INTERDEPENDENCIES AND INTERCONNECTEDNESS IN THE GLOBAL FINANCIAL VILLAGE

Dror Y. Kenett
Department of Physics, Boston University

Outline

(1) Introduction
- Financial time series
- Stock correlations
- Dynamics of stock correlations

(2) Global financial village
- Market intra and meta correlation
- Financial Seismograph

(3) Dependency and Influence

(4) Examples of network projects
I. Cascading failures in industry networks
II. Overlapping communities in networks
III. Failure and recovery in networks
IV. Evolution of networks
V. Cascading failures in the financial system
VI. Interdependent networks

(5) Discussion

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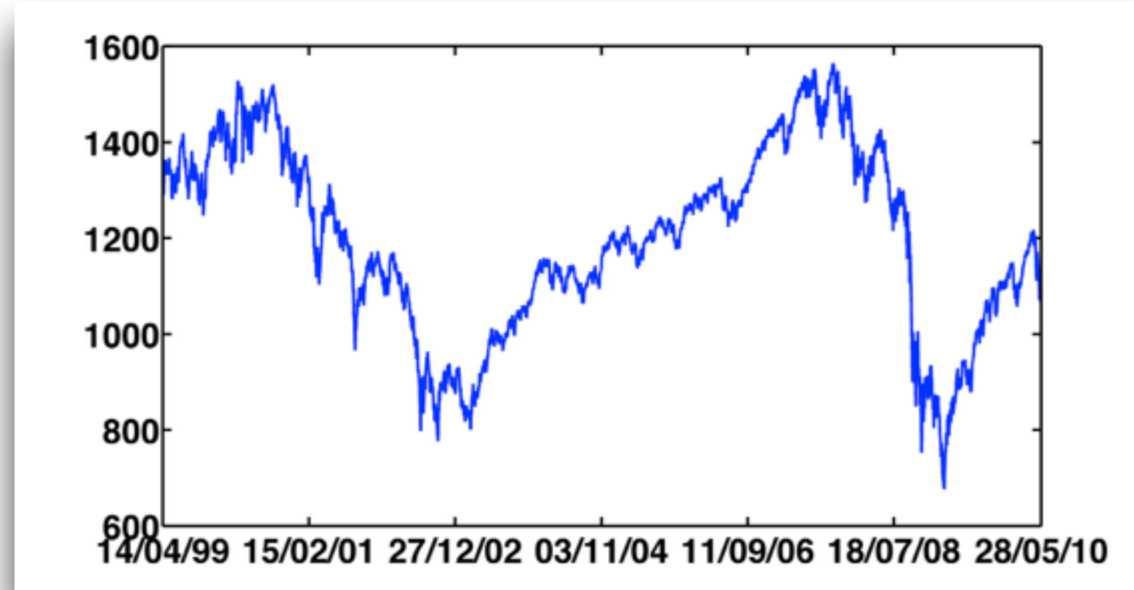
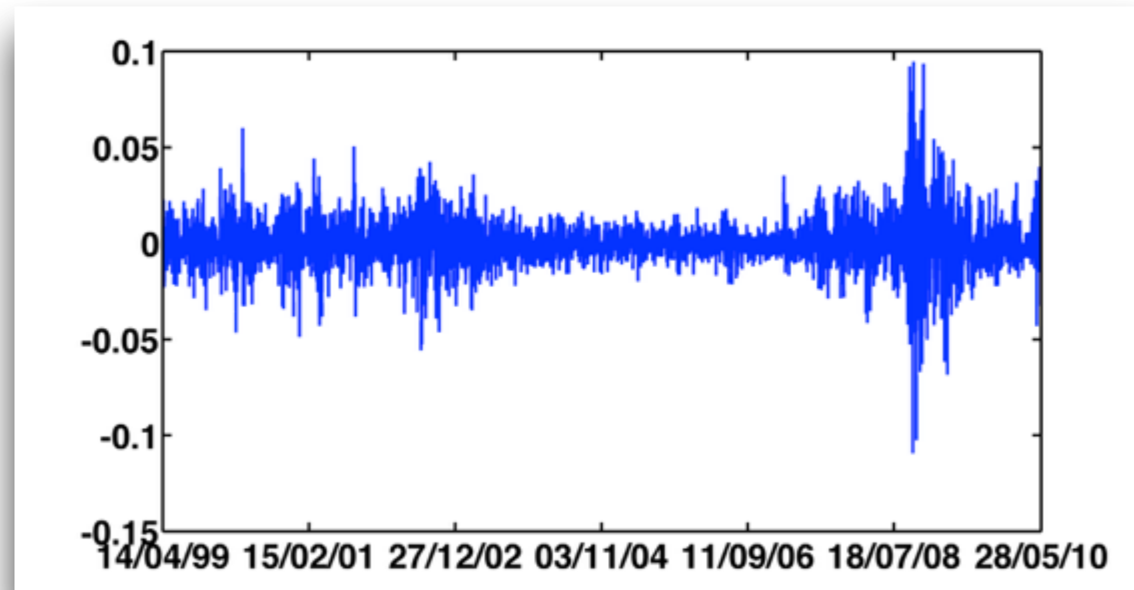
S&P500 Price



$$r_i(t) = \log\left[P_i(t)\right] - \log\left[P_i(t-1)\right]$$

S&P500 Return



Stock correlations

$$C(i,j) = \frac{\left\langle \left(r_i - \left\langle r_i \right\rangle\right) \cdot \left(r_j - \left\langle r_j \right\rangle\right) \right\rangle}{\sigma_i \cdot \sigma_j}$$

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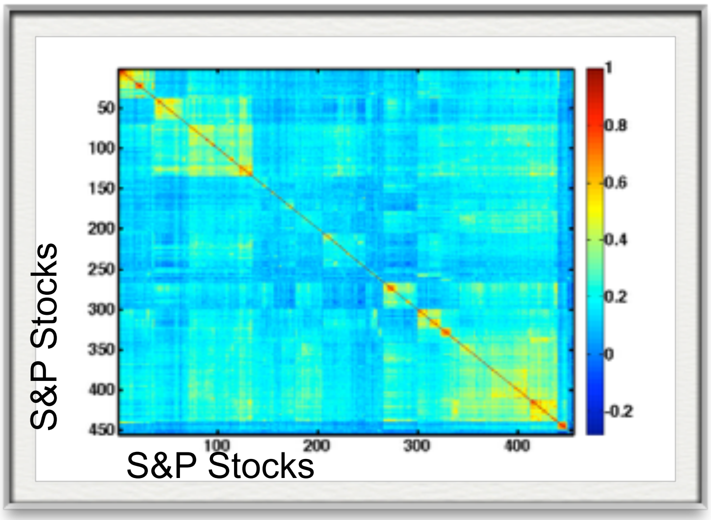

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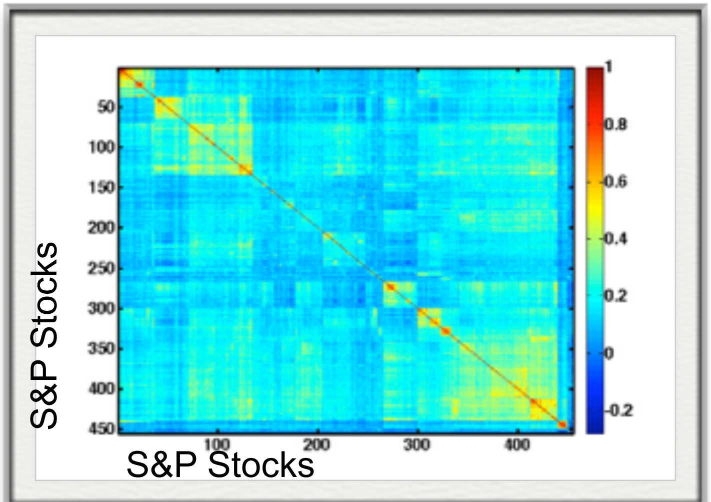

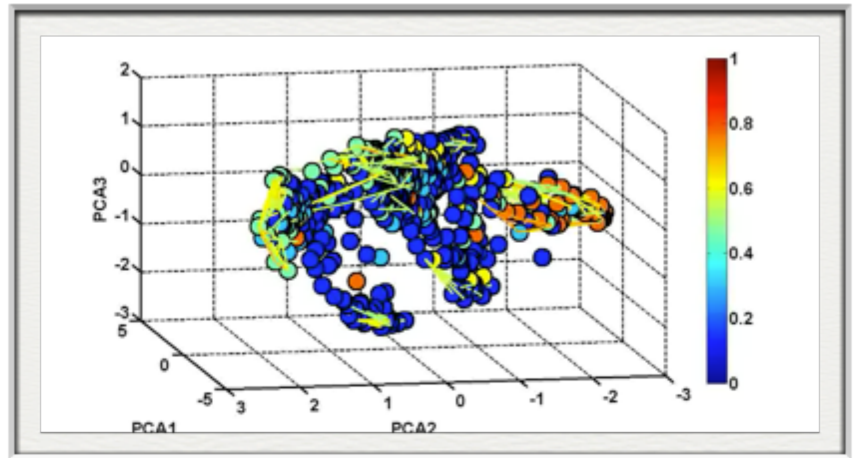

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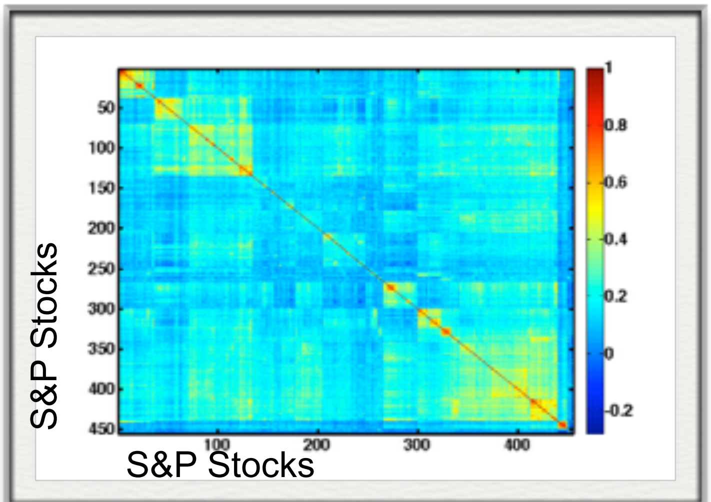

