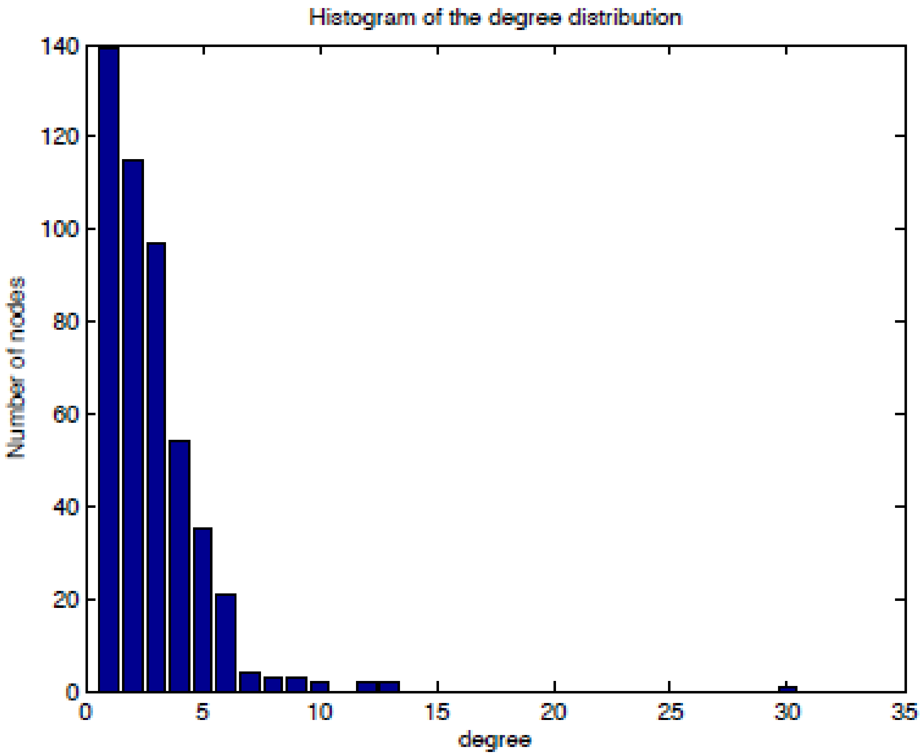
$$C = \frac{1}{N} \sum_{i} C_i \qquad C_i = \frac{E_i}{k_i(k_i - 1)/2}$$

where N is the number of nodes in the network, k_i and E_i are the degree and number of the links among the neighbors of node i respectively.

(4) Betweenness

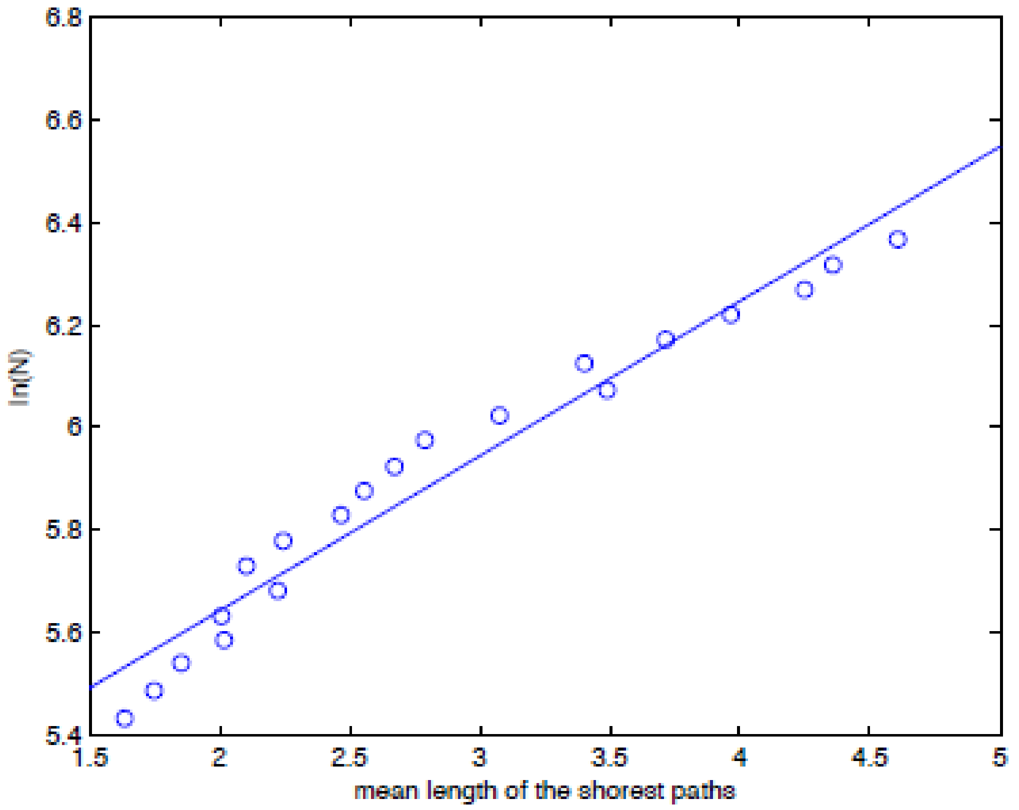
Most companies with high betweenness are located in developed areas.



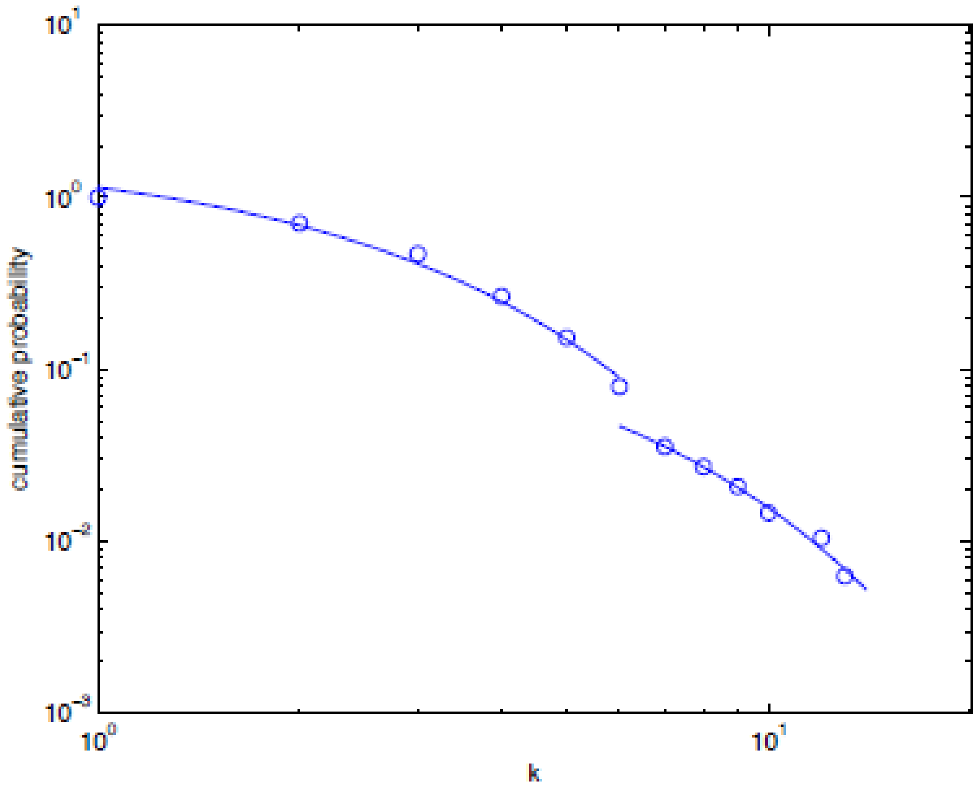


Probability density function of the shortest paths between two nodes of the Chinese VC network

Degree distribution of the Chinese venture capital network



A plot of *ln(N)* vs. $\bar{l}$ for the Chinese VC network. The open circles are the empirical data points and the blue line is its linear fit, $\ln N = 5.04 + 0.3\bar{l}$.



Cumulative degree distribution of the VC network in China. The empirical data gives

$$p = \begin{cases} e^{-0.39k+5.50}, k < 7 \\ e^{-0.27k-1.41}, k \geq 7 \end{cases}$$

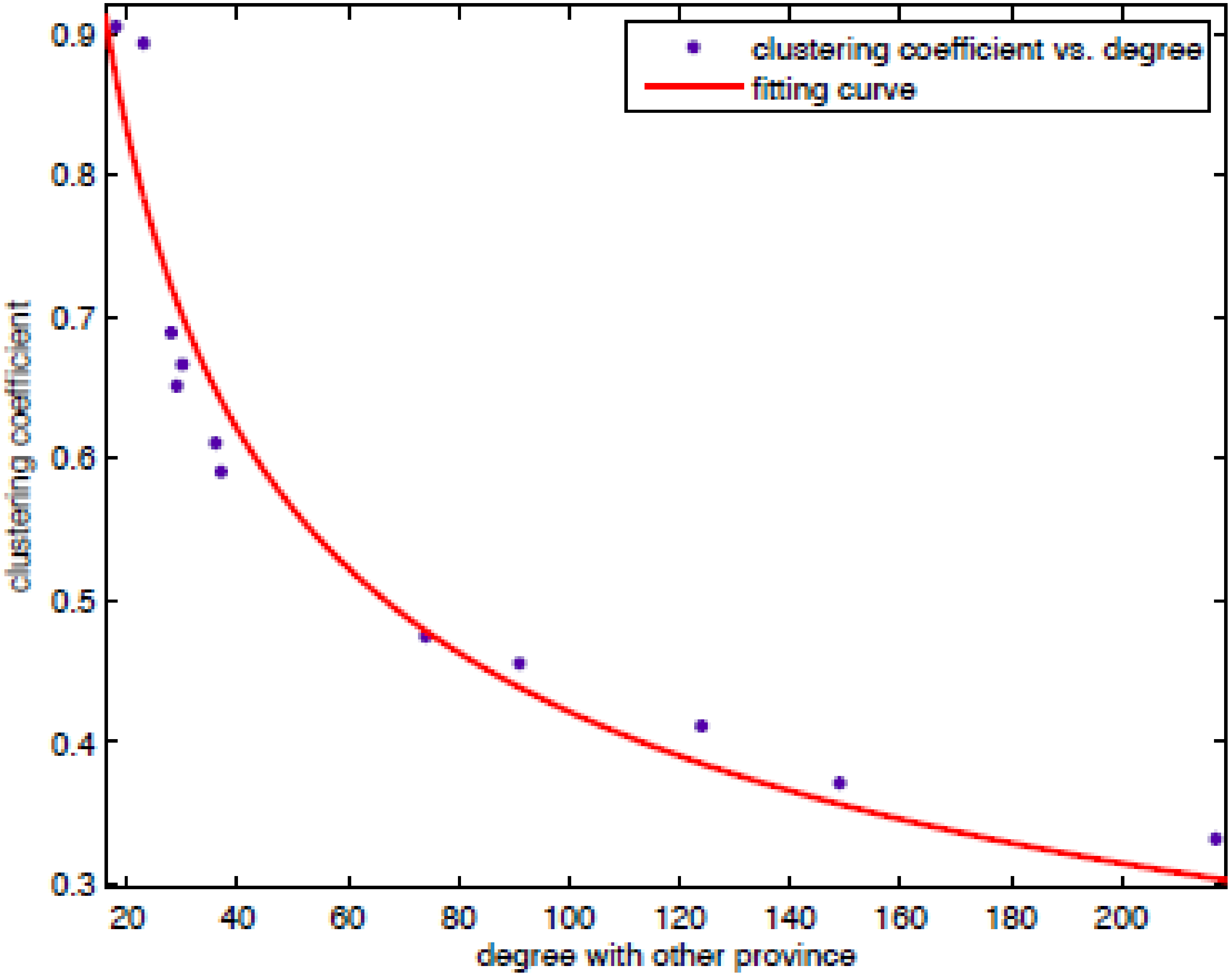
where p is the cumulative probability density function of the degree distribution.

Betweenness and its correlation with node degree

Node degree and district location of 20 venture capital companies with highest betweenness.

Venture capital company	District	Betweenness	Node degree
ShenZhen capital group	Guangdong	4.851	30
IER venture capital Co., Ltd.	Guangdong	1.926	6
ShenZhen OFC investment management Ltd.	Guangdong	1.855	8
ShenZhen CDF-capital company limited	Guangdong	1.532	6
Cowin capital	Guangdong	1.502	13
Guosen Hongsheng	Guangdong	1.497	12
National development creation capital management	Jiangsu	1.198	5
Borong investment	Guangdong	1.076	7
Green investment	Henan	1.012	9
China resources SZITIC trust Co., Ltd.	Guangdong	1.003	13
Fuhai Yintao venture capital	Guangdong	0.855	12
Nanchang venture capital	Jiangxi	0.839	3
Zhongbi fund	Shanghai	0.632	10
Jiangsu high-tech investment group Co., Ltd.	Jiangsu	0.557	8
Guangzhou Haihui growth of venture investment center	Guangdong	0.557	9
Shenzhen Tsinghua leaguer venture capital Co., Ltd.	Guangdong	0.549	5
CSM	Beijing	0.397	7
Shenzhen Hongling venture e-commerce	Guangdong	0.32	6
Hengxiang investment	Guangdong	0.32	10
GTJA innovation investment Co., Ltd.	Beijing	0.32	6

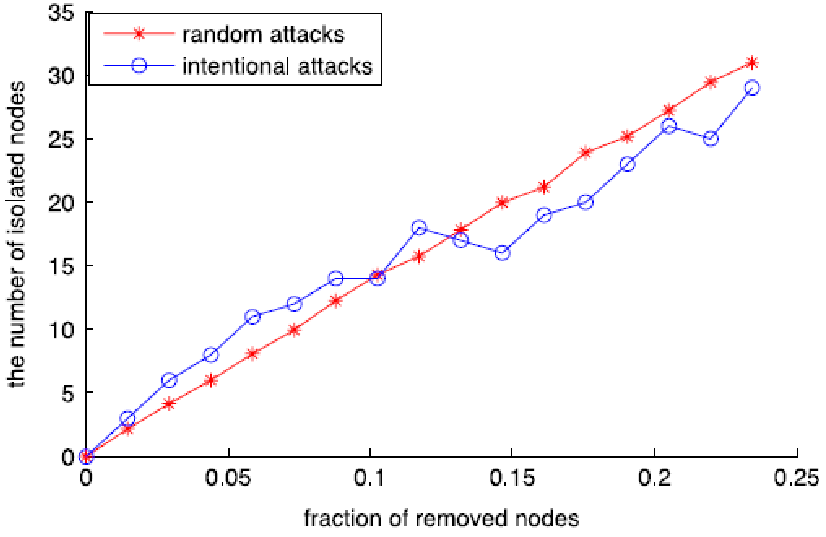
A linear fit gives $y = 0.78x - 1.17 \times 10^{-16}$, where y and x denote betweenness and degree respectively.