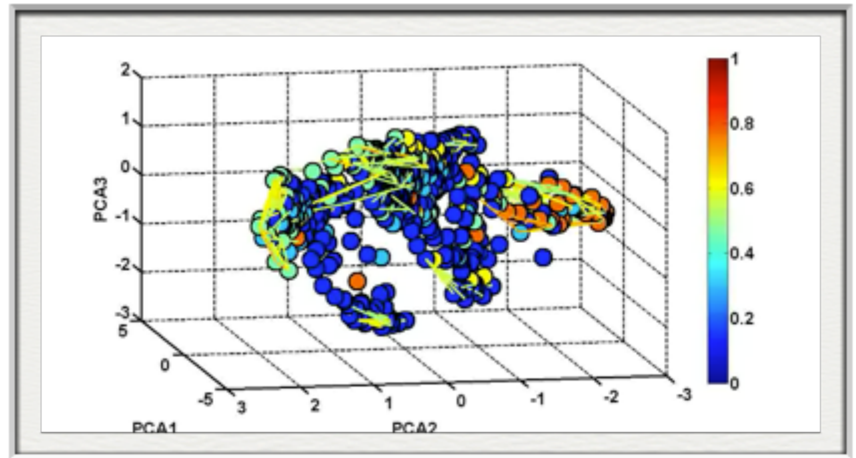

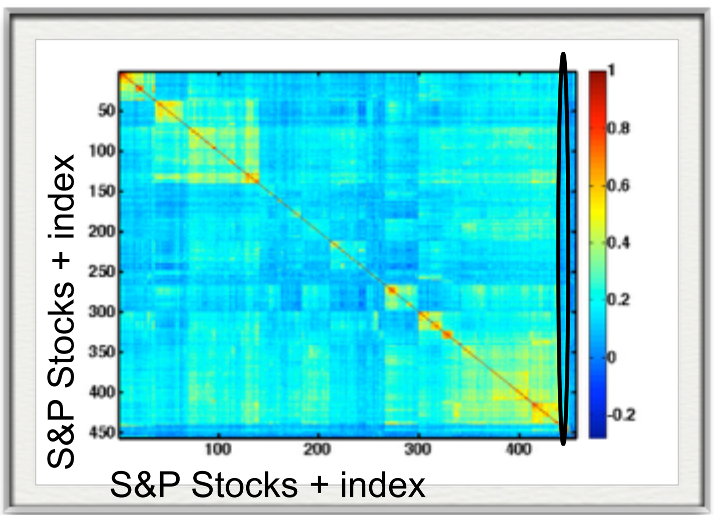

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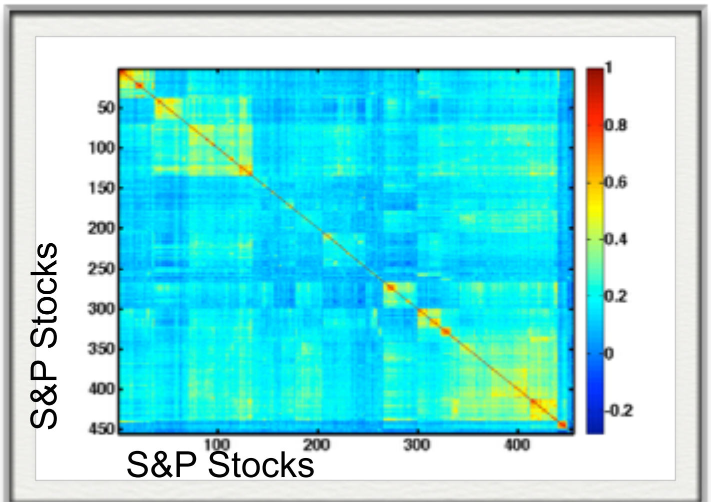
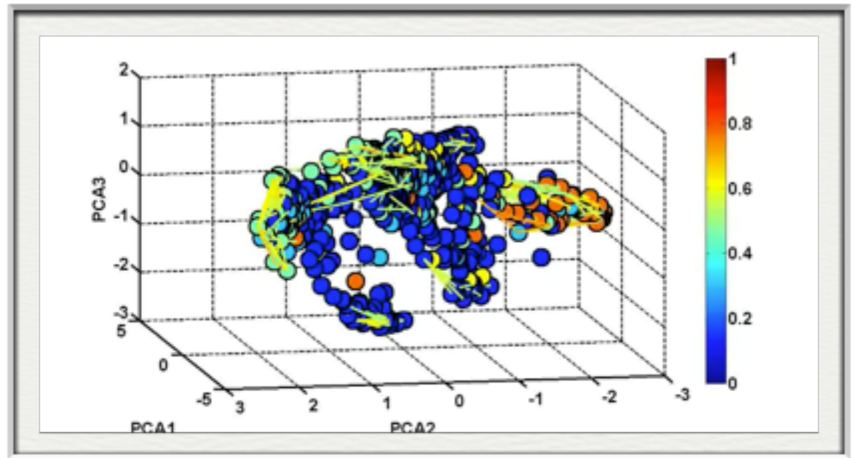
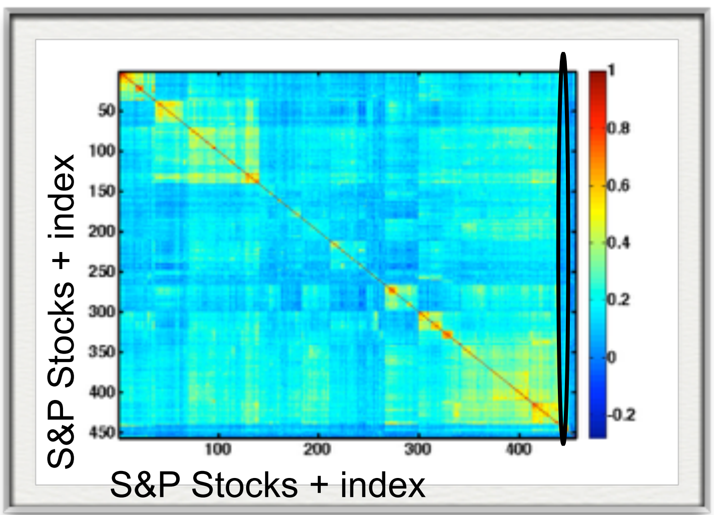
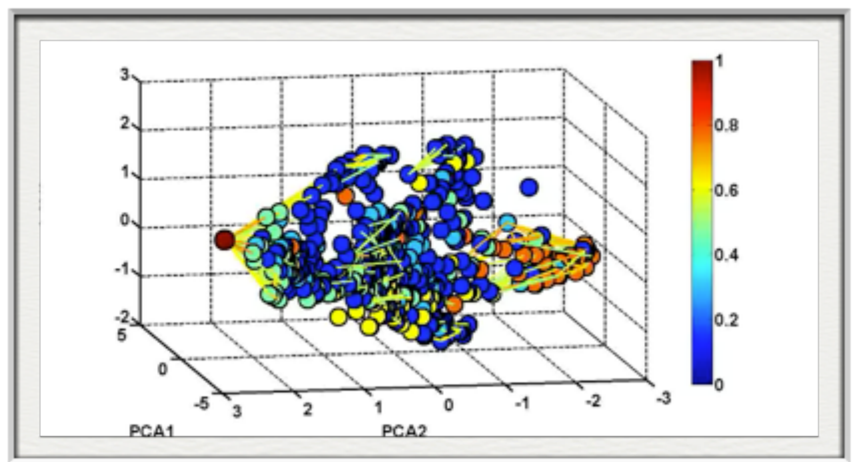
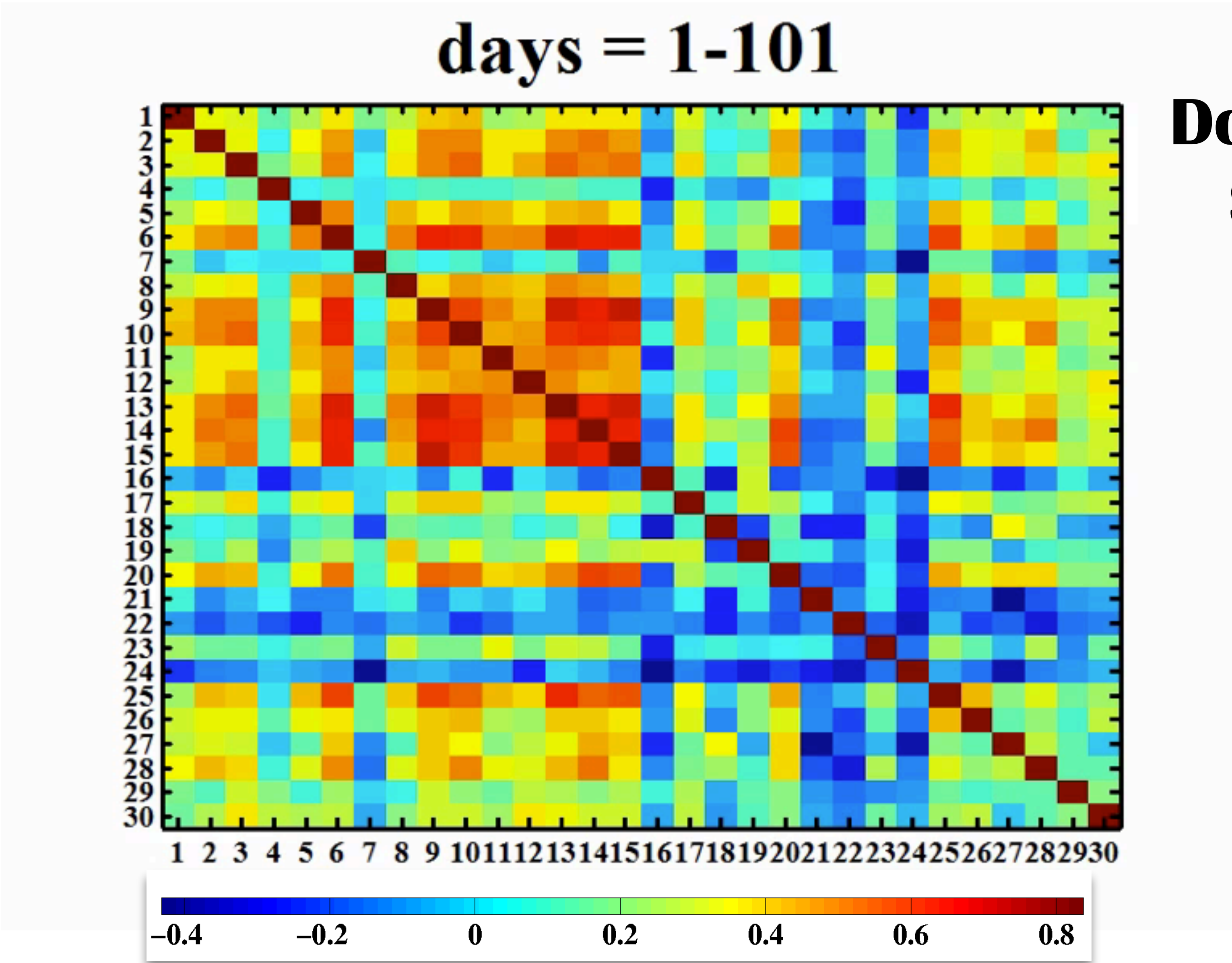






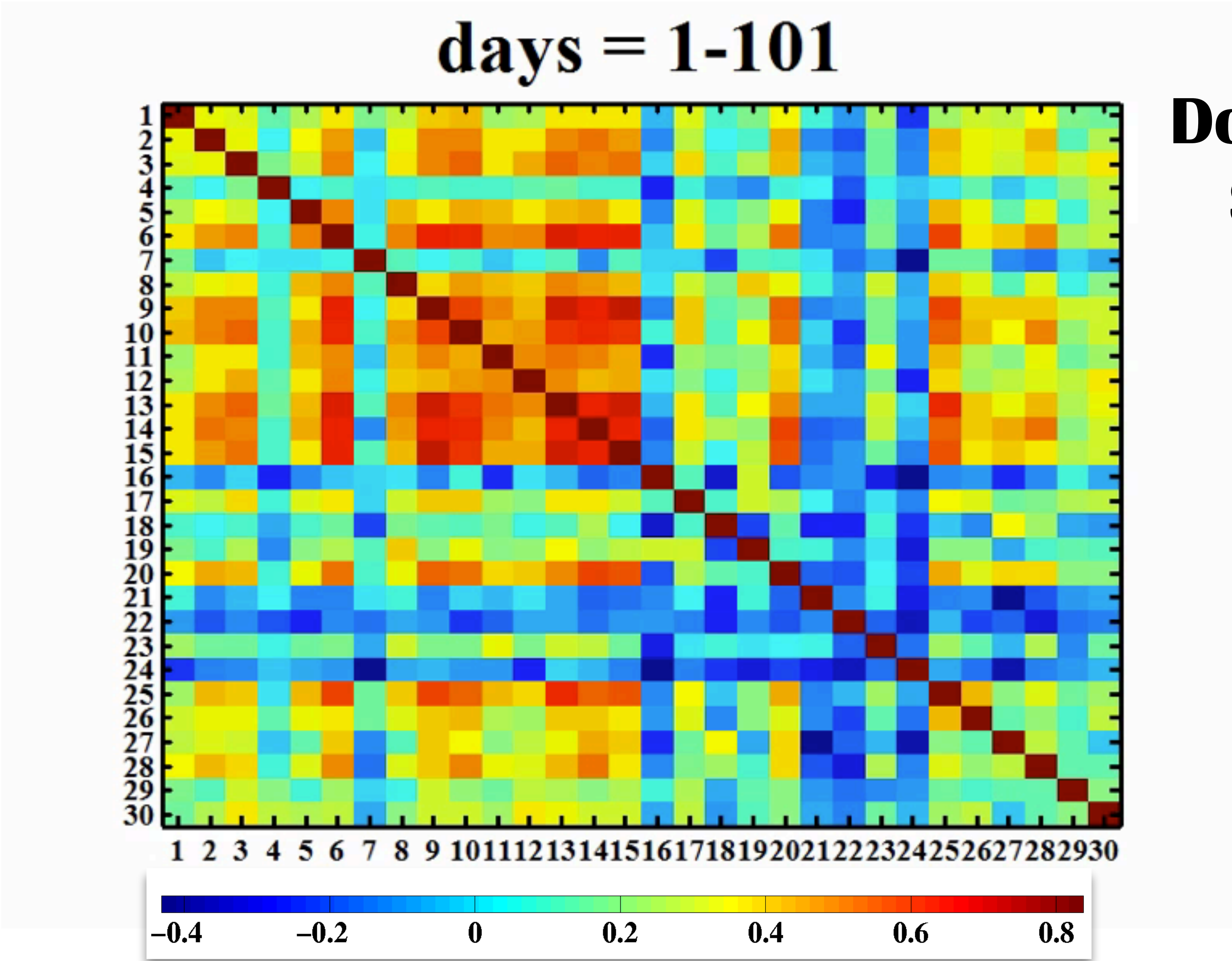


Dynamics of stock correlations



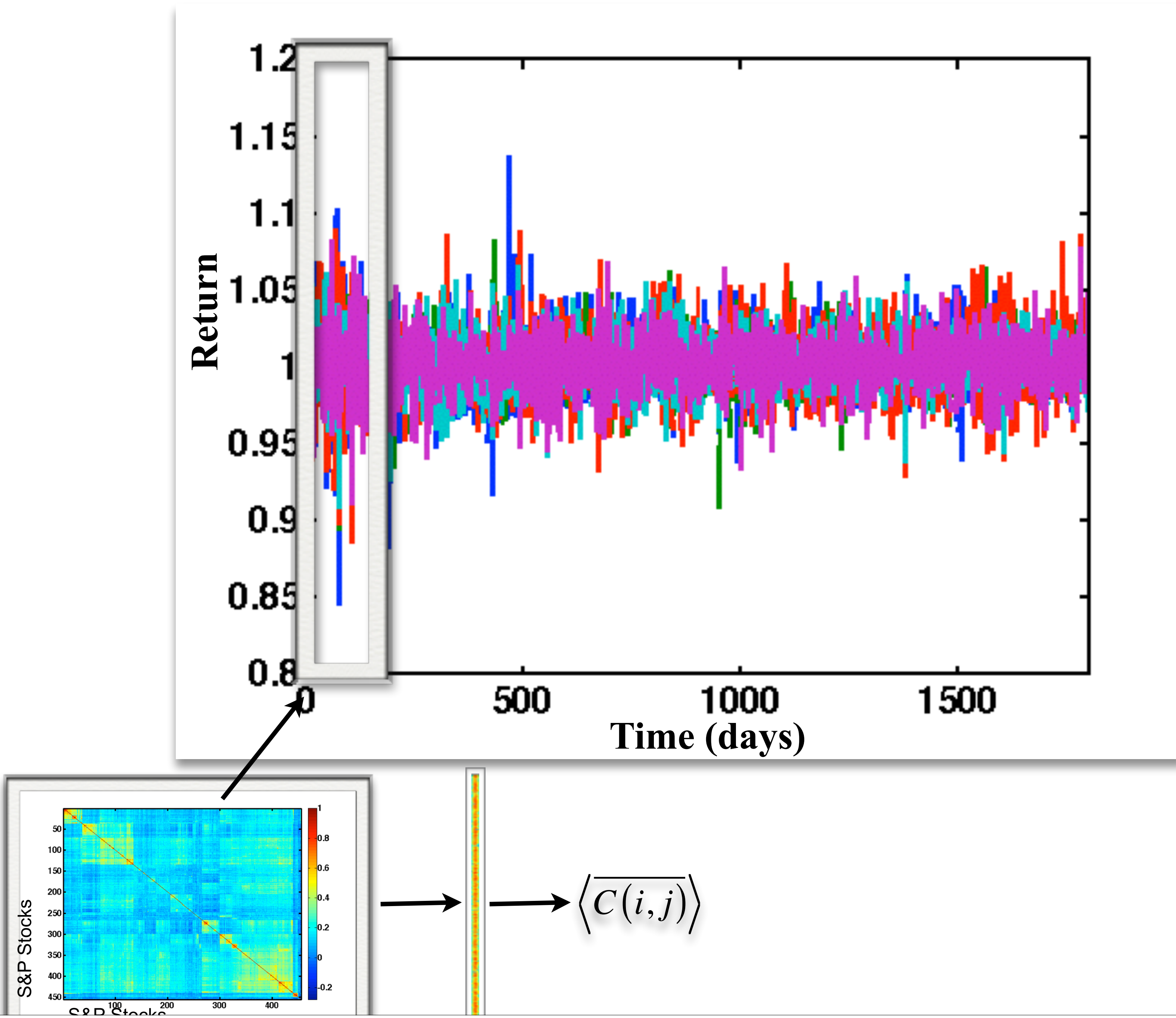
Dow Jones Stocks

Dynamics of stock correlations



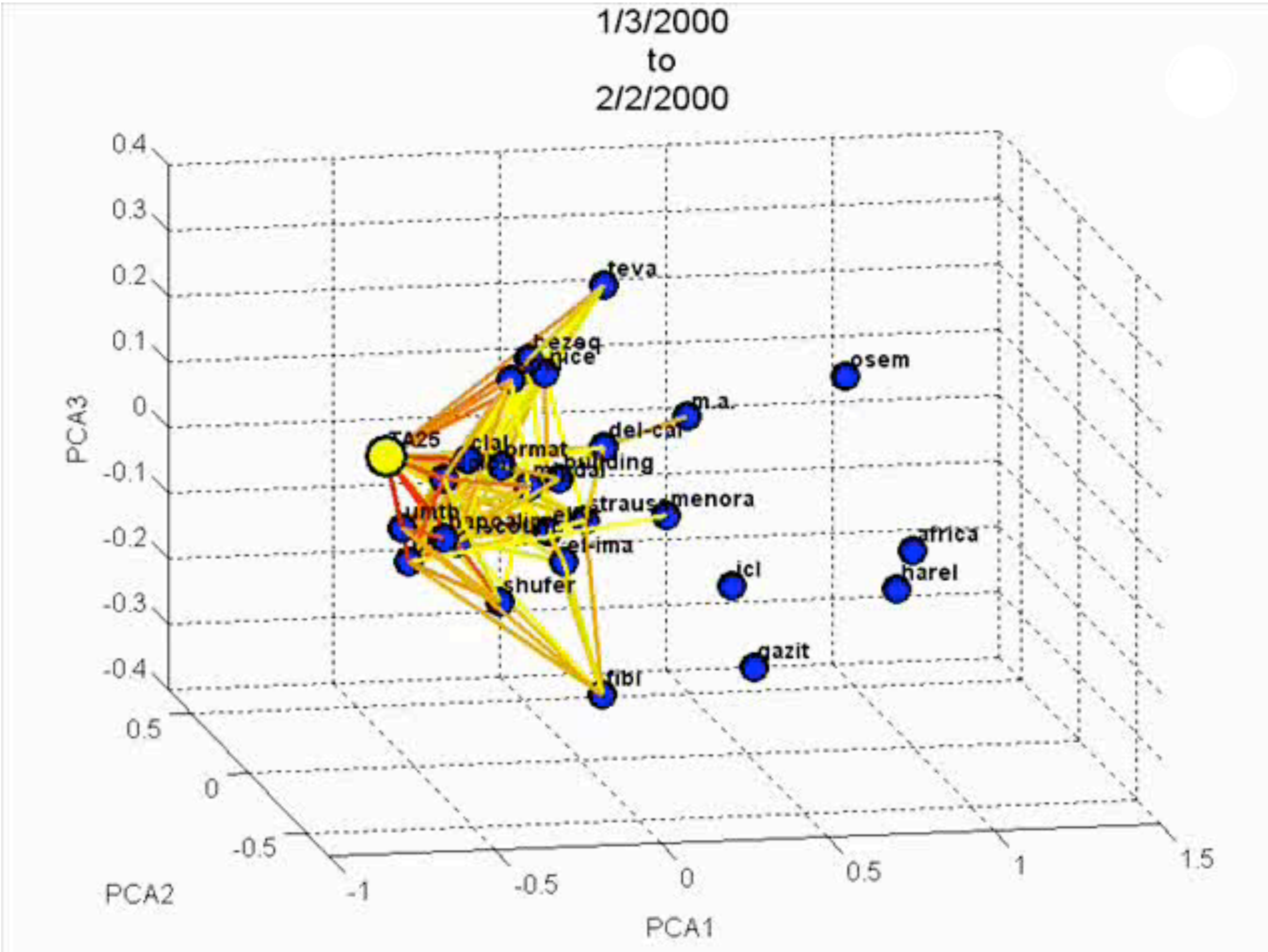
Dow Jones Stocks

Dynamics of stock correlations



$$\left\langle \overline{C(i,j)} \right\rangle$$

Example: Tel-Aviv market



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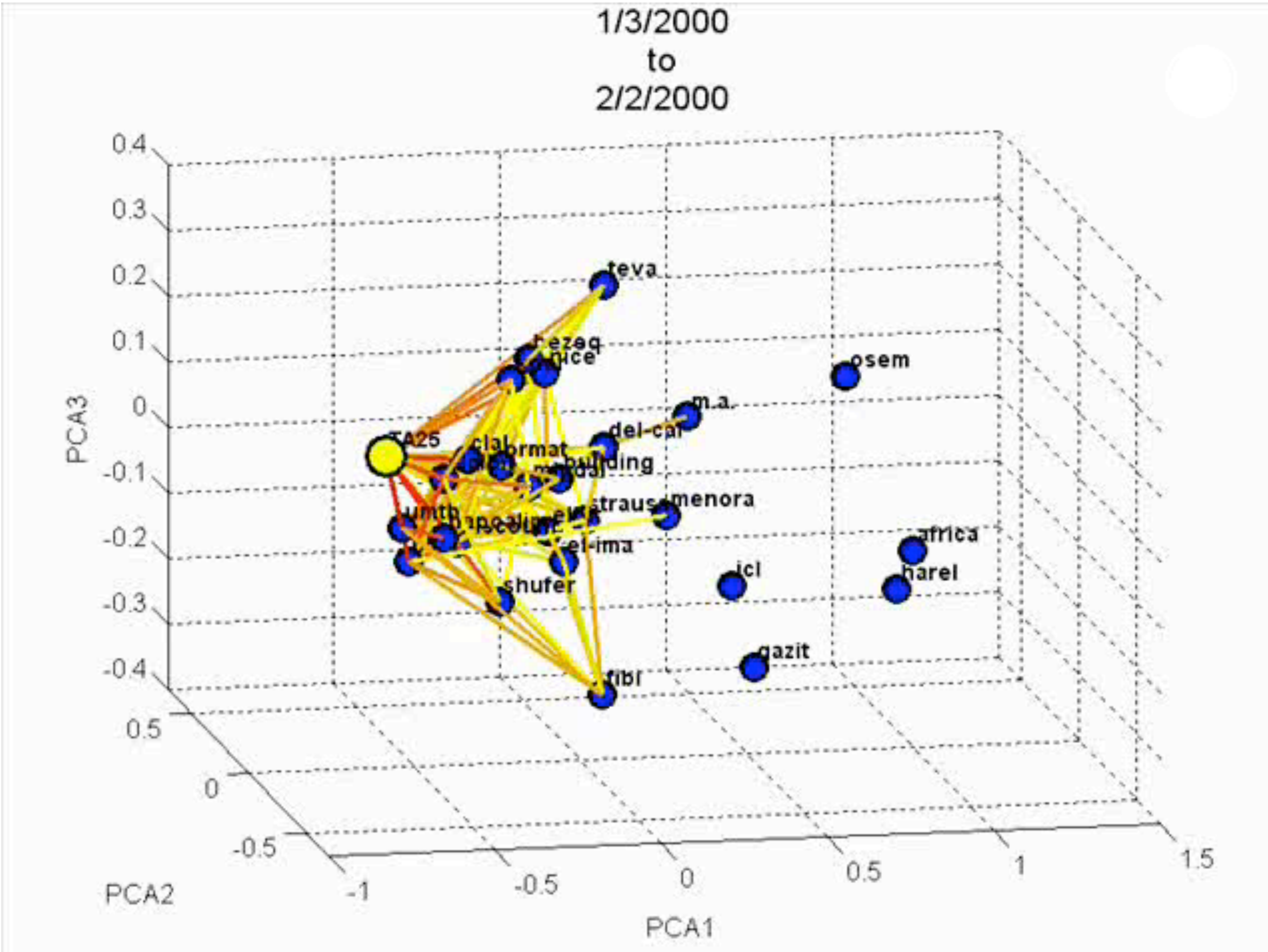
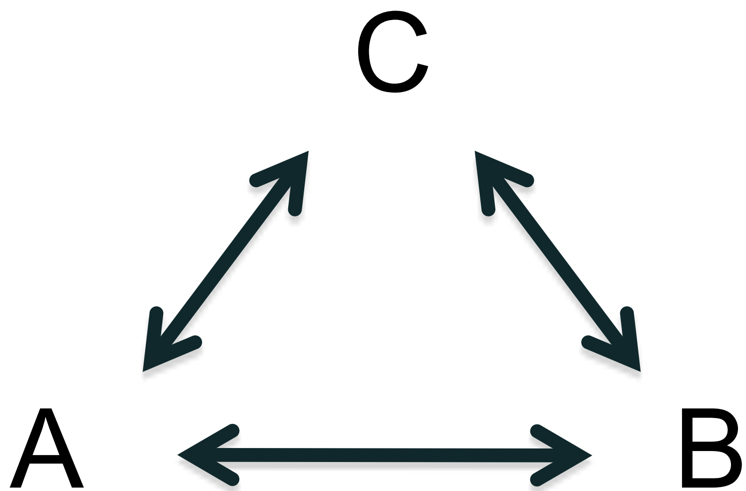


Quantifying functional relationships

Correlation



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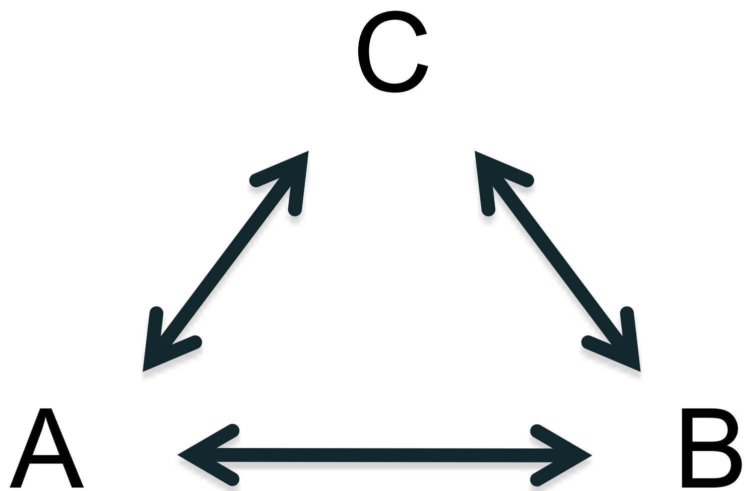
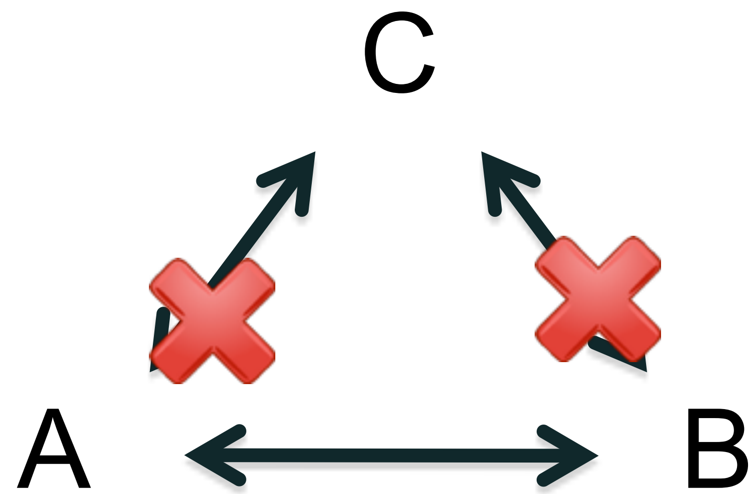


$$C(i,j)=\frac{\left\langle \left(r_i-\langle r_i\rangle\right)\cdot\left(r_j-\langle r_j\rangle\right)\right\rangle}{\sigma_i\cdot\sigma_j}$$

Partial Correlation