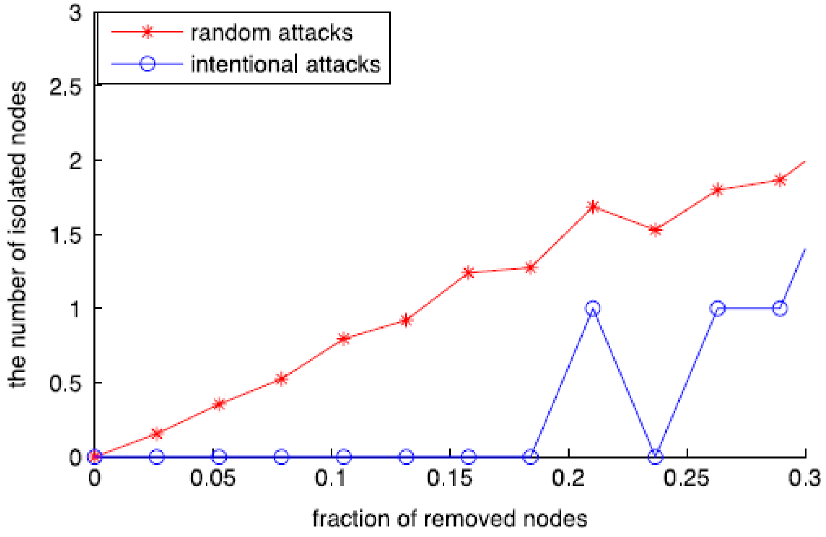
Clustering coefficient of a province/district as a function of its out-degree. One can fit the data points with an approximate power law function $y = 2.94x^{-0.42}$

Robustness

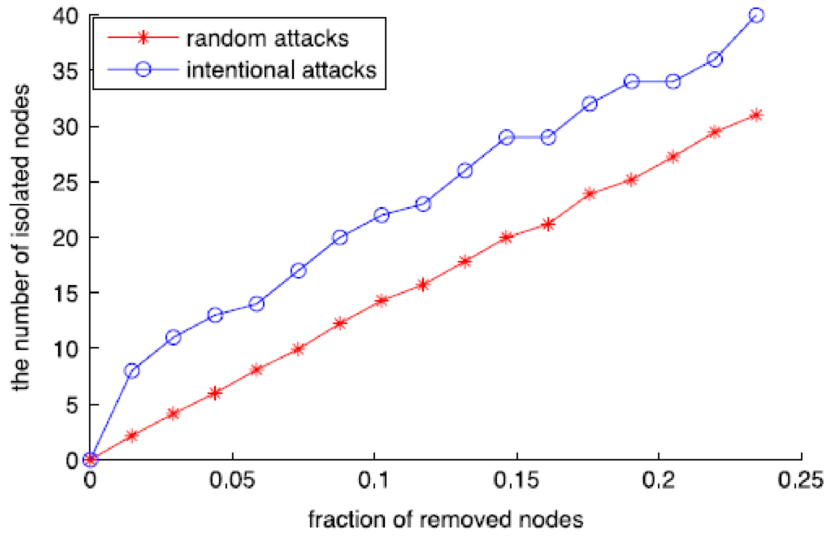
Number of isolated nodes vs. fraction of removed nodes in the VC network/the largest subnetwork. The red curve refers to random attacks (case 1) while the blue curve is for intentional attacks (case 2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



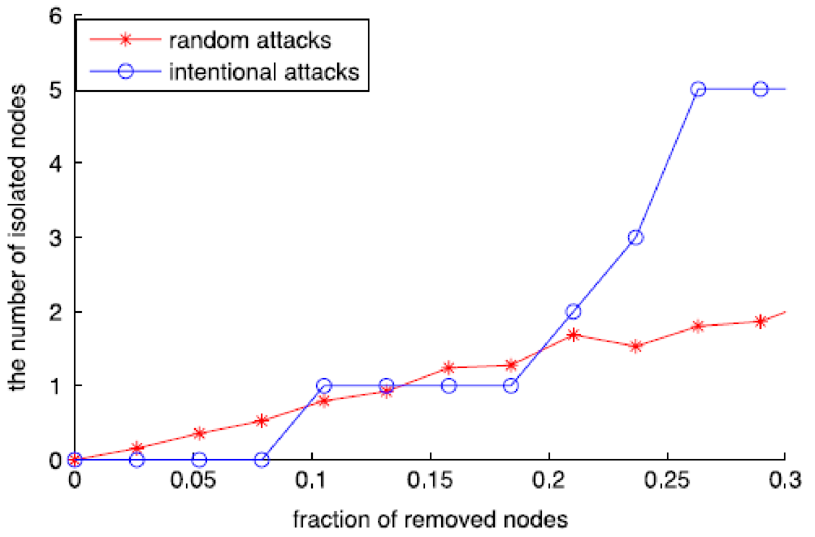
(a) The robust of the network using the method without recalculation.



(b) The robust of the largest subnetwork using the method without recalculation.



(c) The robust of the network using the method with recalculation.



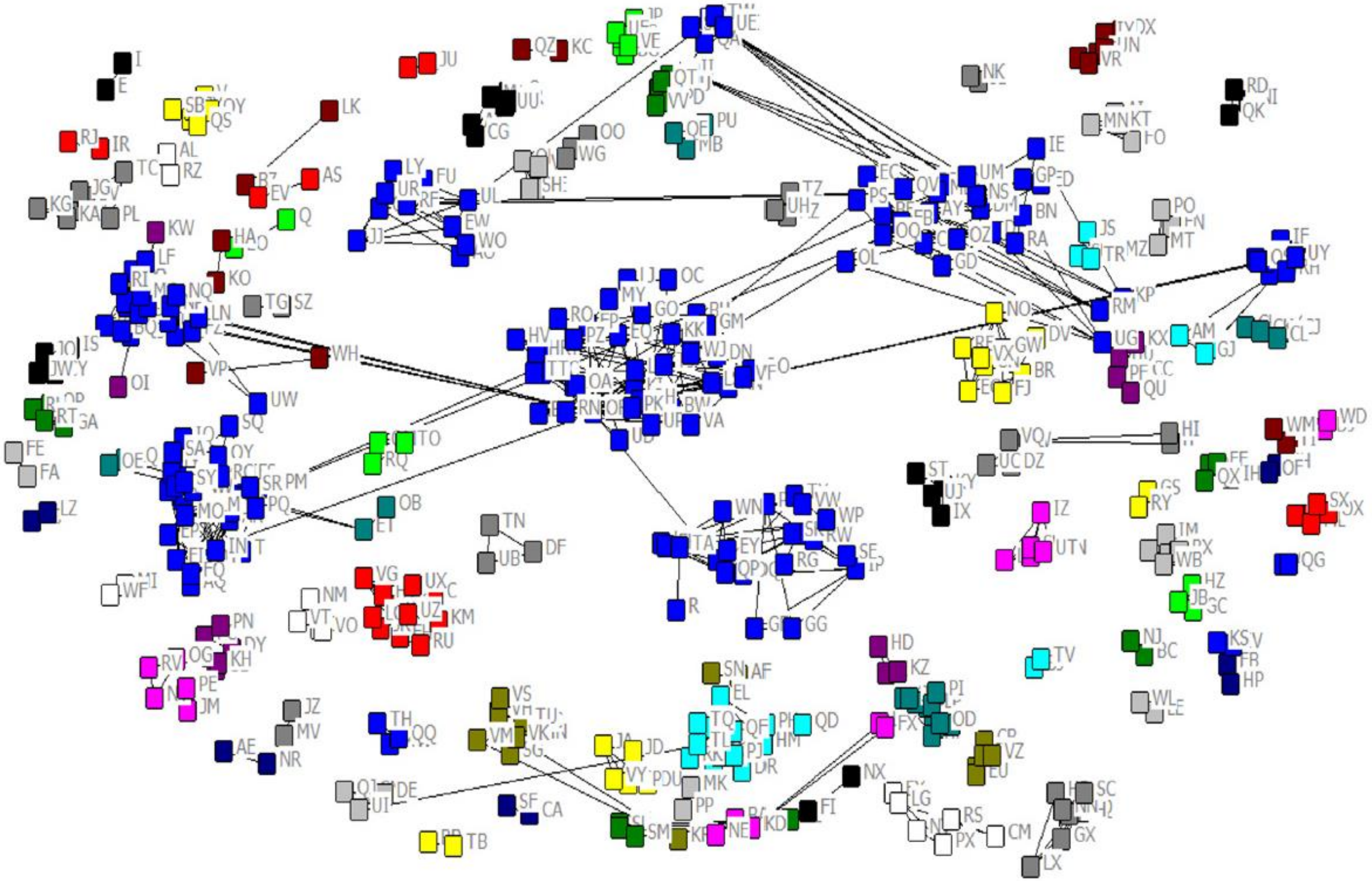
(d) The robust of the largest subnetwork using the method with recalculation.

Community detection of venture capital networks

We here adopt the *Girvan–Newman* method in the community detection of the Chinese venture capital network. Recall that the algorithm is generally stated as follows:

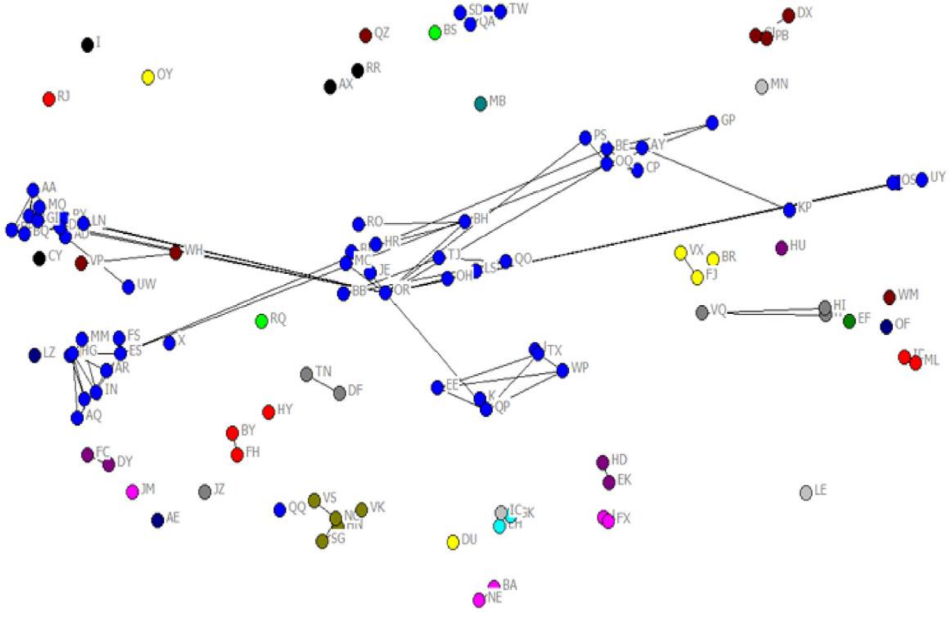
1) Compute the betweenness scores for all edges in the network;
2) Remove the edges with the highest betweenness scores;
3) Recalculate the betweenness scores for the network after the removal of edges;
4) Repeat steps 2 and 3 until the whole network is divided into N components.

Y.H. Jin et al., *Topological Properties and Community Detection of Venture Capital Network: Evidence from China*, Physica A442(2016)300-311.

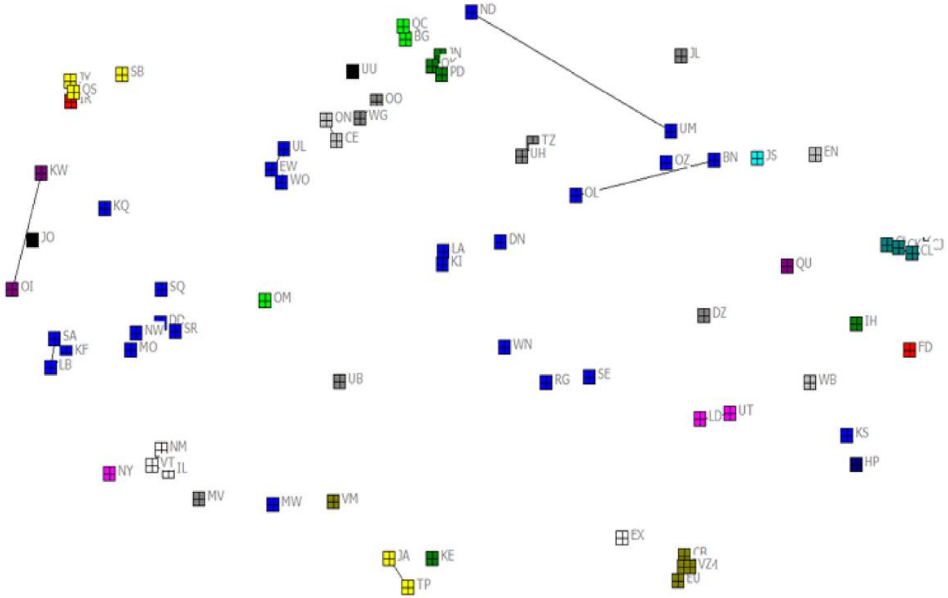


Community structure of the Chinese VC network using Girvan–Newman algorithm. The largest community has 38 nodes, and the smallest ones only comprise two nodes. The number of communities which consist of nodes more than 5 is 22.

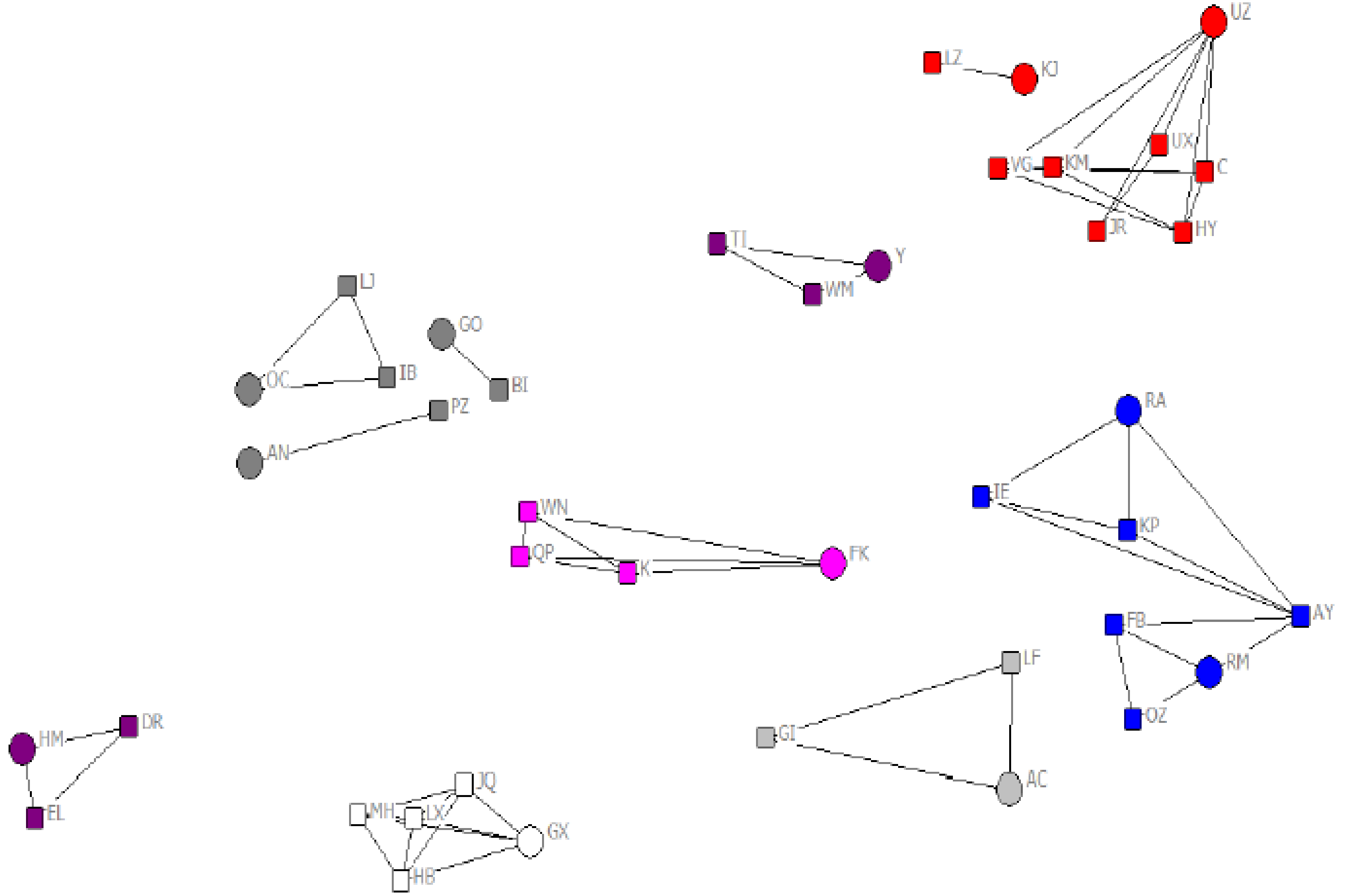
The VC network of
(a) Guangdong and,
(b) Shanghai.



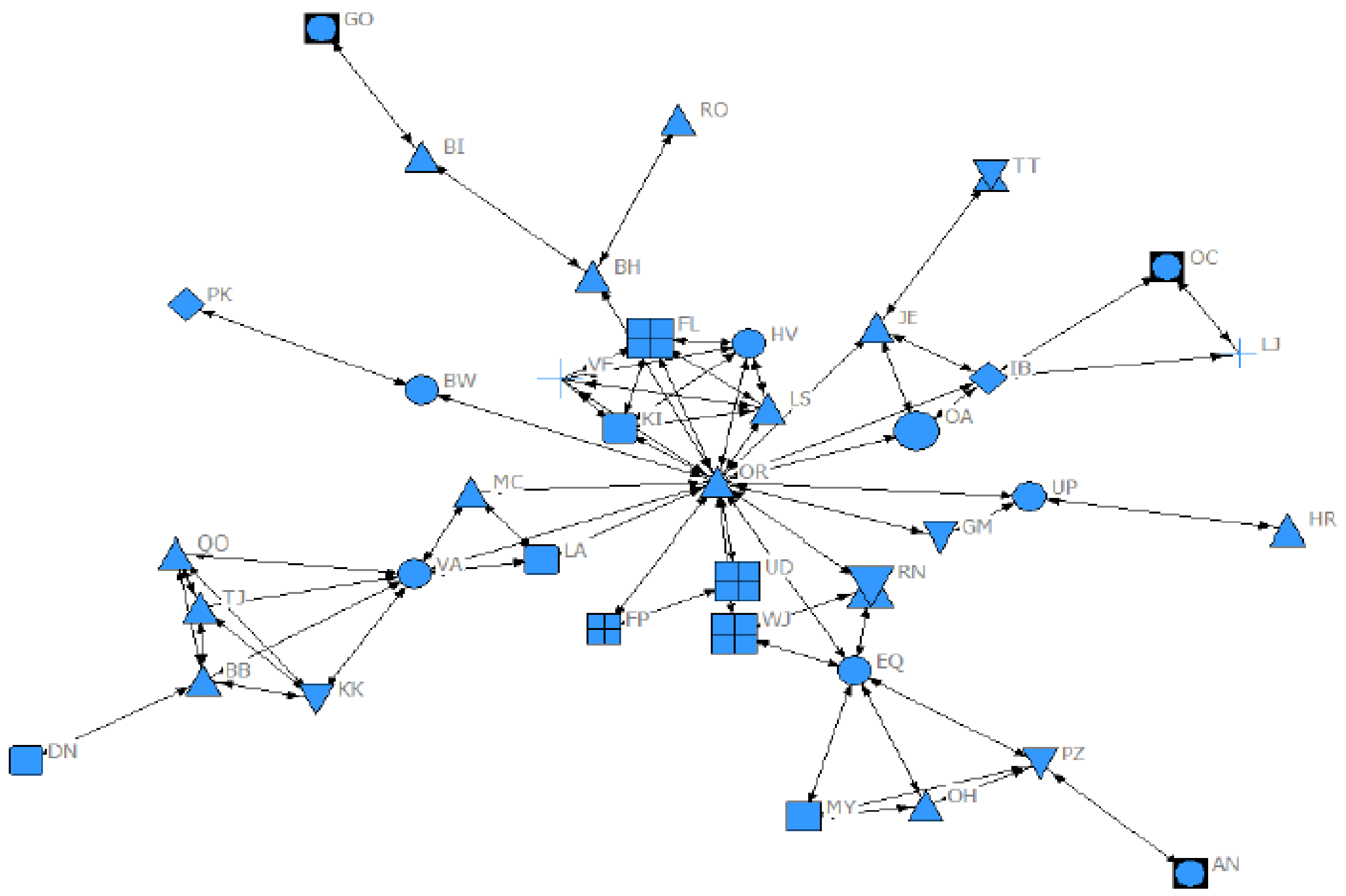
(a)



(b)

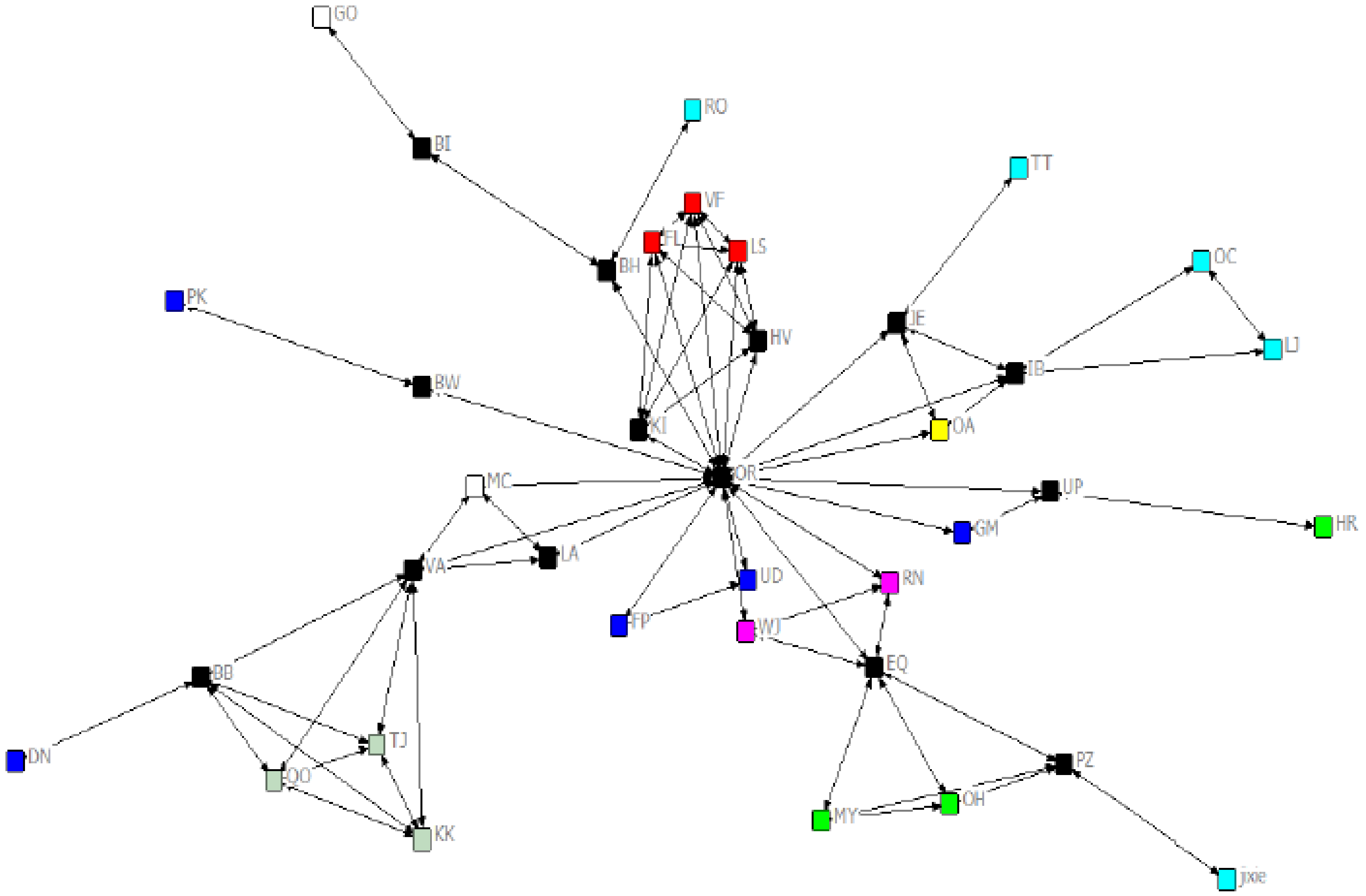


Connection of Hunan's venture capital companies and their ego-networks. Circles represent nodes in Hunan.



District location of VC networks largest community

District	Number of nodes	Color	District	Number of nodes	Color
Beijing	5	Circle	Jiangsu	2	Diamond
Fujian	1	Large size circle	Liaoning	1	Plus
Guangdong	12	Uptriangle	Shandong	1	Thing
Hainan	1	Square	Shanghai	3	Rounded square
Henan	1	Box	Sichuan	1	Large size plus
Hubei	3	Downtriangle	Tianjin	1	Large size thing
Hunan	3	Circlebox	Zhejiang	3	Large size box



Invested industry distribution of the largest community (Different colors indicate different industries, a node in black indicates that it invests in more than one industry)

Relationship with Regional Economy of the VC Network

Hypotheses:

H1: The ***economic aggregate*** of a region is positively correlated with the degree and the clustering coefficient of the VC sub-network of the region.

H2: The ***upgrade of industrial structure*** of a region is positively correlated with the degree and the clustering coefficient of the VC sub-network of the region.

H3: The ***employment rate*** of a region is positively correlated with the degree and the clustering coefficient of the VC subnet of the region.

H4: The ***remuneration of the resident*** of a region is positively correlated with the degree and the clustering coefficient of the VC subnet of the region.

Summary of clustering in the Chinese Venture Capital Network:

The clustering in the Chinese venture capital network is analyzed both the aspects of district location and invested industries.

Venture capital companies are mainly located in developed areas, such as Beijing, Guangdong, Shanghai, and Jiangsu, which offer VC companies more opportunities.

For a given district, the connection within the area only accounts for a small portion of links, implying that venture capital companies in developed areas are more willing to syndicate with companies in other districts.

Nodes within the largest community come from different district locations, suggesting that companies are more likely to co-invest with companies in other areas.

Industry investment is diversified within communities, meaning that the more industries the node invests, the larger degree it has. There are close connections among companies investing the same industry within communities, but is rare for companies between communities.

Economic indices of a region are all positively correlated with the degree and the clustering coefficient of the VC sub-network of the region, suggesting that the development of the VC industry has substantial effects on regional economy in China. (Y.H. Jin et al., PLOS ONE(2015)0137172.)

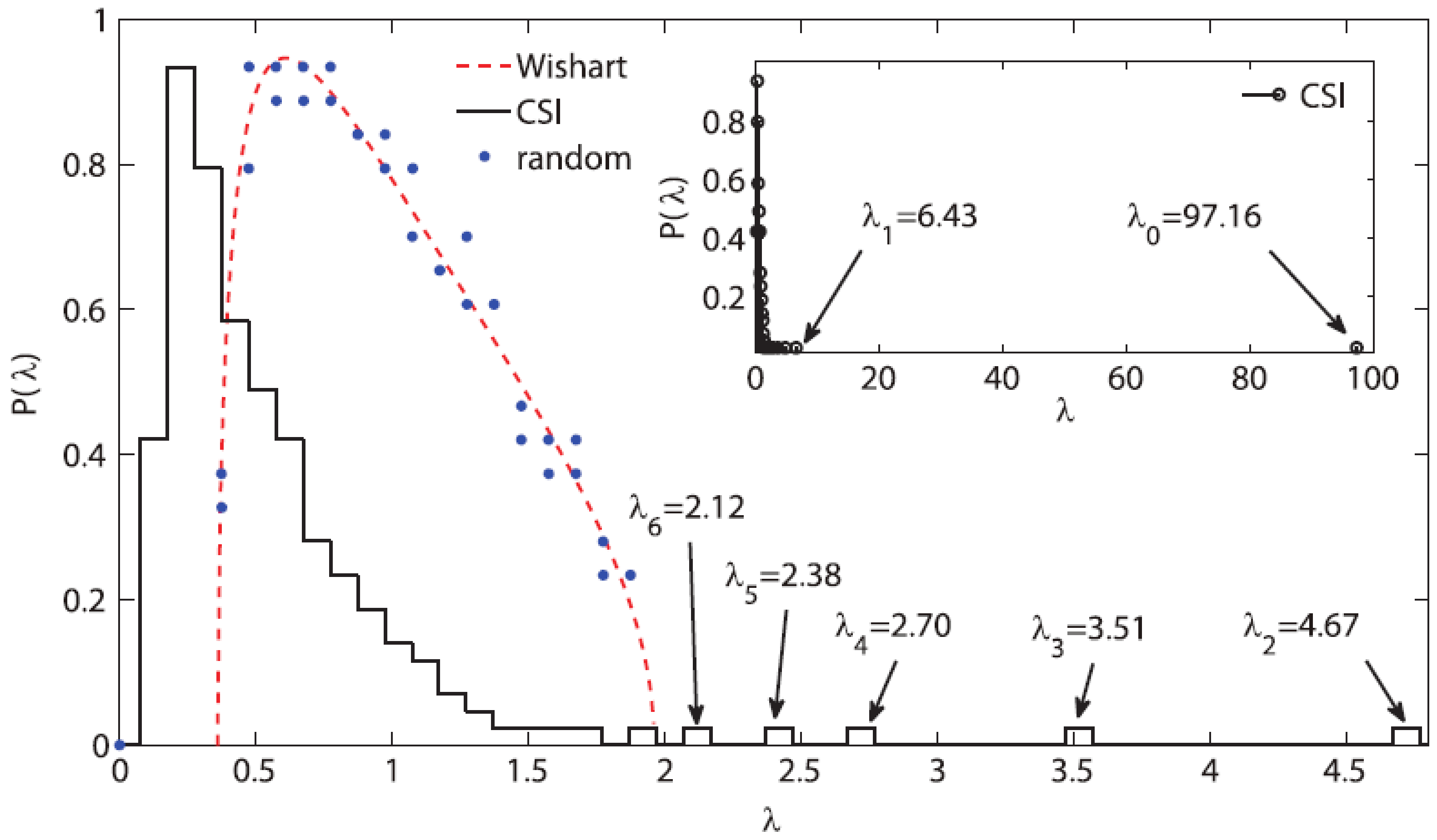
The Shanghai Stock Exchange Composite Index

“Analysis of Network Clustering Behavior of the Chinese Stock Market”, with Y. Mai and H. Chen, Physica A414(2014)360-7