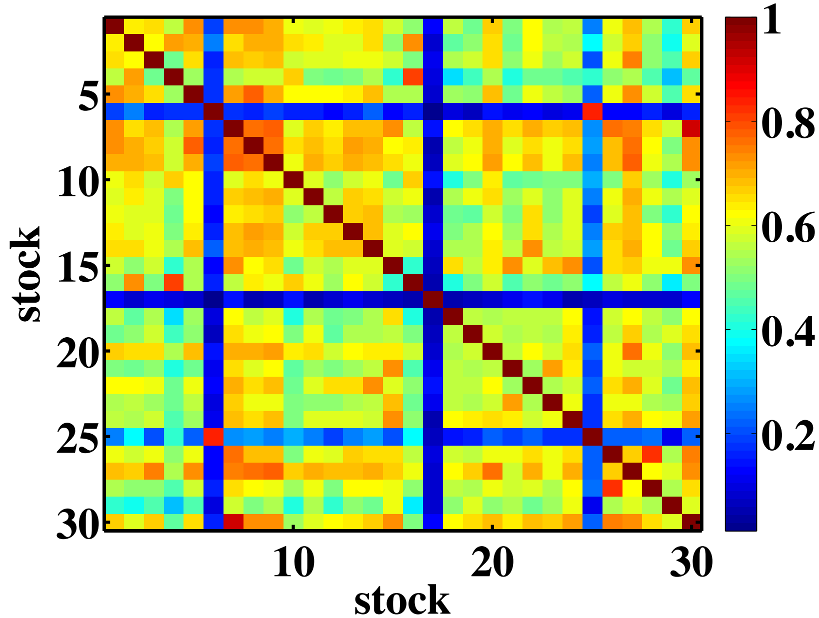
$$PC(i,j\,|\,m)=\frac{C(i,j)-C(i,m)\cdot C(j,m)}{\sqrt{\left(1-C^2(i,m)\right)\cdot\left(1-C^2(j,m)\right)}}$$

PARTIAL CORRELATION:

The partial correlation (residual correlation) between *i* and *j* given *m*, is the correlation between *i* and *j* after removing their dependency on *m*; thus, it is a measure of the correlation between *i* and *j* after removing the affect of *m* on their correlation

Quantifying functional relationships

Correlation



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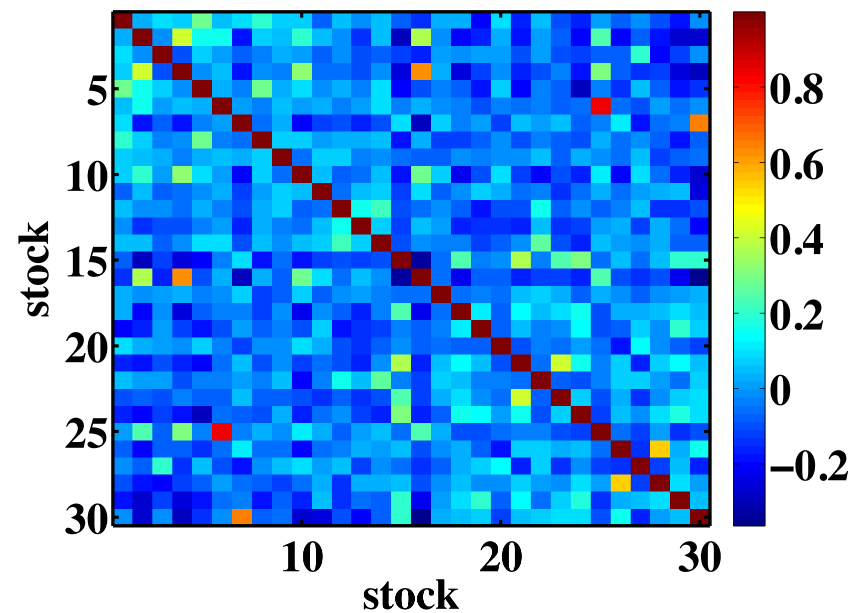

$$PC(i,j \mid m) = \frac{C(i,j) - C(i,m) \cdot C(j,m)}{\sqrt{\left(1 - C^2(i,m)\right) \cdot \left(1 - C^2(j,m)\right)}}$$

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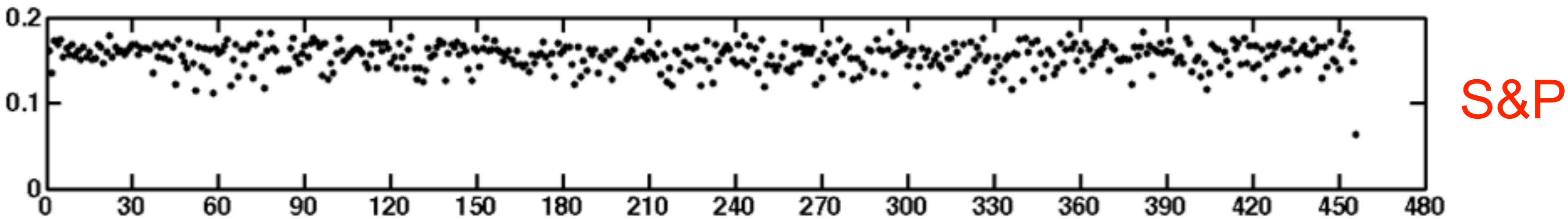
Partial Correlations Example