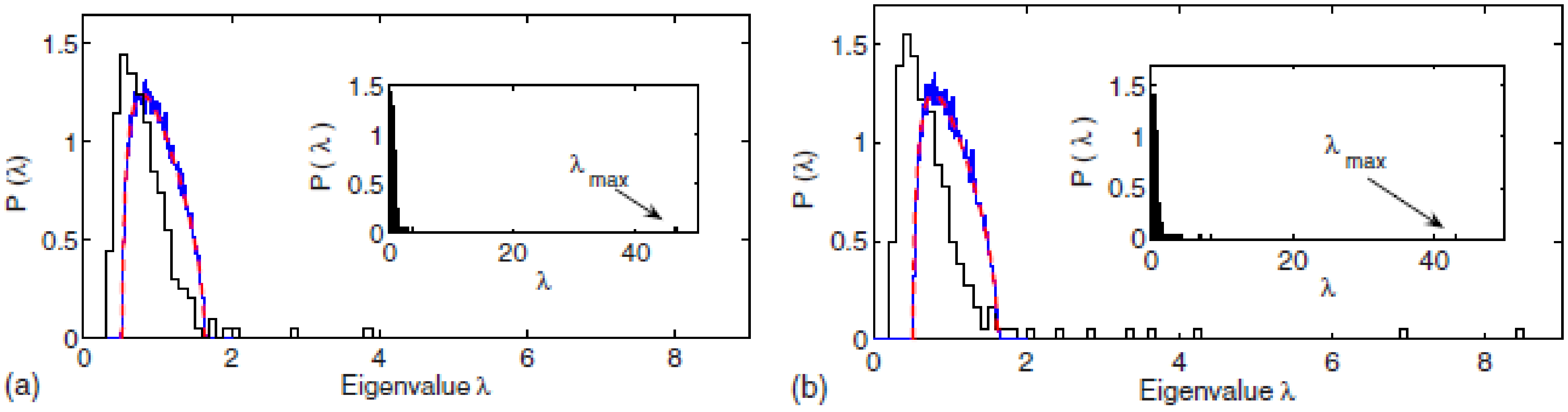
Table 1. China Industrial Classification Standard of CSI300

Industry	Code	Number of stocks	Closing price average	Closing price SD
Industrials	*IN*	64	14.19	29.90
Financials	*FI*	52	13.08	15.15
Materials	*MA*	51	16.52	36.60
Materials	*MA*	51	16.52	36.60
Consumer discretionary	*CD*	27	15.67	22.19
Energy	*EN*	23	20.13	32.50
Health care	*HC*	16	26.70	44.93
Consumer staples	*CS*	14	33.25	81.87
Utilities	*UT*	13	8.49	7.36
Information technology	*IT*	8	14.28	16.48
Telecommunication services	*TS*	3	14.28	29.44

** During the period October 9, 2007 through March 29, 2013, we choose 214 stocks, each has 1334 observations.

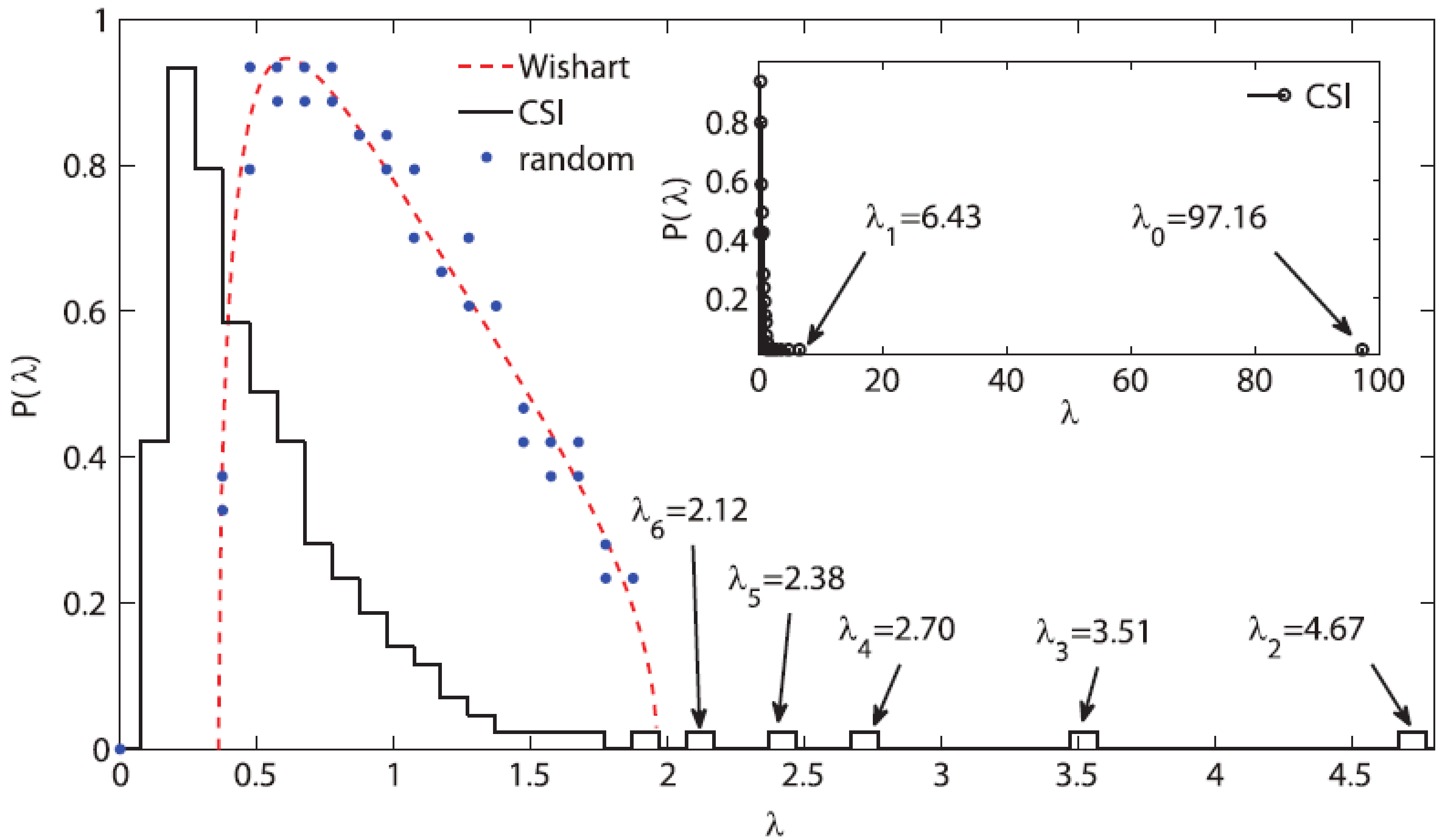


The probability distribution of the eigenvalues of the correlation matrix C for CSI300. (The red dotted curve is the distribution of the Wishart Matrix. The black curve is the probability distribution of the eigenvalues of the correlation matrix C. The blue data points are the distribution of the eigenvalues of the correlation matrix C for the reshuffled time series.)

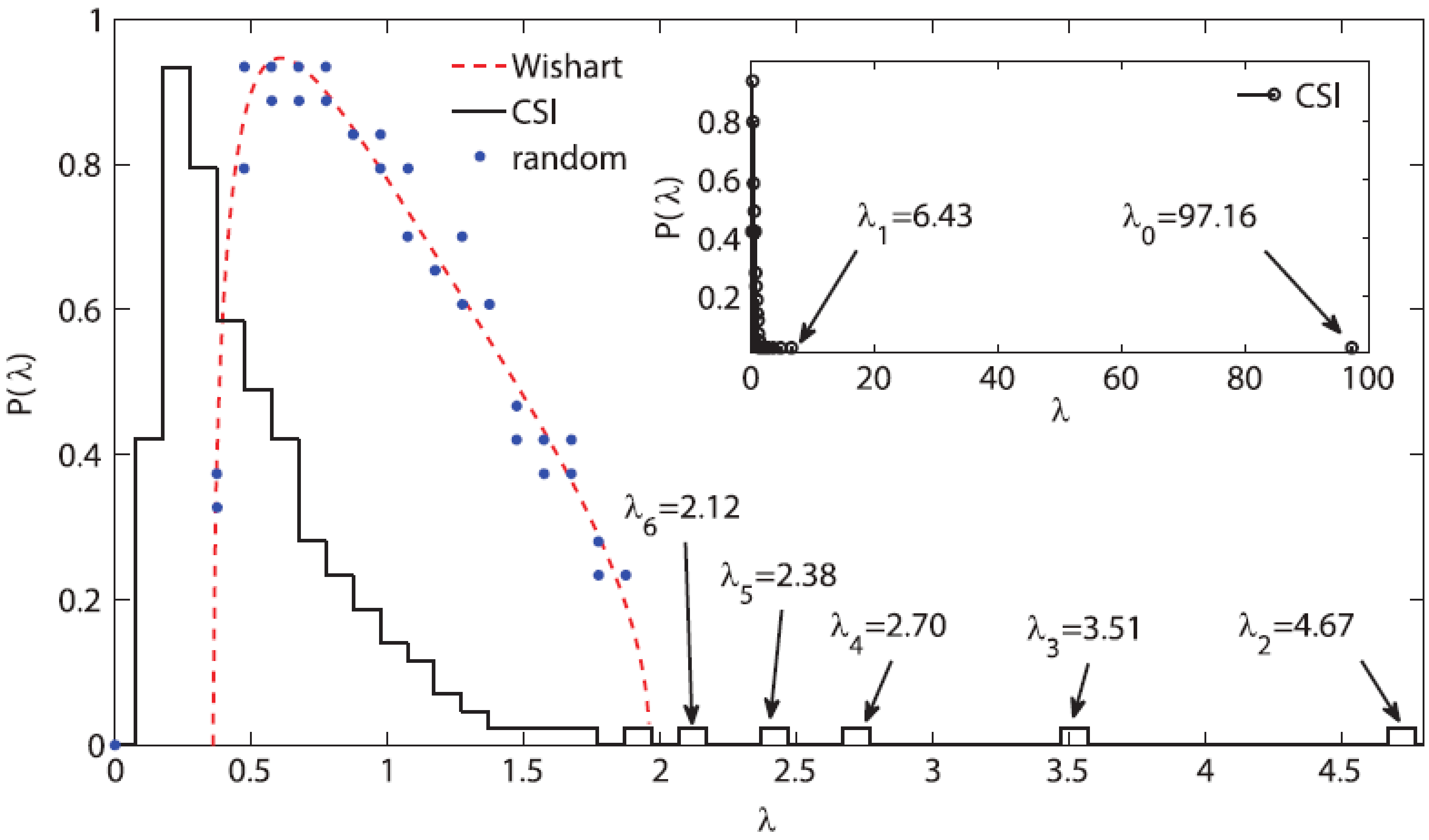


The probability density function of the eigenvalues of the correlation matrix C for (a) NSE (India) and (b) NYSE. For comparison, the theoretical distribution predicted by Wishart Matrix is shown using broken curves, which overlaps with the distribution obtained from the surrogate correlation matrix generated by randomly shuffling each time series.

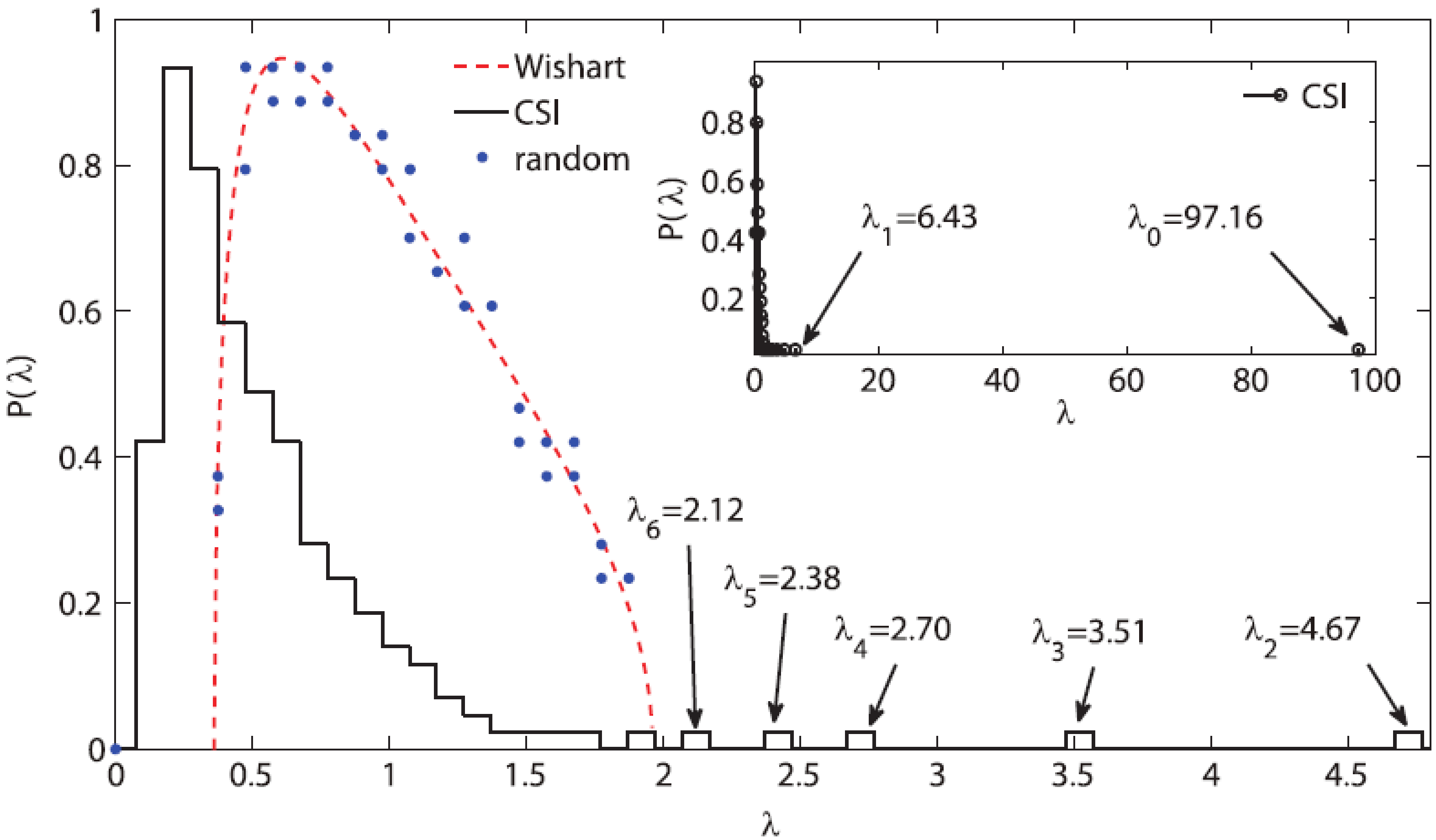
** R.K. Pan and S. Sinha, Phys. Rev. E 76 (2007) 046116.



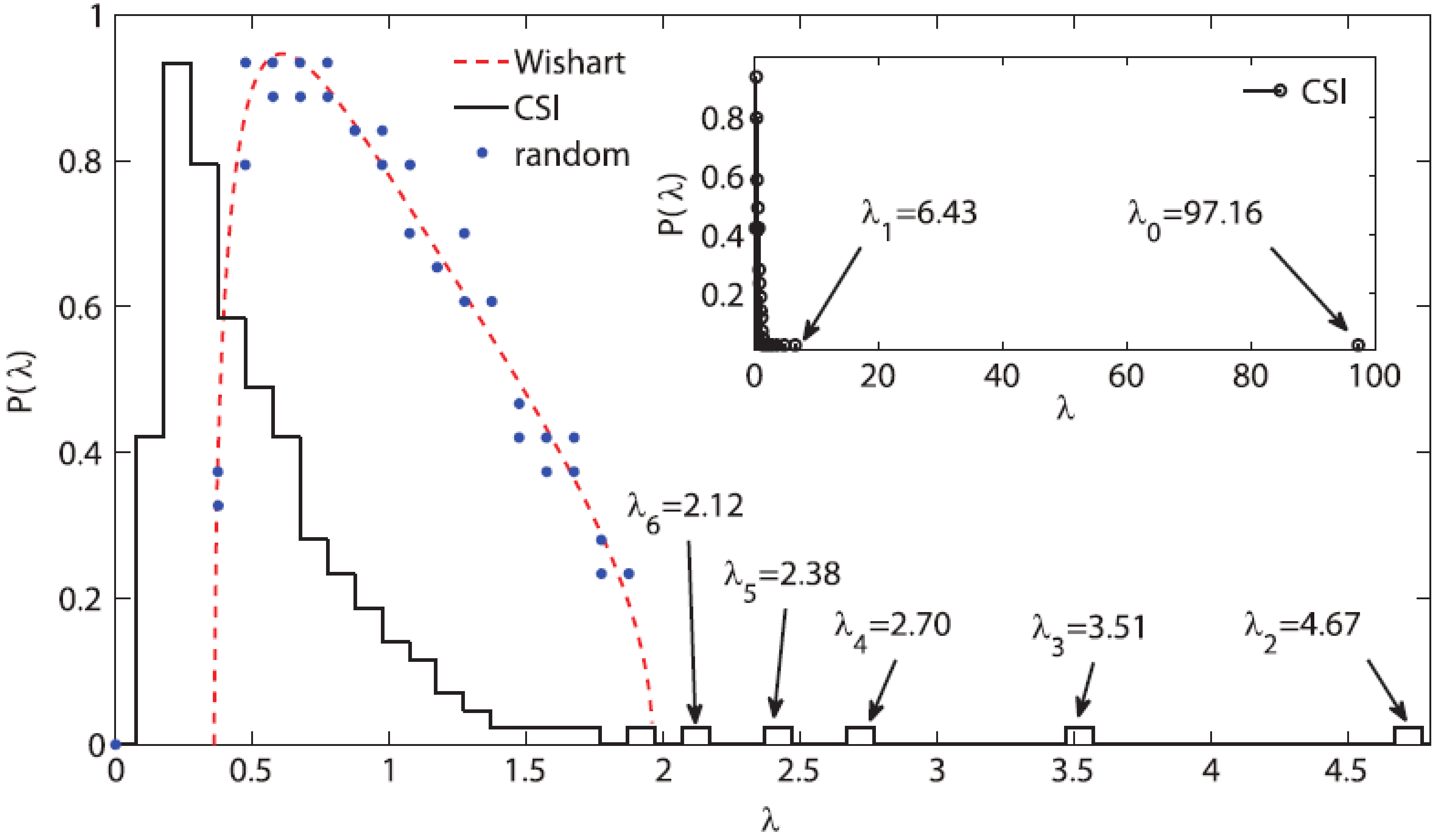
The bulk of the cross-correlation matrix eigenvalue spectrum $P(\lambda)$ is similar to $P_{rm}(\lambda)$, but some large eigenvalues exceed the upper bound of $\lambda_{\max}^{\text{ran}}$, suggesting non-random interactions. The largest eigenvalue λ_0 is associated with the market mode. The other large eigenvalues (λ_i, $\lambda_i > \lambda_{i+1}$, i=1,…) are more related to the dynamics of different sectors of the market.



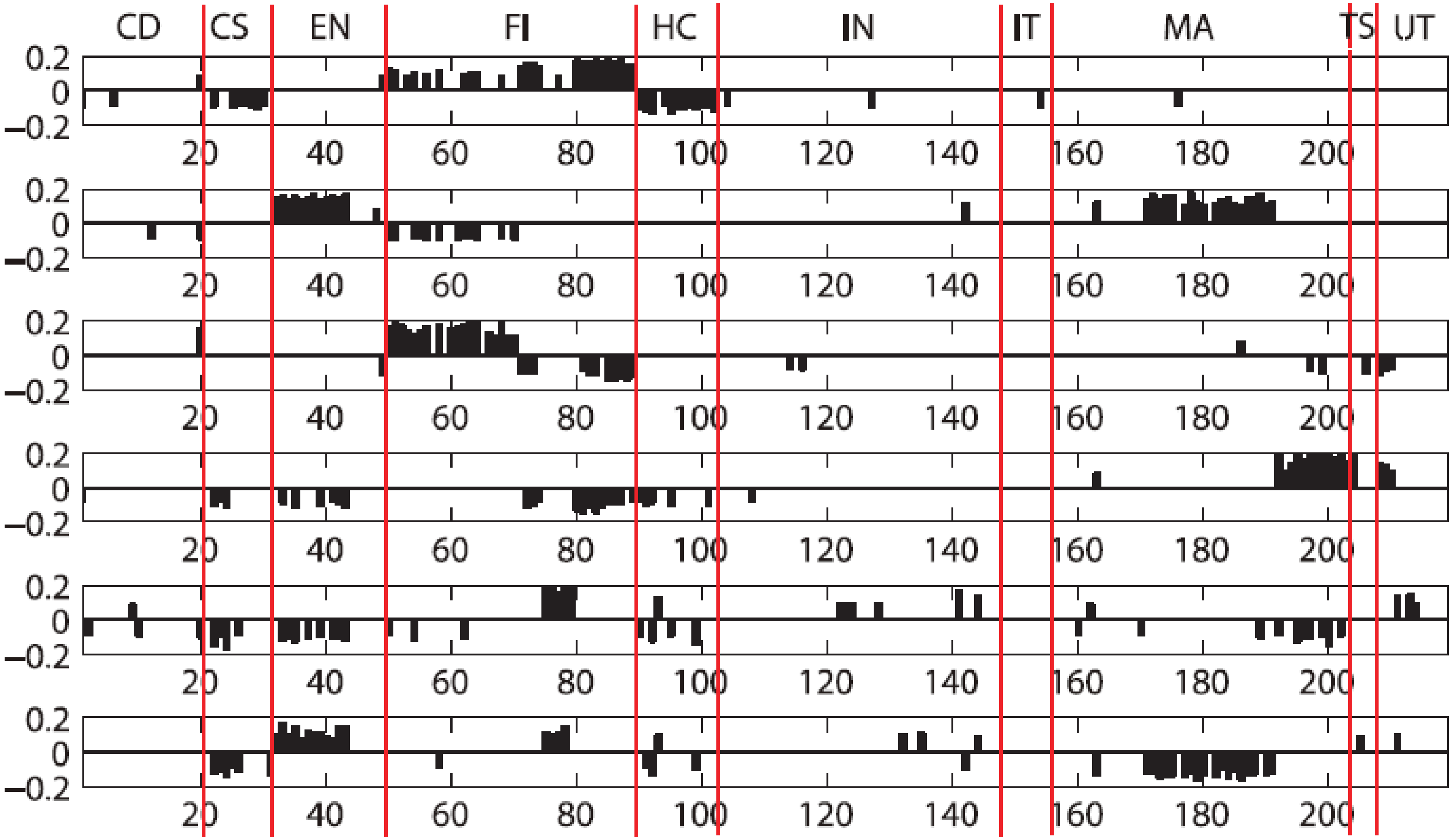
The largest eigenvalue λ_0 is about 97, more than 49 times the maximum value predicted by RMT and also much larger than the values of New York Stock Exchange (NYSE) and Indian National Stock Exchange (NSE), suggesting that the Chinese market is more vulnerable to external stimulation such as global financial crisis and austerity measures taken by the Chinese government.



We use $u_\alpha(i)$ to represent the *i-th* component of the eigenvector corresponding to eigenvalue λ_α . To identify the sector corresponding to a large eigenvalue λ_α, we introduce thresholds $u^+{}_c$ and $u^-{}_c$, and separate the sector into two subsectors, positive subsector with $u_\alpha(i) \geq u^+{}_c$ and negative subsector with $u_\alpha(i) \leq u^-{}_c$. We can study the anti-correlation property of the two subsectors.



As an example, we use $u^{\pm}{}_{c} = \pm u_c$ with $u_c \geq 1/\sqrt{N}$ (we use 0.08 in our analysis here).



Eigenvectors $u_{1,\ldots,6}$ of the six largest eigenvalues $\lambda_{1,\ldots,6}$ of the correlation matrix C. Each stock i in the eigenvector satisfies $|u_\alpha(i) \geq 0.08|$. The codes at the top correspond to the different sectors as listed in Table 1.

The cross-correlation $\boldsymbol{C}$ of the stocks can now be represented as

$$\boldsymbol{C} = \sum_{i=0}^{N-1} \lambda_i \boldsymbol{u}_i \, \boldsymbol{u}_i^{\,T}$$

where N is the total number of eigenvalues. One can decompose the correlation matrix into three components: the market component $\boldsymbol{C}^m$, the group component $\boldsymbol{C}^g$ and the random component $\boldsymbol{C}^r$.

$$\boldsymbol{C} = \boldsymbol{C}^m + \boldsymbol{C}^g + \boldsymbol{C}^r =$$
$$\lambda_0 \boldsymbol{u}_0 \boldsymbol{u}_0^{\,T} + \sum_{i=1}^{n} \lambda_i \boldsymbol{u}_i \, \boldsymbol{u}_i^{\,T} + \sum_{i=n+1}^{N-1} \lambda_i \boldsymbol{u}_i \, \boldsymbol{u}_i^{\,T}$$

$\boldsymbol{C}^g \left(= \sum_{i=1}^{n} \lambda_i \boldsymbol{u}_i \, \boldsymbol{u}_i^{\,T}\right)$ can be used to construct an interaction network for the stocks to understand the interaction nature of stocks within sectors and to compare with the results shown in Table 2.

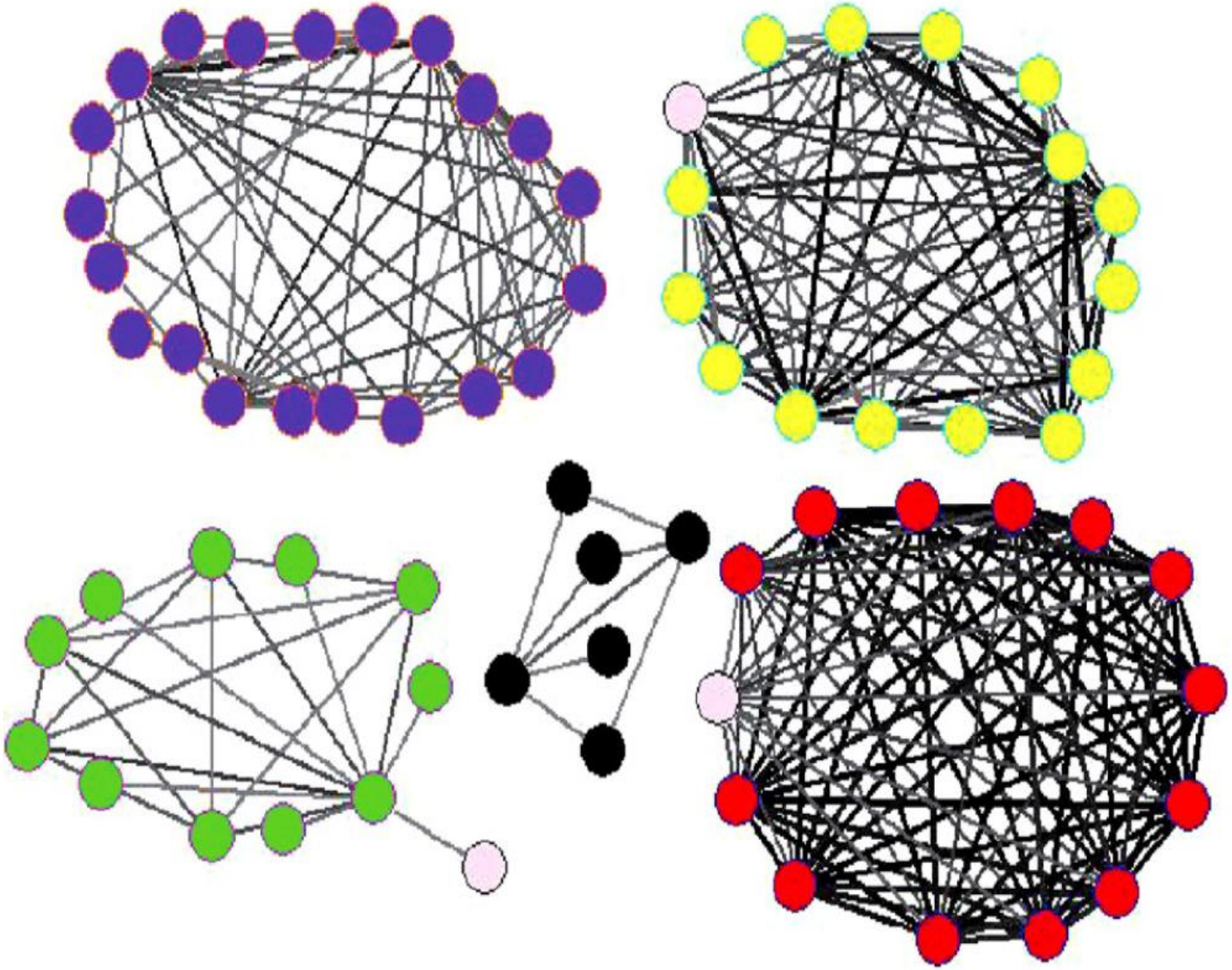
Define A to be the linking matrix of the stock interaction network.

If $C^g{}_{ij} > c_{th}$, where c_{th} is a preset threshold value, then $A_{ij} = C^g{}_{ij}$, i.e., there is a link between stock i and stock j, otherwise, A_{ij} = 0.

Table 2. Subsector structure of the CSI300 for the period from 2007 through 2013

	λ_1		λ_2		λ_3		λ_4	
Sign	+	−	+	−	+	−	+	−
Dominant industry	CB&RE	PH&DV	MI	RE	RE	CB	ST	\
$u_c^{\pm} = 0.08$	25/29	22/30	38/40	22/24	19/27	13/23	12/24	\
$u_c^{\pm} = 0.09$	23/24	18/24	36/38	20/21	18/21	12/15	12/20	\
$u_c^{\pm} = 0.10$	19/20	12/15	25/26	16/16	14/15	12/13	12/16	\

** "Sign" here refers to the sign of their components of the corresponding eigenvectors. The denominator represents the total number of stocks within the subsector and the numerator represents the number of stocks of the dominant industry.



The interaction network when the threshold c_{th}=0.16. (The yellow, red, green, purple and black nodes denote stocks in the RE, CB, PH&DV, MI, and ST sectors respectively. The pink nodes denote stocks from other sectors.

Network Construction of MST and PMFG

Define the logarithmic price return $R_i(t)$ of stock *i* on trading day *t* as

$$R_i(t) = \ln p_i(t) - \ln\, p_i(t-1)\,,$$

where $p_i(t)$ is the closing price of the i^{th} stock on trading day *t*. To compare the result of different datasets, we further normalize the logarithmic price return as follows

$$r_i(t) = \frac{R_i(t) - <R_i(t)>}{\sqrt{<R_i(t)^2> - <R_i(t)>^2}}$$

where <*X*> stands for the average of *X* during the trading period.

We define the cross-correlation of stocks *i* and *j* as

$$C_{ij} = < r_i(t) r_j(t) >$$

C_{ij} is a symmetric matrix with values between -1 and 1.

Network Construction of MST and PMFG (cont'd)

The correlation coefficients are converted into distances by the following equation,

$$d(i,j) = \sqrt{2\left(1 - C_{ij}\right)} \ ,$$

which ranges between 0 and 2.