Yoash Shapira, Dror Y. Kenett, and Eshel Ben-Jacob, ______________________________
Physical Journal B. vol. 72, no. 4, pp. 657-669 (2009)

Partial Correlations Example



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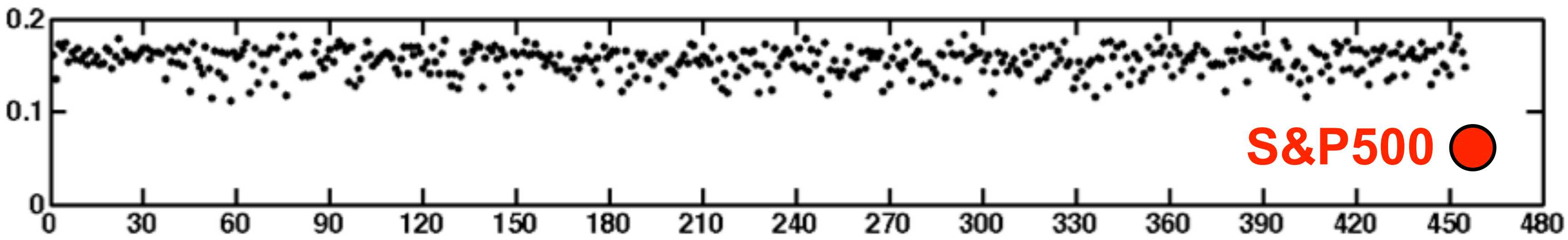

S&P

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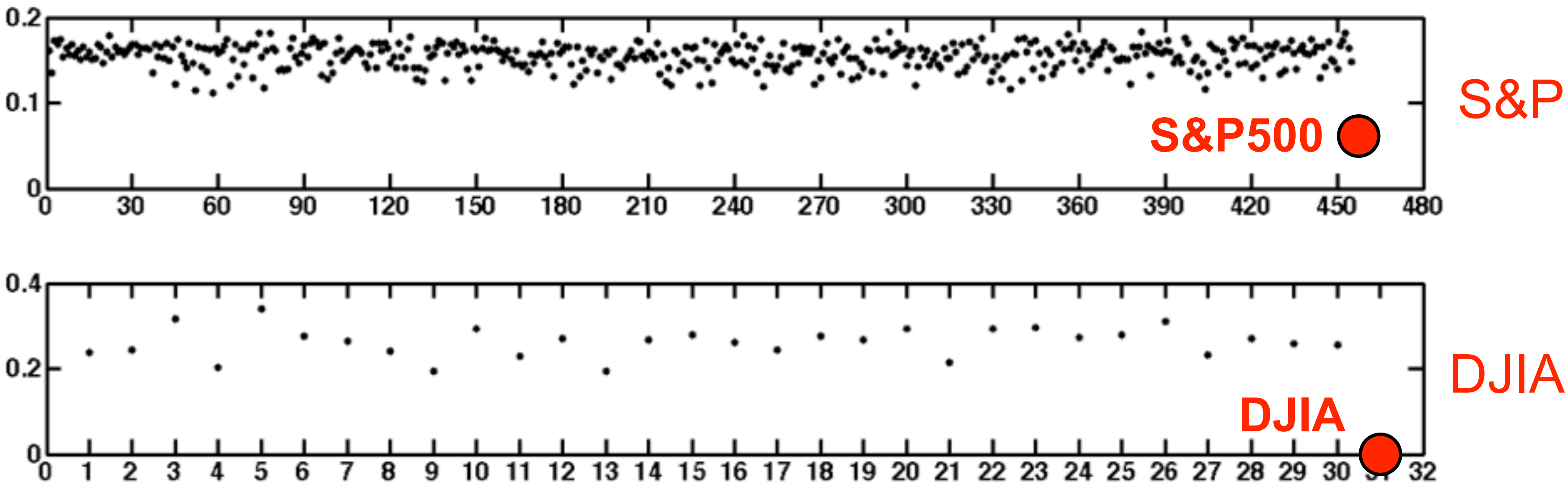

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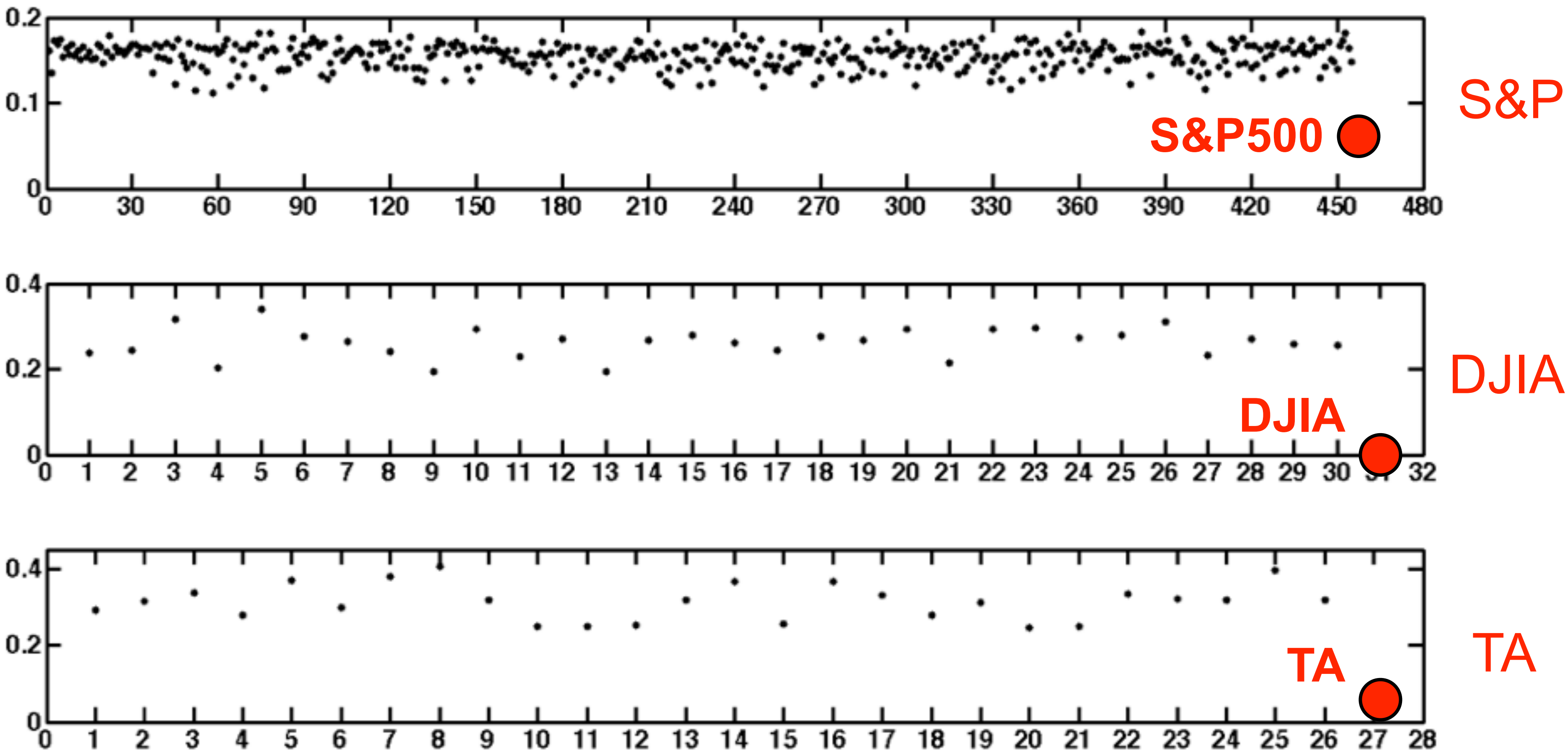

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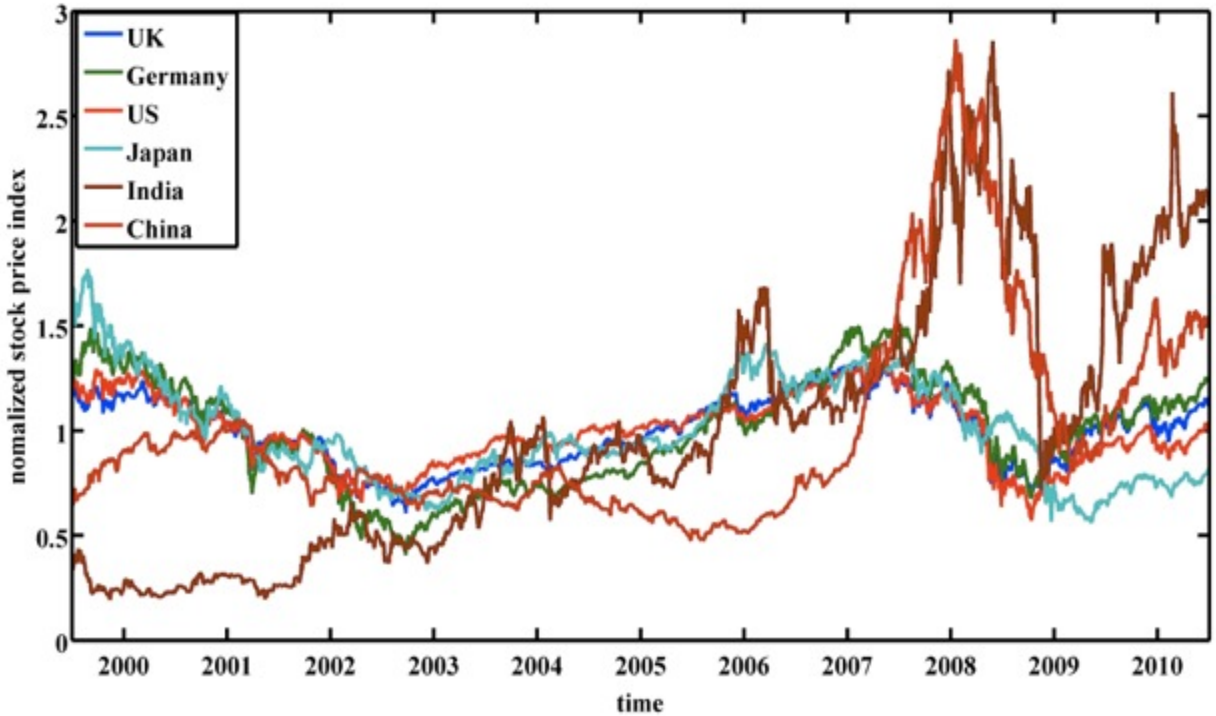
Financial Global village



Market	*Stocks used*	*Index used*	*# before*	*# filtered*
US	S&P 500	S&P 500	500	403
UK	FTSE 350	FTSE 350	356	116
Germany	DAX Composite	DAX 30 Performance	605	89
Japan	Nikkei 500	Nikkei 500	500	315
India	BSE 200	BSE 100	193	126
China	SSE Composite	SSE Composite	1204	69

Dror Y. Kenett, Matthias Raddant, Thomas Lux, and Eshel Ben-Jacob (2012), Evolvement of uniformity and volatility in the stressed global financial village, PLoS ONE 7(2), e31144