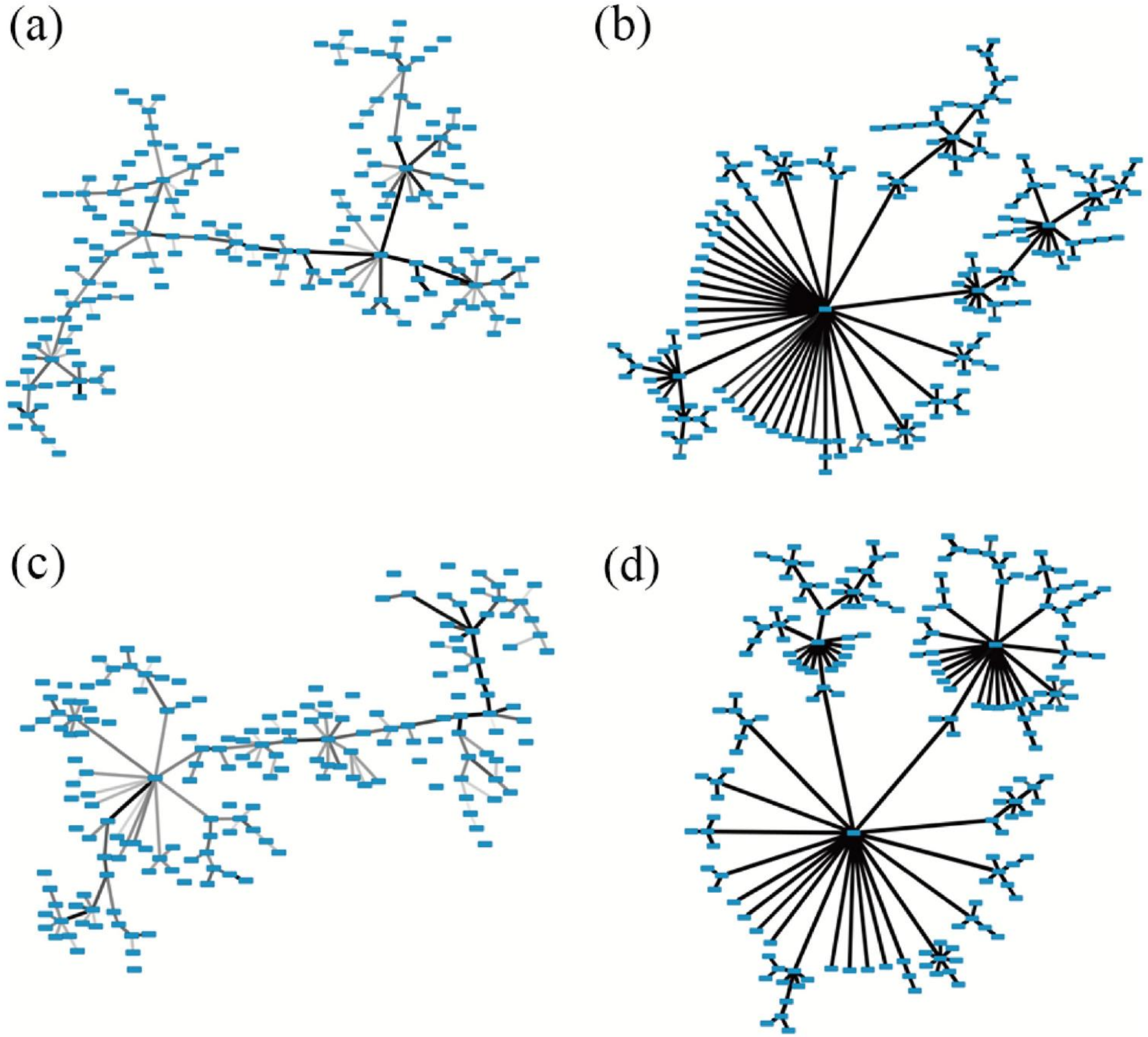
For PMFG, we use the following procedures:

(1) Rank the distance elements between all pairs of stocks in an ascending order.

(2) Add an edge between the nearest nodes, the pair with the smallest distance, if and only if the resulting graph can still be embedded on a planar without any curves crossing after such edge insertion.

(3) Repeat the previous step until no more edge can be added.

Applications in Portfolio Management



Evolution of network structure. (a) MST network for the Shanghai A-Share market in the period from January 1, 2000 to October 31, 2000; (b) MST network for the Shanghai A-Share market in the period from January 1, 2008 to October 31, 2008; (c) MST network for the Shenzhen A-Share market in the period from January 1, 2000 to October 31, 2000; (d) MST network for the Shenzhen A-Share market in the period from January 1, 2008 to October 31, 2008. Distances between stocks are indicated by line width: A thicker line represents a shorter distance while a thinner line represents a longer distance.

Applications in Portfolio Management

A dynamic portfolio strategy based on the time-varying structures of MST networks in Chinese stock markets, where the market condition is further considered when using the optimal portfolios for investment.

Comprises two stages:

First, select the portfolios by choosing central and peripheral stocks in the selection horizon using five topological parameters, namely *degree, betweenness centrality, distance on degree criterion, distance on correlation criterion* and *distance on distance criterion.*

Second, use the portfolios for investment in the investment horizon.

The optimal portfolio is chosen by comparing central and peripheral portfolios under different combinations of market conditions in the selection and investment horizons. Market conditions include *drawup, drawdown* and *stable conditions* by using four criteria: *(I) trading day criterion, (II) amplitude criterion, (III) "OR" criterion, and (IV) "AND" criterion.*

Applications in Portfolio Management

- Degree *K*, the number of neighbor nodes connected to a node. The larger the *K* is, the more the edges that are associated with this node.

- Betweenness centrality *C*, reflecting the contribution of a node to the connectivity of the network. Denote V as the set of nodes in the network. For nodes *i* and *j*, *C* of a node *k* can be calculated as

$$C = \sum_{i,j \in V} \frac{\sigma_{ij}(V)}{\sigma_{ij}},$$

  where σ_{ij} is the number of shortest routes from node *i* to node *j*, $\sigma_{ij}(V)$ is a subsector of σ_{ij} whose routes pass through this node *k*.

- Distance on degree criterion D_{degree}, a central node is the node that has the largest degree.

- Distance on correlation criterion $D_{correlation}$, a central node is the node with the highest value of the sum of correlation coefficients with its neighbors;

- Distance on distance criterion $D_{distance}$, a central node is the node that gives the smallest value for the mean distance.

Applications in Portfolio Management

(I) Trading day criterion. The ratio r_d of the number of days with rising index to the total number of trading days in a specific time window is given by

$$r_d = \frac{N_i^+}{N_i},$$

where N_i^+ is the number of days in which the closing price is larger than that of the previous day and N_i is the total number of trading days in the i^{th} time window. The ratio r_d ranges from 0 to 1. A large value of r_d represents a drawup condition while a small value of r_d represents a drawdown condition. With the thresholds θ_+ and θ_-, we identify a drawup condition if $r_d > \theta_+$, a drawdown condition if $r_d < \theta_-$, and a stable condition if $\theta_- \leq r_d \leq \theta_+$.

(II) Amplitude criterion. The ratio r_f of the sum of the amplitudes of the trading days with rising index to the sum of the amplitudes of the total trading days in a specific time window is given by

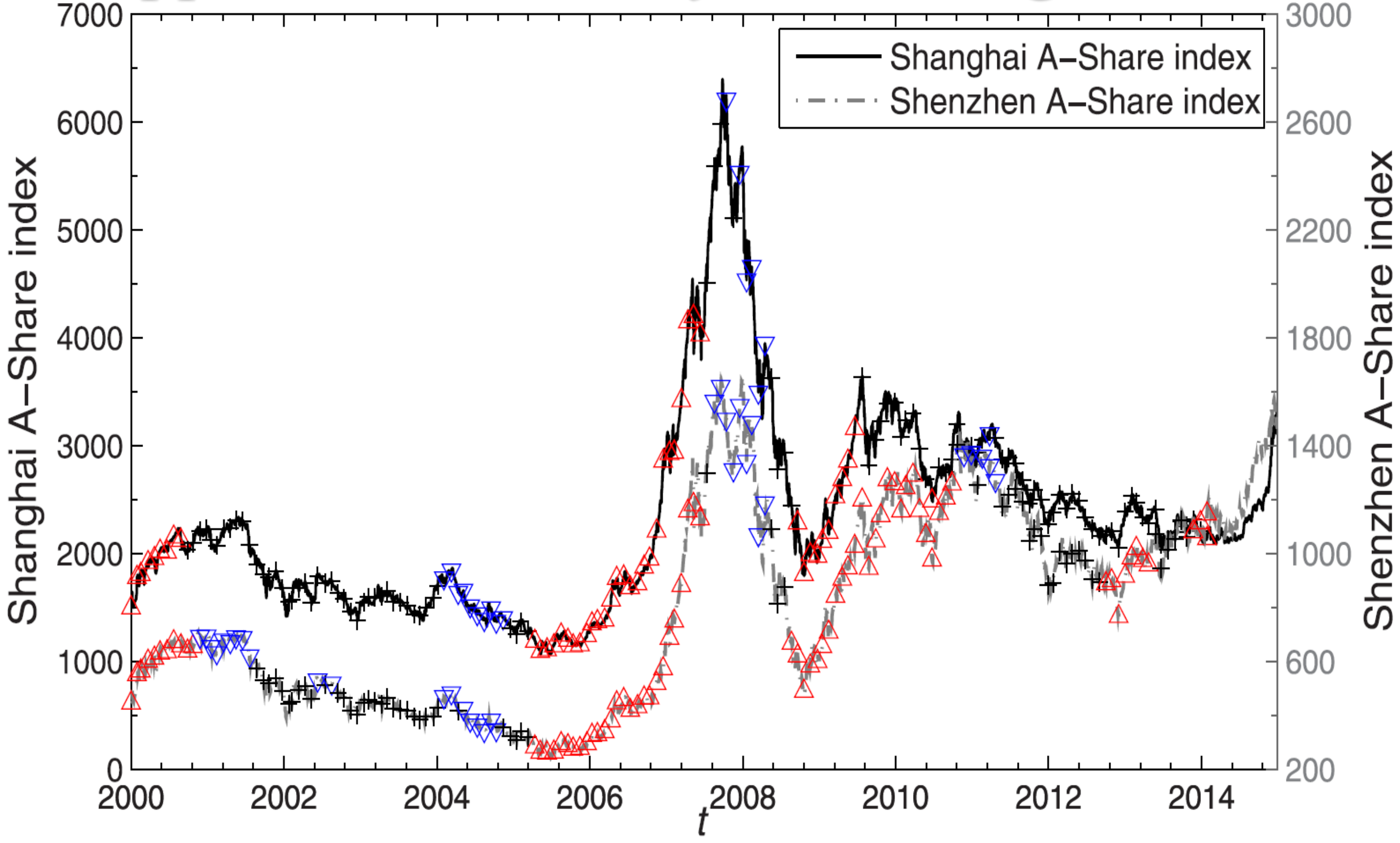
$$r_f = \frac{\sum_{t \in T_i^+} |P(t) - P(t-1)|}{\sum_{t \in T_i} |P(t) - P(t-1)|},$$

where T_i^+ is the set of days in which the closing price is larger than that of the previous day, T_i is the set of all the trading days in the i^{th} time window, and $P(t)$ is the closing price on the t^{th} day. Similarly, with the thresholds θ_+ and θ_-, we identify a drawup condition if $r_f > \theta_+$, a drawdown condition if $r_f < \theta_-$, and a stable condition if $\theta_- \leq r_f \leq \theta_+$.

(III) "OR" criterion. We identify a drawup condition if $r_d > \theta_+$ or $r_f > \theta_+$, and a drawdown condition if $r_d < \theta_-$ or $r_f < \theta_-$. A stable condition is identified if $\theta_- \leq r_d \leq \theta_+$ and $\theta_- \leq r_f \leq \theta_+$. Situations like if $r_d > \theta_+$ and $r_f < \theta_-$, or $r_f > \theta_+$ and $r_d < \theta_-$ do not exist for the thresholds that we choose.

(IV) "AND" criterion. We identify a drawup condition if $r_d > \theta_+$ and $r_f > \theta_+$, and a drawdown condition if $r_d < \theta_-$ and $r_f < \theta_-$. A stable condition is identified if $\theta_- \leq r_d \leq \theta_+$ or $\theta_- \leq r_f \leq \theta_+$. Situations like $r_d > \theta_+$ and $r_f < \theta_-$, or $r_f > \theta_+$ and $r_d < \theta_-$ do not exist for the thresholds that we choose.

Applications in Portfolio Management



Market conditions identified based on trading day criterion for the Shanghai and Shenzhen A-Share markets. Market conditions include drawup (upright triangle), drawdown (inverted triangle) and stable (cross) conditions.

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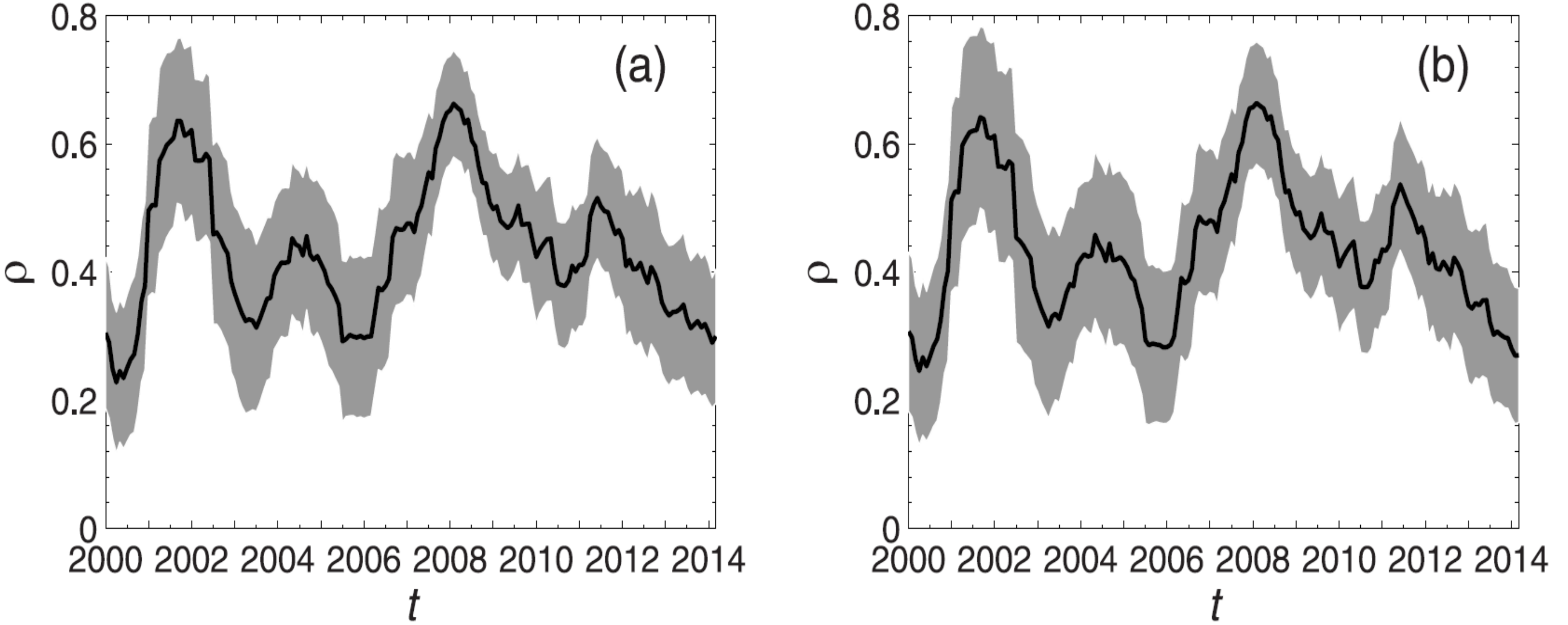

Evolution of the average of the correlation coefficients in the Shanghai A-Share market (a) and Shenzhen A-Share market (b). The average of the correlation coefficients are shown by the black solid lines in the center, and correlation coefficients ranging within one standard deviation of the average are shown in the grey area.

F. Ren et.al., PLOS ONE, http://dx.doi.org/10.1371/journal.pone.0169299 , 2017.

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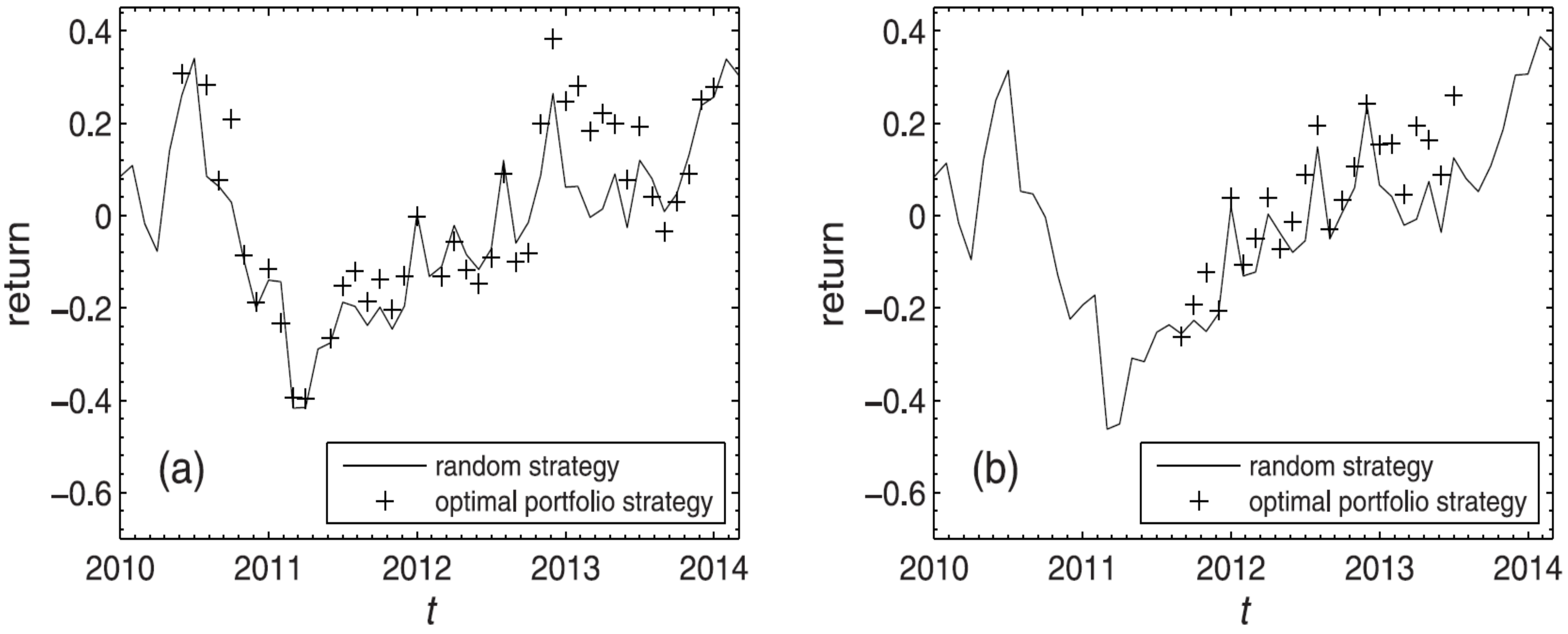


Average returns of the most profitable strategy (cross) and random strategy (black solid line) for the Shanghai A-Share market (a) and the Shenzhen A-Share market (b).

Applications in Portfolio Management

Example of Extension: Incorporating momentum effect and market trend prediction

Construct three types of portfolio: Central, Peripheral and Dispersed.

The momentum effect – Rising stocks will continue to rise and the falling stocks will continue to fall.

Buy stocks that had high returns over the recent past, and sell those that had poor returns over the same period.

Define a score is to measure the average past performance of a portfolio weighted by a time factor

$$score^{i}(\tau) = \Sigma_{T=1}^{6} R_{\tau,T}^{i} \times weight_{T}$$

$$weight_{T} = \frac{T}{\Sigma_{T=1}^{6} T}$$

Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

Applications in Portfolio Management

Market trend prediction methods:

(1) Linear regression (LR) model $\Rightarrow$ $\widetilde{IR_\tau} = \beta_0 + \Sigma_{T=1}^{6} \beta_T IR_{\tau,T}^{ob}$

(2) Weighted moving average (WMA) model $\Rightarrow$ $\widetilde{IR_\tau} = \Sigma_{T=1}^{6} weight_T IR_{\tau,T}^{ob}$

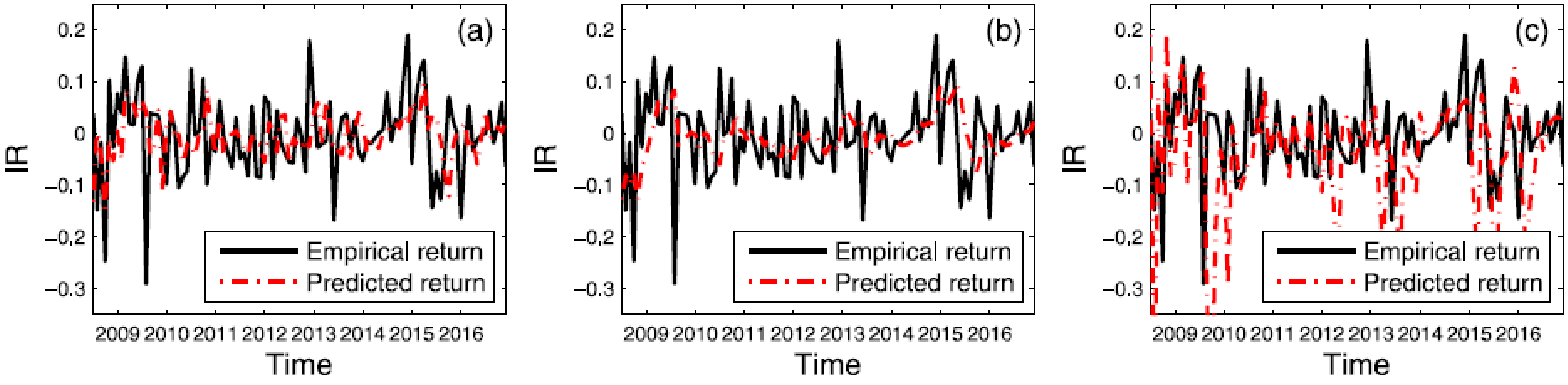
(3) Back Propagation (BP) neural network model $\Rightarrow$ $\widetilde{IR_\tau} = \Sigma_{y=1}^{Y} \alpha_y f(\Sigma_{T=1}^{6} Q_{yT} IR_{\tau,T}^{ob} - \vartheta_y)$

IR_τ and $\widetilde{IR_\tau}$ are the empirical and predicted index returns.

$$Hit = \frac{1}{N}\Sigma_{i=1}^{N}\eta_i \quad ; \quad \eta_i = 1 \text{ if } IR_\tau \widetilde{IR_\tau} > 0, \text{ and } \eta_i = 0 \text{ otherwise}$$

Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

Applications in Portfolio Management



Comparison between the empirical index return and the predicted index returns using three types of models: (a) linear regression model, (b) weighted moving average model, and (c) BP neural network model. The black solid curve represents the empirical return, and the red dashed curve represents the predicted return.

Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

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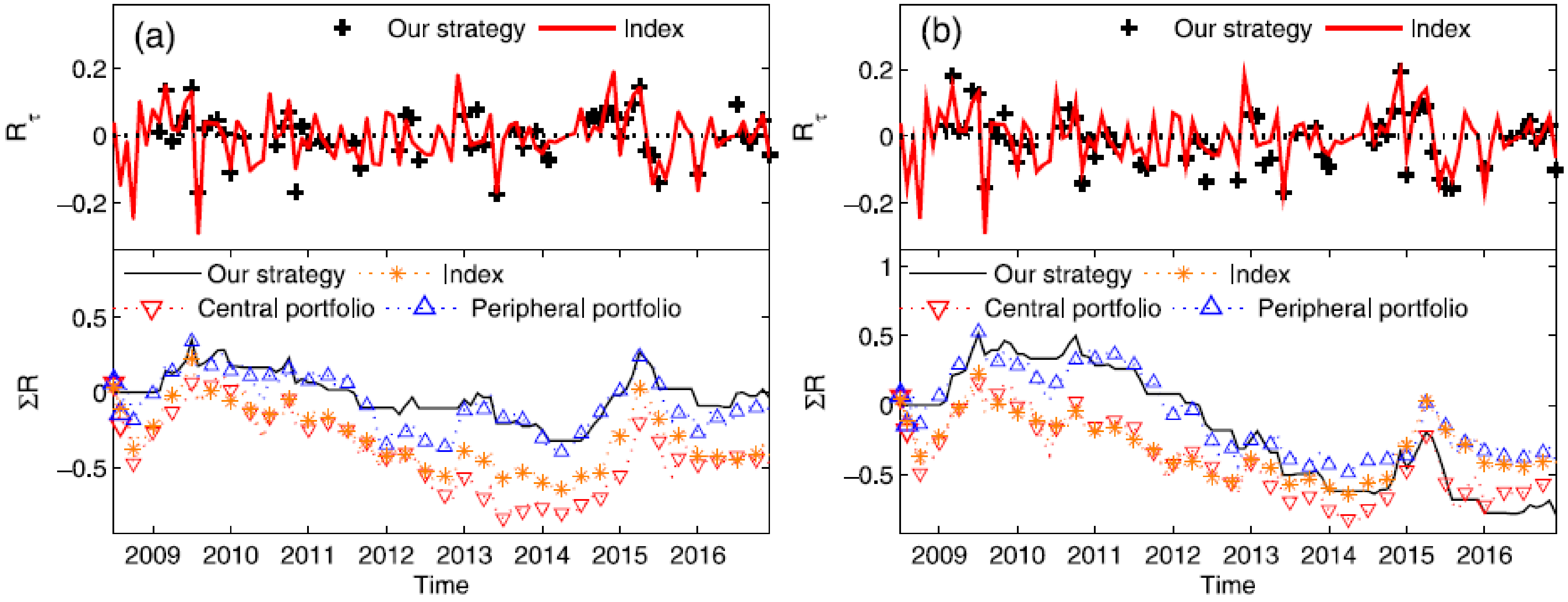
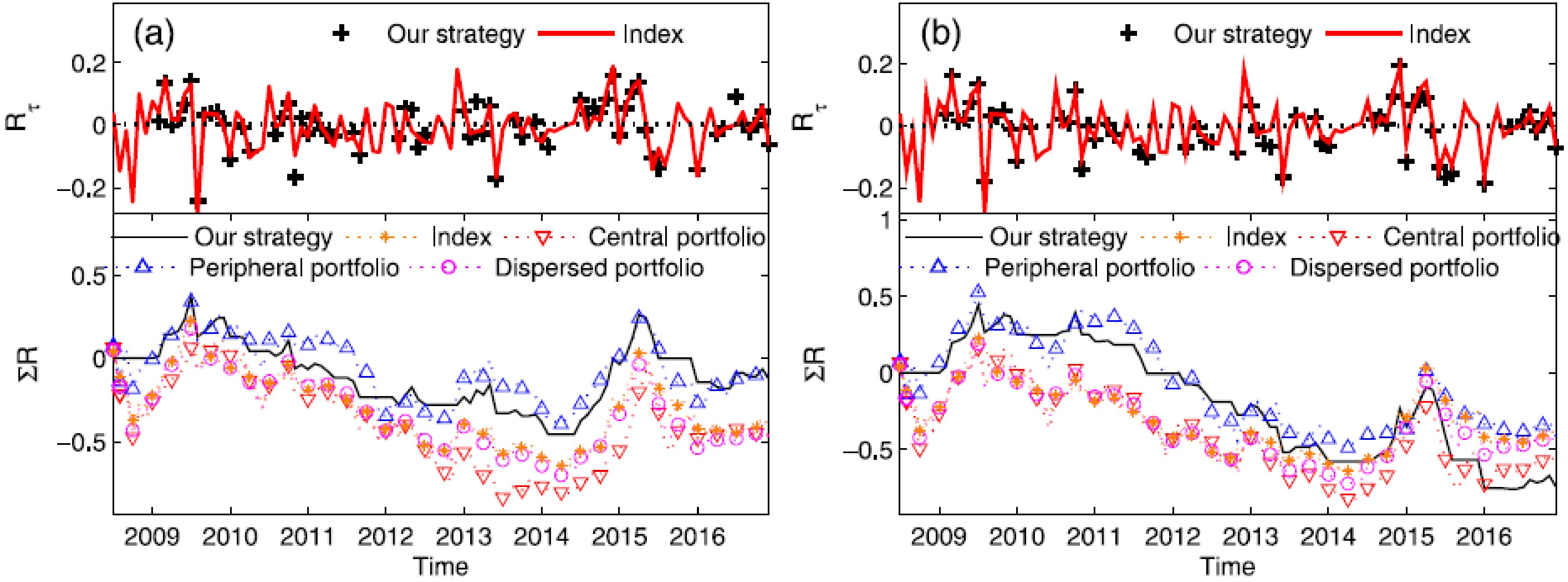


Monthly return R_τ and cumulative return ΣR of the strategy comprising two portfolios when threshold $\theta = 0.01$ vs. time. The results here are the average of R_τ and ΣR over 200 repeated runs. Fig. (a) and (b) represents the results using unweighted modularity Q_{unw} and weighted modularity Q_{wei} respectively.

Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

Applications in Portfolio Management



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Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

Applications in Portfolio Management

Results:

- Peripheral portfolios are more diversified and gain more than central and dispersed portfolios in general, and dispersed portfolios randomly selected from each cluster show average monthly returns similar to the market index
- Strategies constructed using unweighted modularity perform better than those using weighted modularity
- Introduction of the market trend prediction improves the investment result of our strategy, since the prohibition of using the optimal portfolio to invest can avoid the loss in drawdown periods

The BP neural network model gives the most accurate return prediction, and the strategy comprising two portfolios constructed using the BP model and unweighted modularity has the best investment return, showing a mean of average monthly return 2.09% and a mean of maximum cumulative compounded return 152.77%, significantly larger than 0.33% and 28.23% for the Markowitz portfolio under short-sale constraint.

Y.N. Lu et al., Chaos, Solitons and Fractals 117(2018)1-15.