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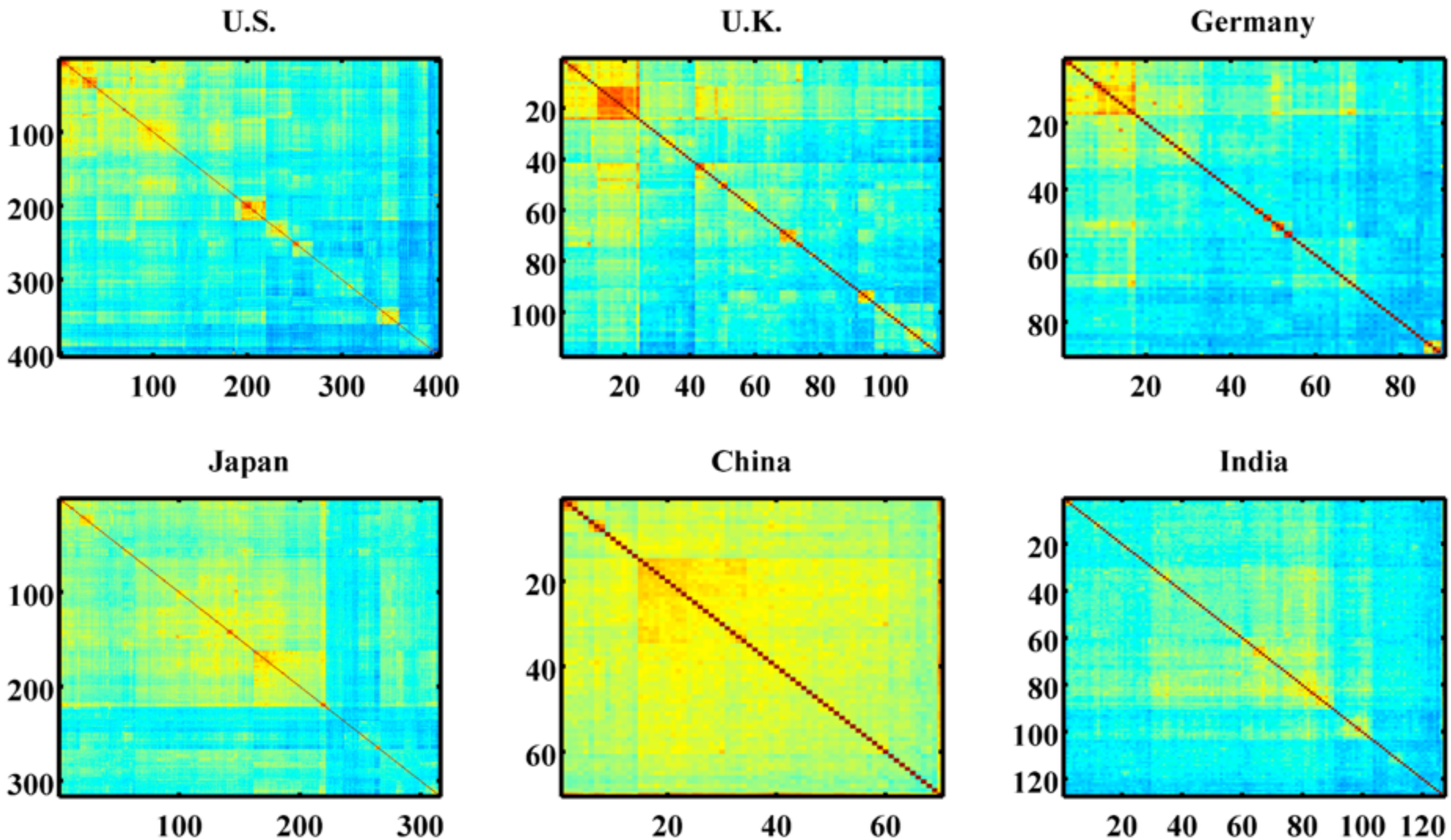
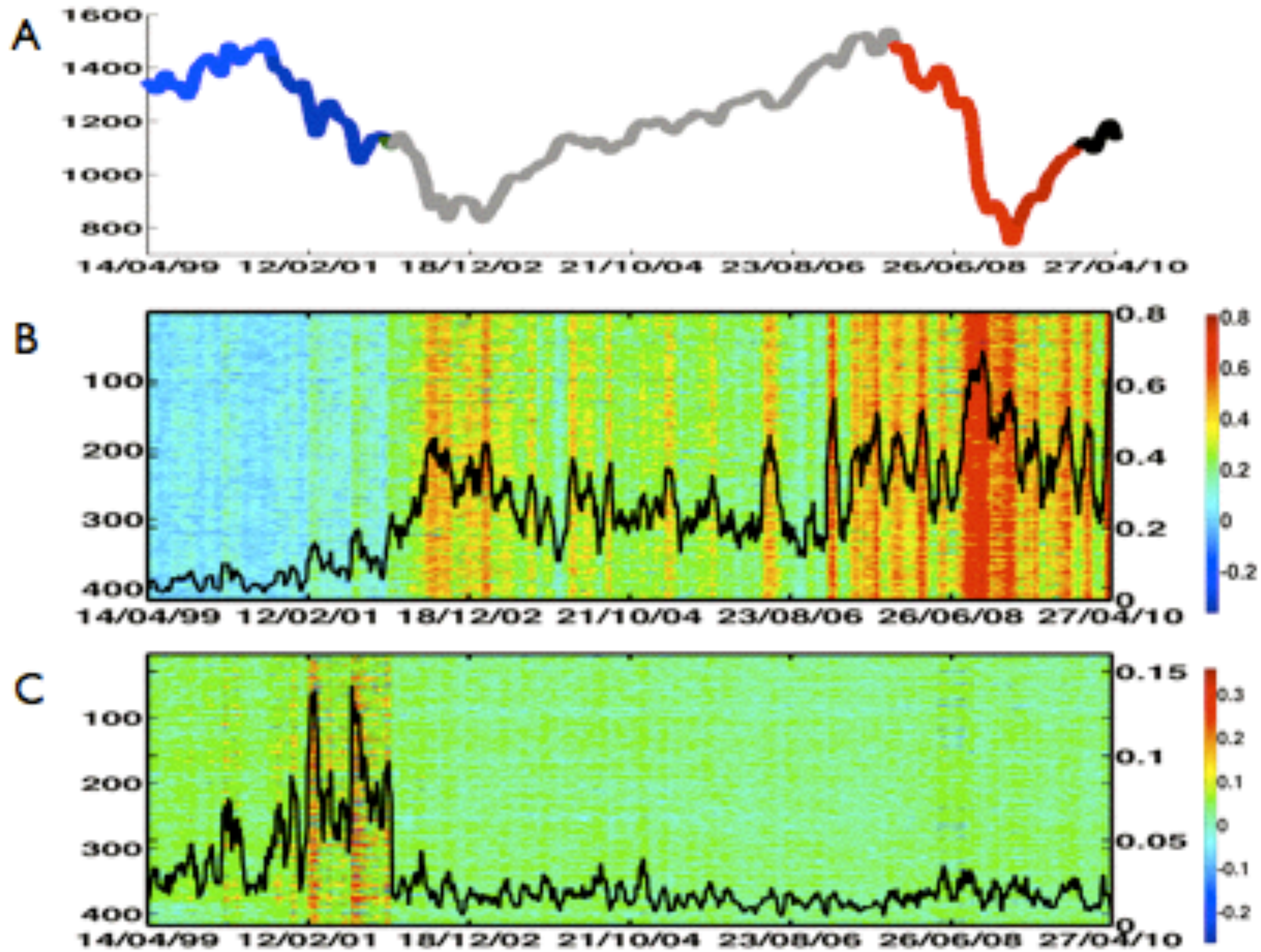


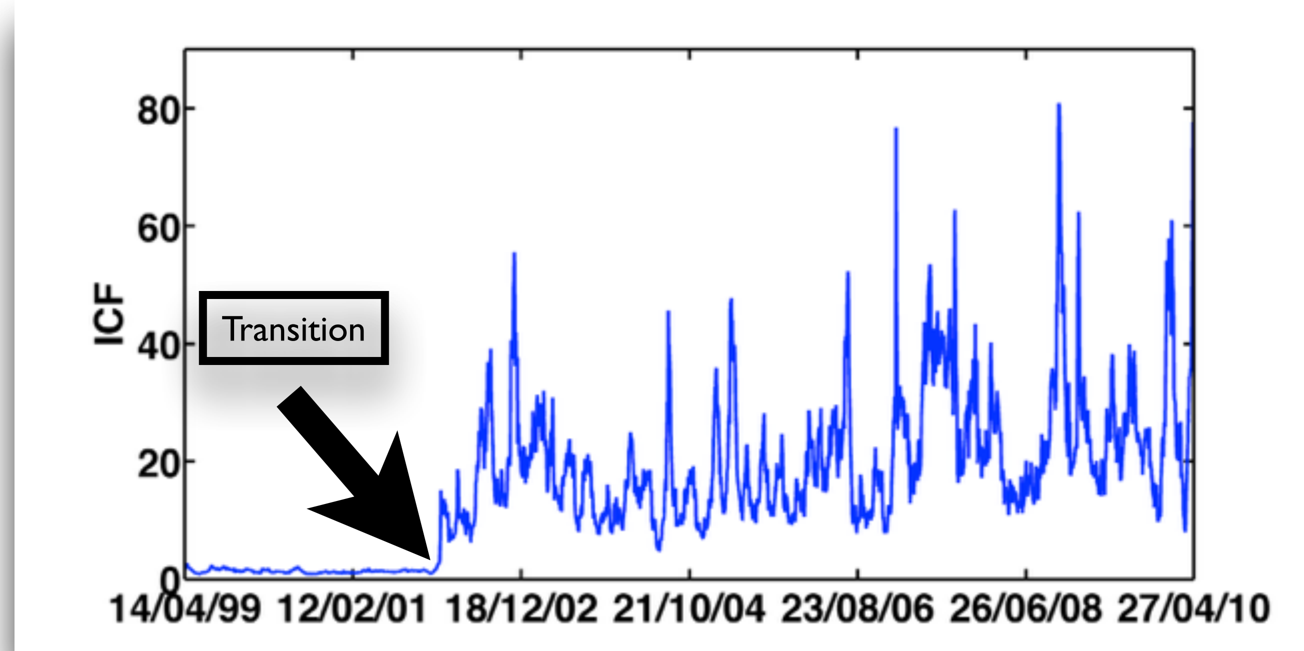
Example: Dynamics of correlations of S&P500 stocks, in the US market

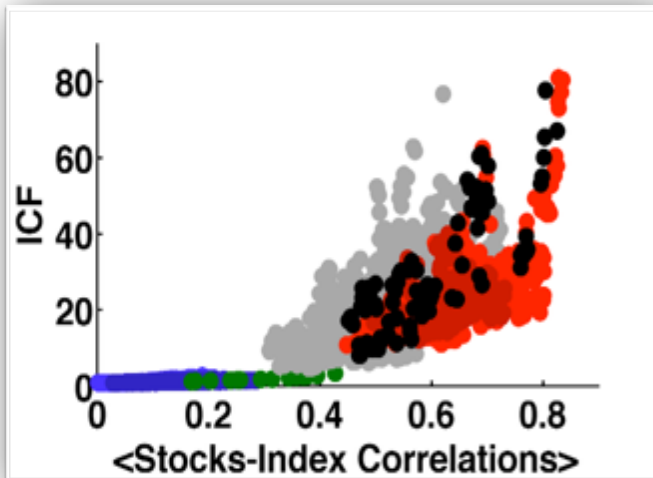


Dror Y. Kenett, Yoash Shapira, Asaf Madi, Sharron Bransburg-Zabary, Gitit Gur-Gershgoren, and Eshel Ben-Jacob (2011), Index cohesive force analysis reveals that the US market became prone to systemic collapses since 2002, PLoS ONE 6(4): e19378