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Other Extensions:

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Portfolio optimization based on network topology

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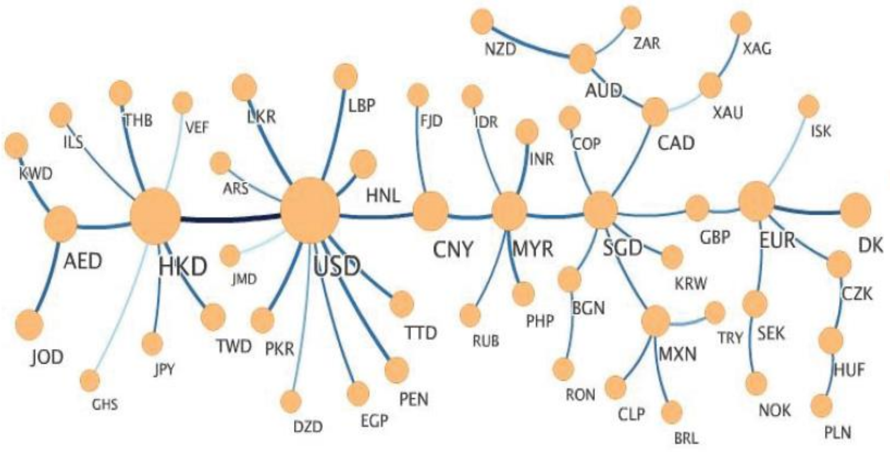
HIGHLIGHTS

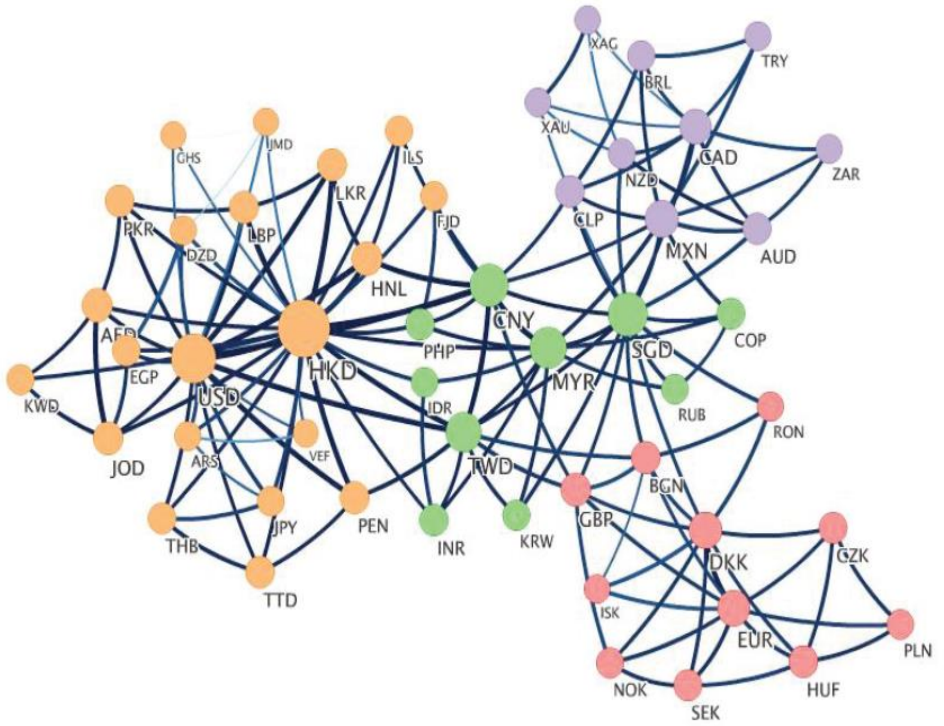
- The structure–function relation of a network is of current interest.
- Dynamic structural features of the core and periphery nodes are investigated.
- Network peripherality is an indicator for identifying optimal assets.
- Market mode the noise interference of dynamic networks.
- Market mode shows significant advantage in portfolio optimization.

………… *(Use your imagination!!!)*

More Examples: Foreign Exchange (FX) Market

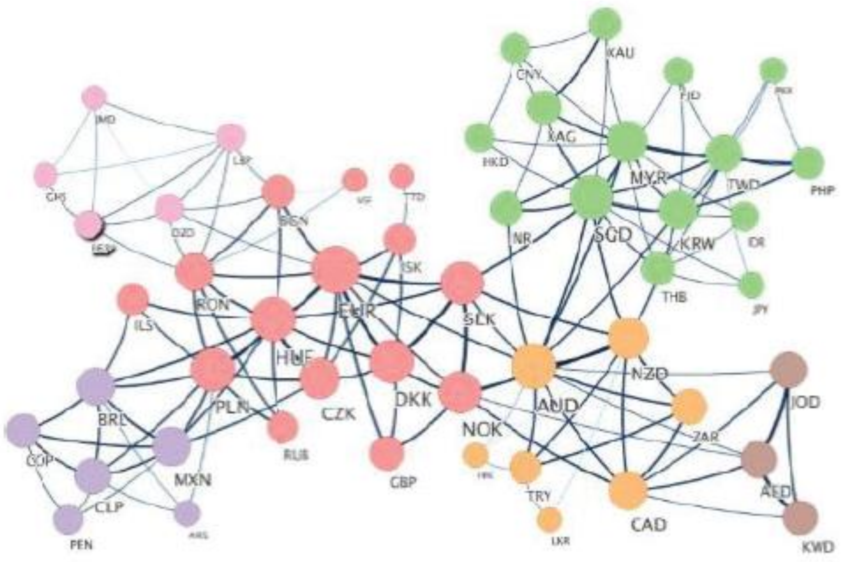


The MST graph of the global FX market. The bigger the size of a node, the larger the degree it is associated with; the thicker the link, the stronger the correlation between the nodes.

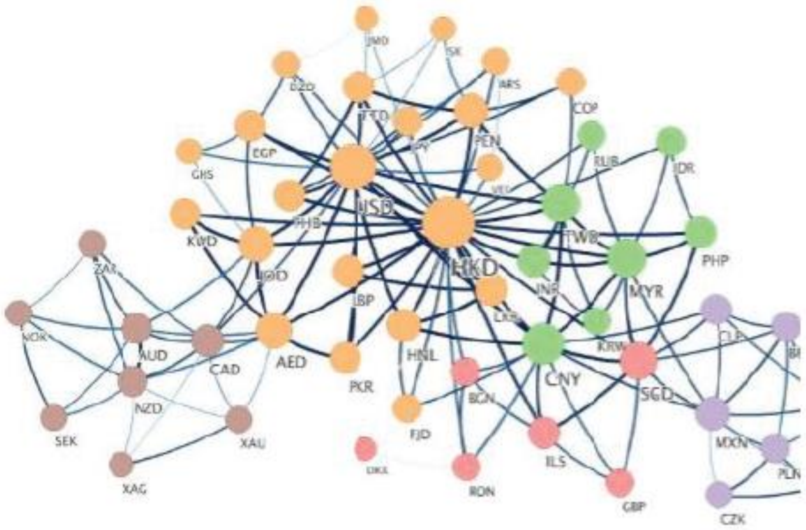


The PMFG graph of the global FX market. The bigger the size of a node, the larger the degree it is associated with; the thicker the link, the stronger the correlation between the nodes. The color of a node indicates the module that the currency belongs to.

“Currency Co-movement and Network Correlation Structure of Foreign Exchange Market”, Y. Mai et.al., Physica A492(2018)65-74.



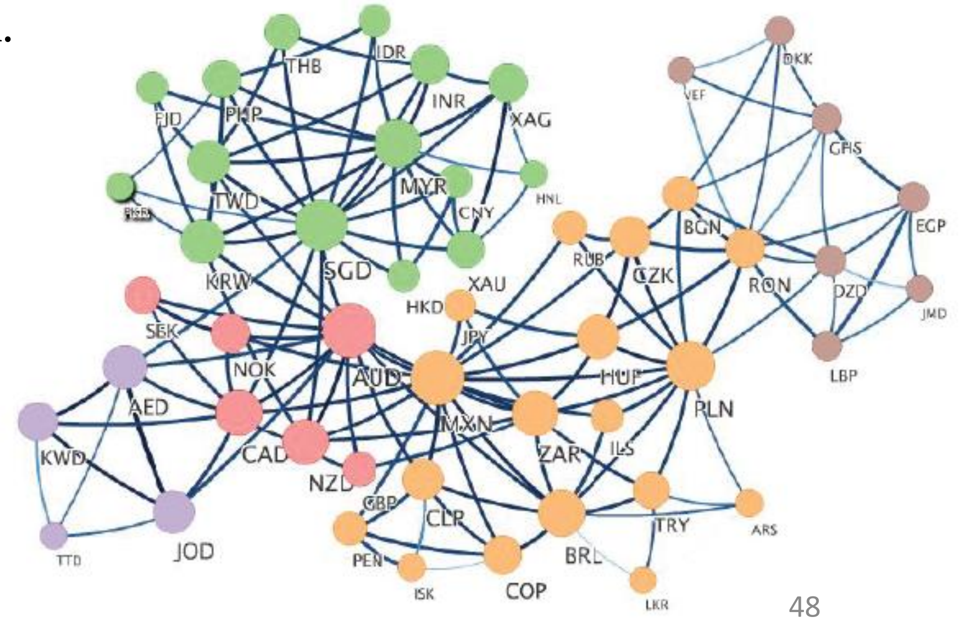
(a)



(b)

Currency correlation networks after the removal of the (a) US and (b)EUR.

The currency correlation network of the global FX market after one removes both the USD and EUR by the impact elimination method.



Further Applications

Example: Network Games

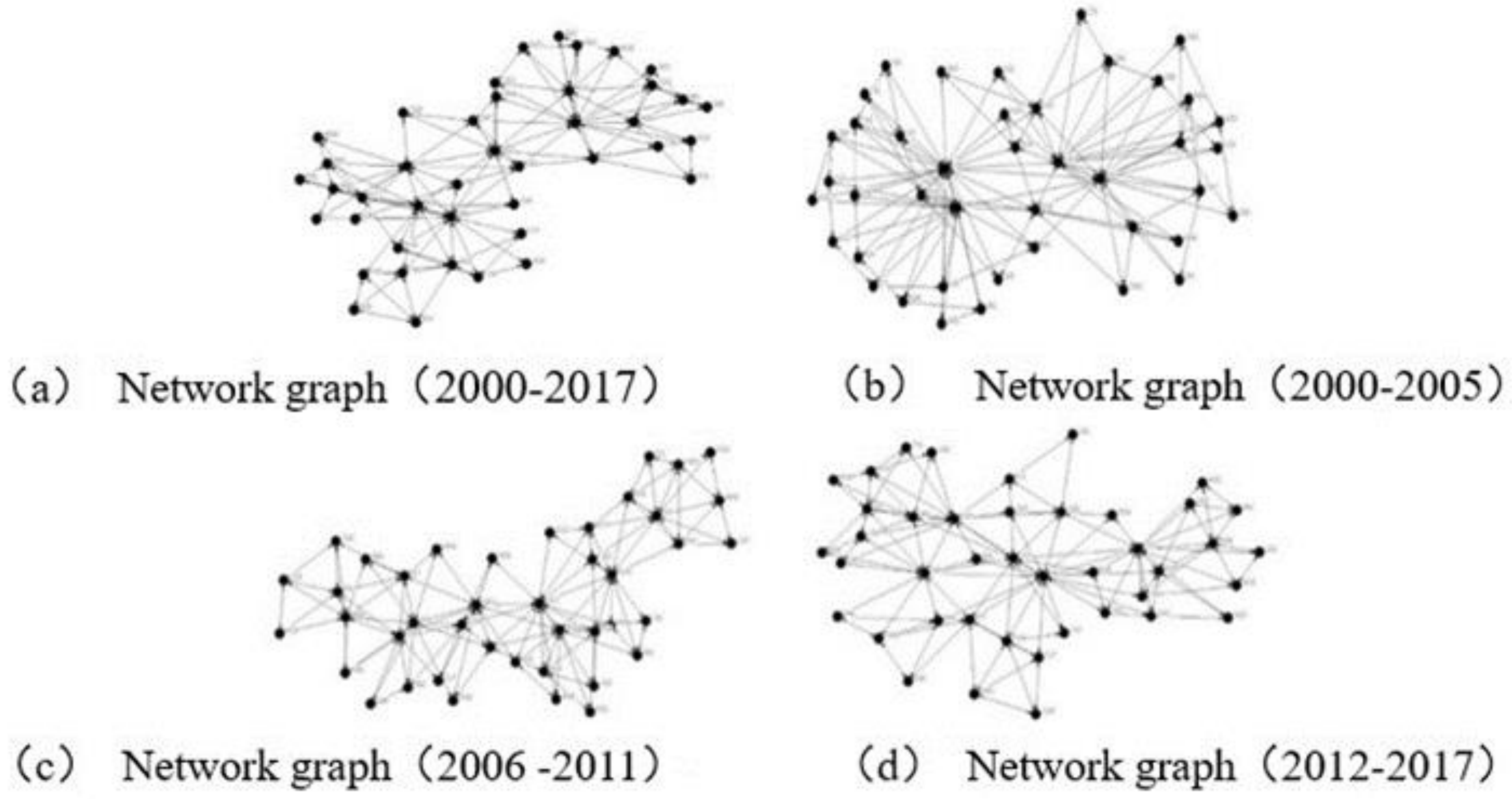
Study of multinational currency co-movement and exchange rate stability

- An application by using both complex network theory and game theory.
- We extend currency game between two countries to a network consists of several dozens of currencies, thus becoming a network game.
- We use this network game to study the stability of multinational exchange rates which is an important criterion for the sustained growth of regional economy.

“Study of multinational currency co-movement and exchange rate stability base on network game”, Finance Research Letters, 2022
https://www.sciencedirect.com/science/article/pii/S1544612321005407

Applications

Example: Network Games



（a） Network graph（2000-2017）

（b） Network graph（2000-2005）

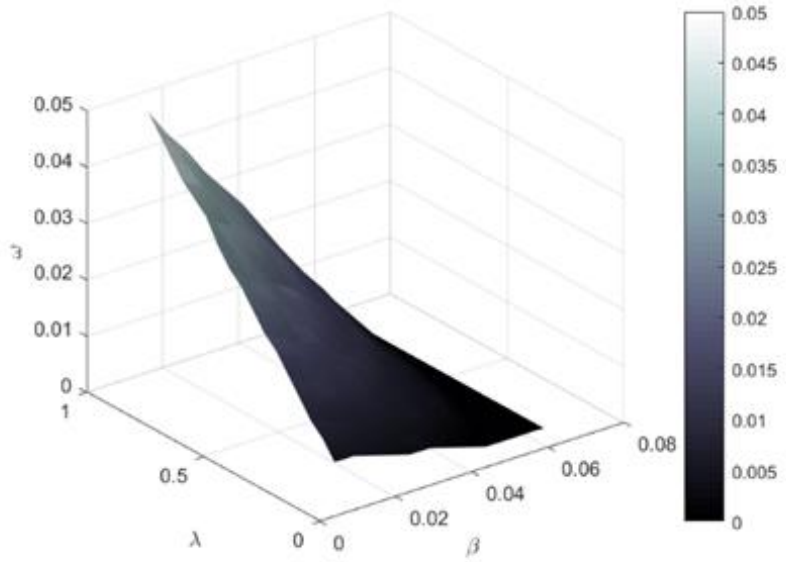
（c） Network graph（2006 -2011）

（d） Network graph（2012-2017）

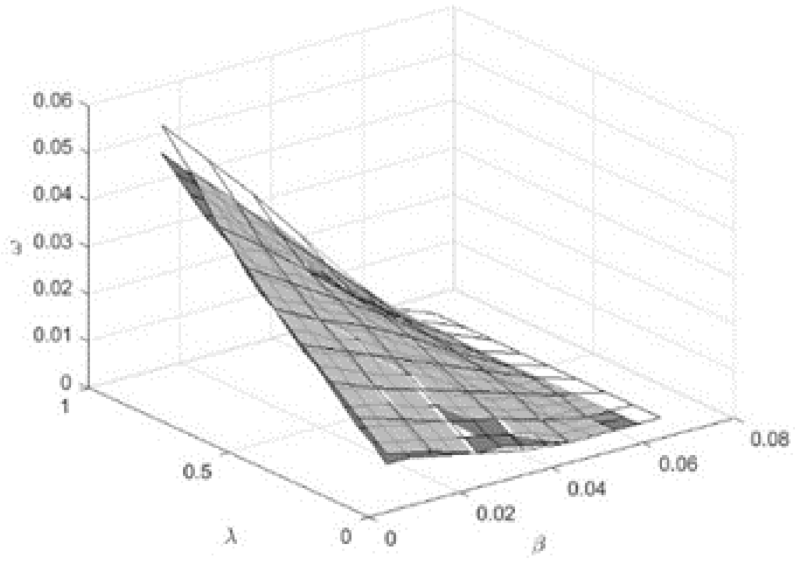
Global monetary correlation network graph of 42 currencies in four different periods

Applications

Example: Network Games



Three-dimensional parameter space diagram of the multi-currency game with q = 0.3 and P_0 = 0.5.



Three-dimensional parameter space diagram of the multi-currency game with q=0.3 (black critical surface) and q = 0.5 (white critical surface).