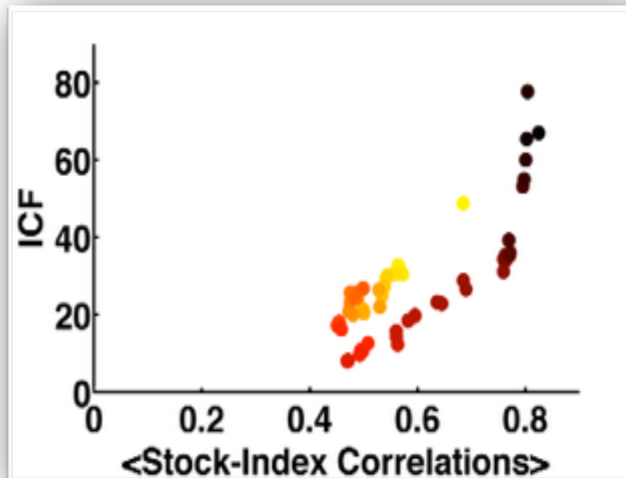
Correlations of S&P500 stocks, in the US market: Phase Transition?

$$ICF(\tau) \equiv \frac{\langle C(i,j) \rangle_\tau}{\langle PC(i,j \mid m) \rangle_\tau}$$



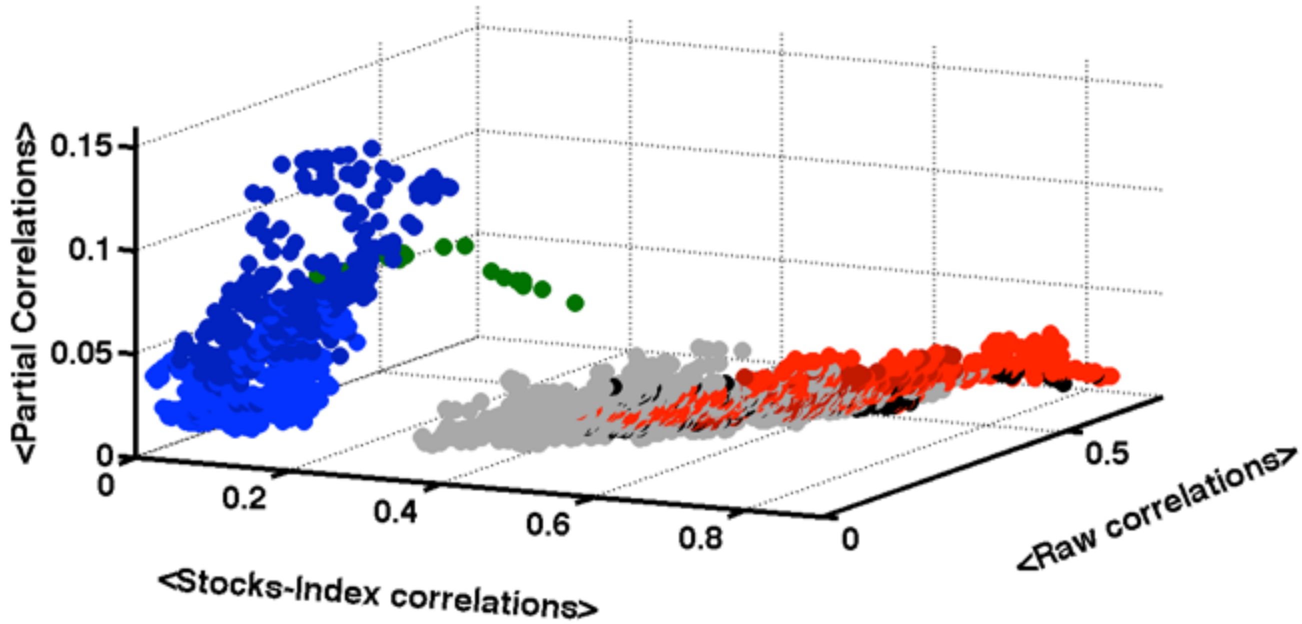


1999 - 2010



2010

Financial States and Transitions



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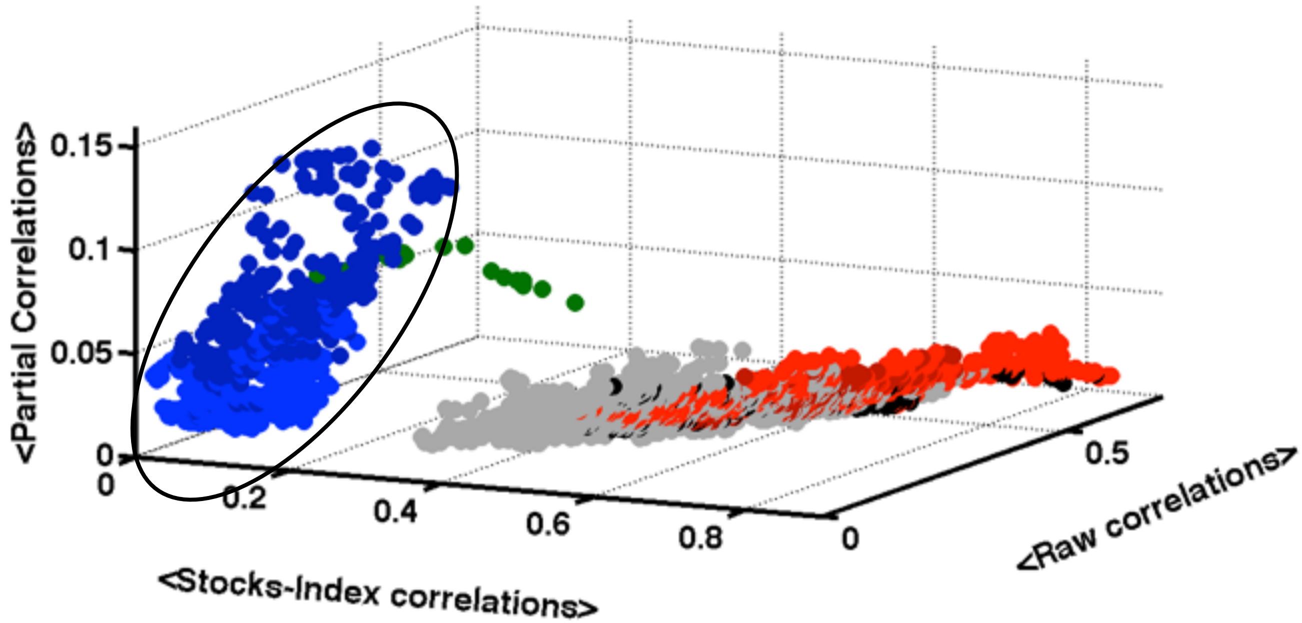

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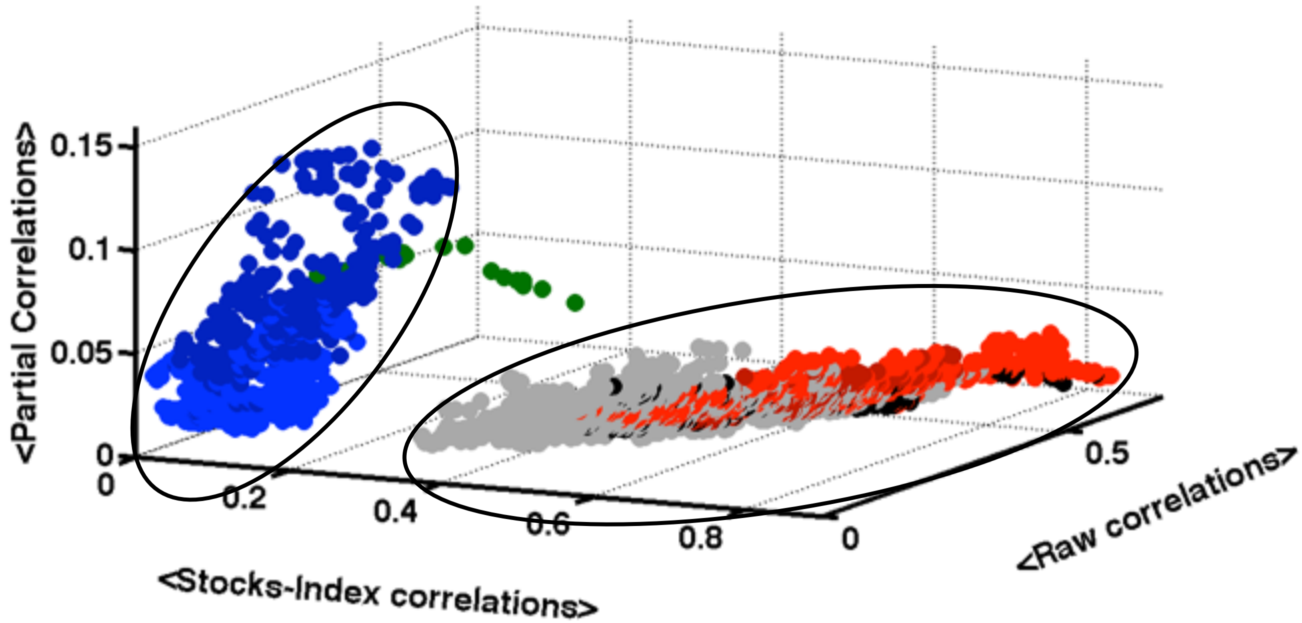

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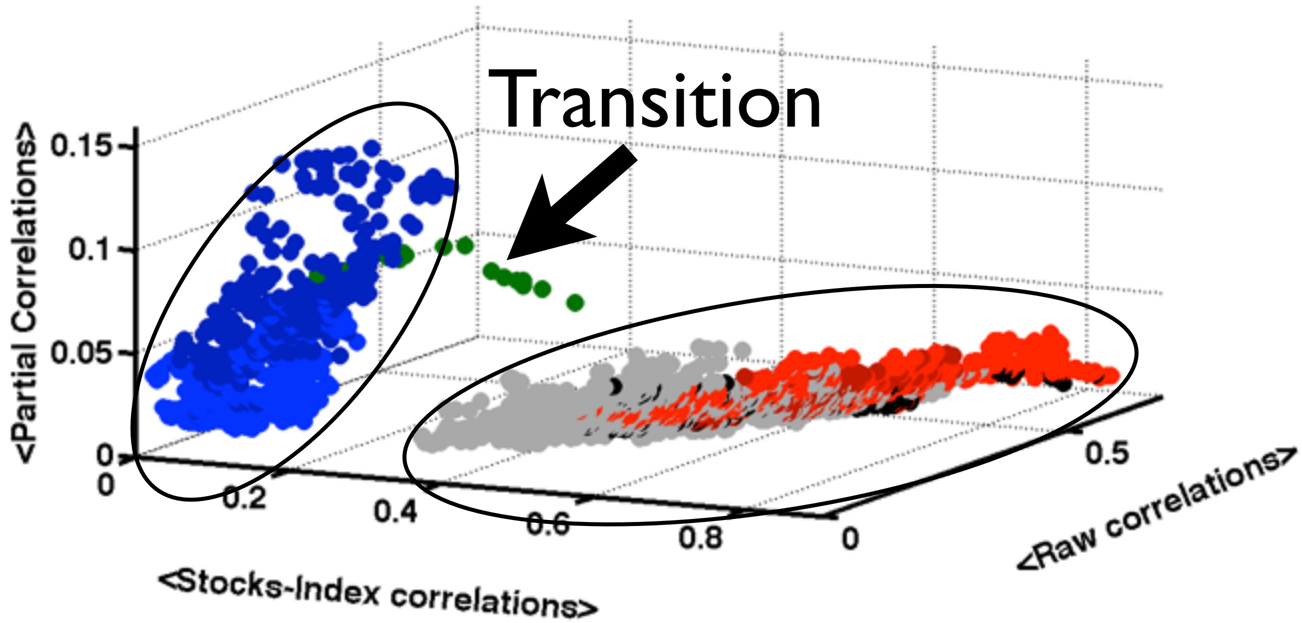

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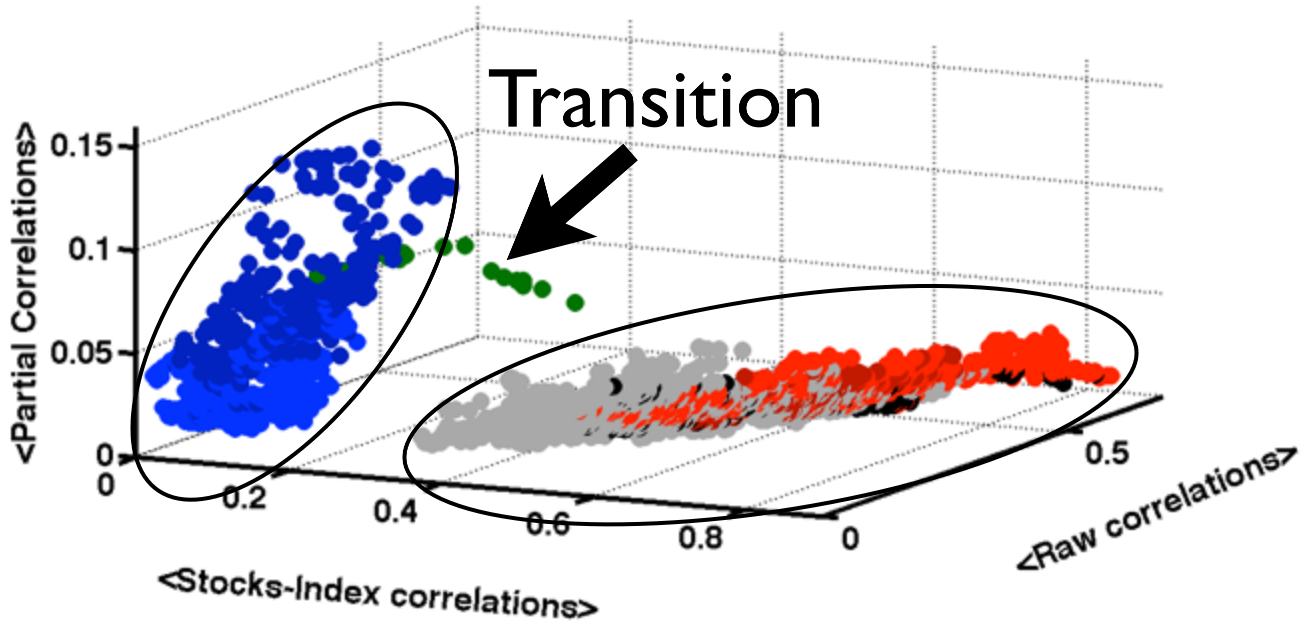

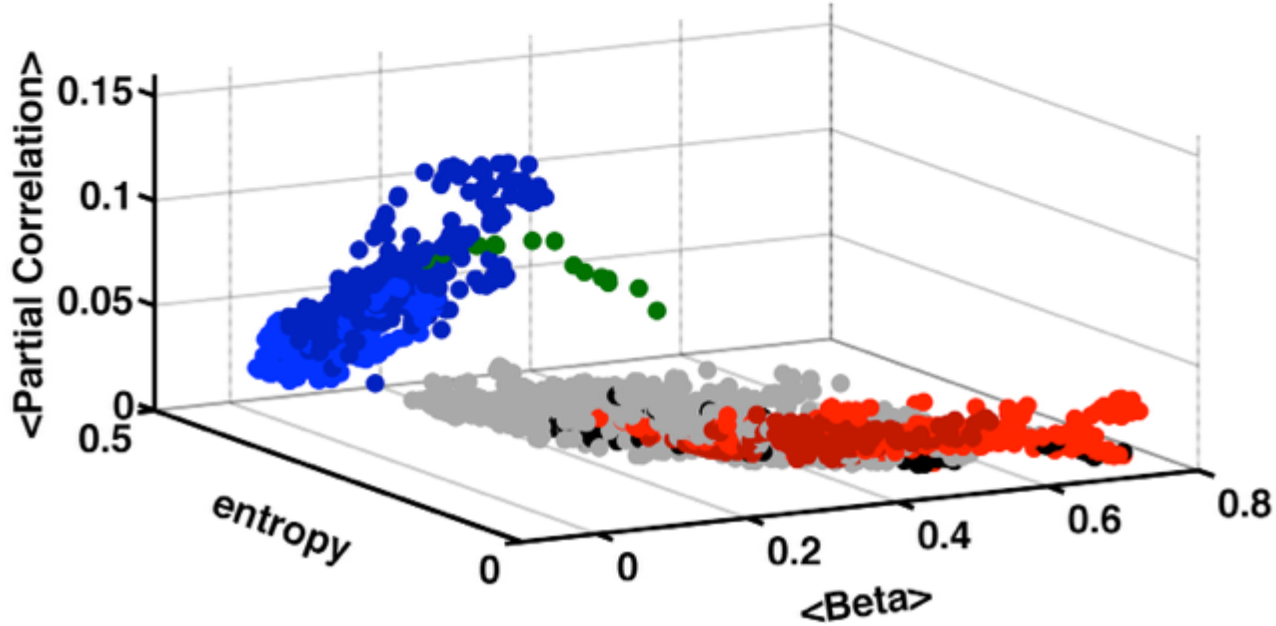

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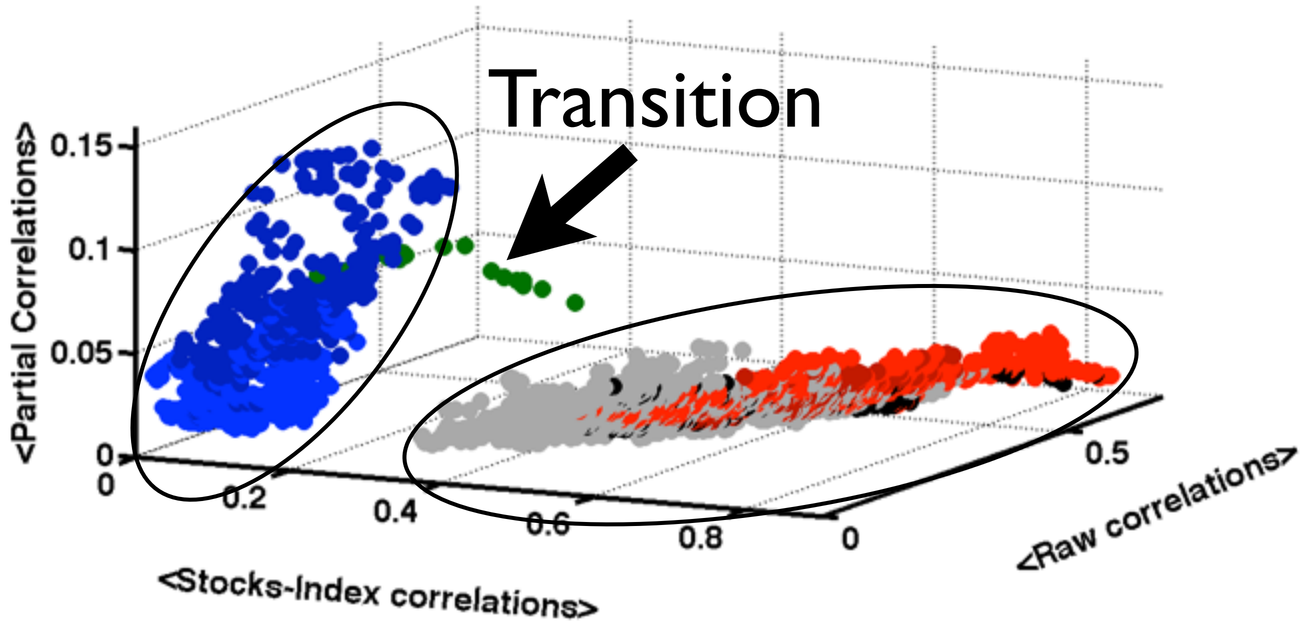
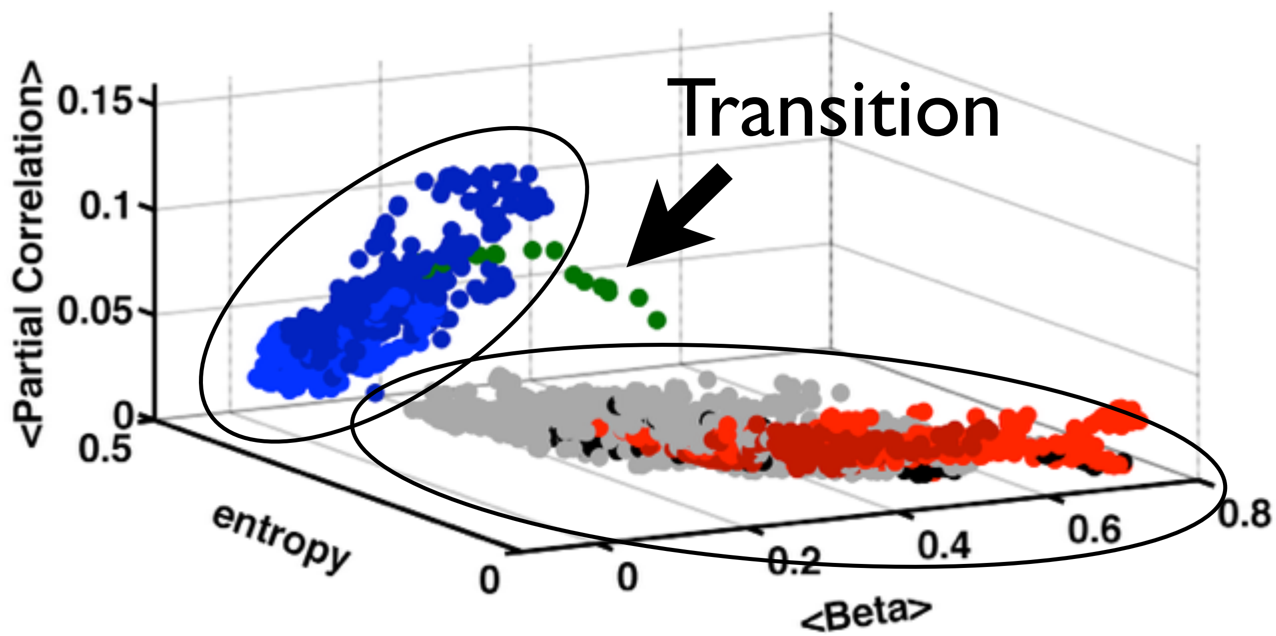
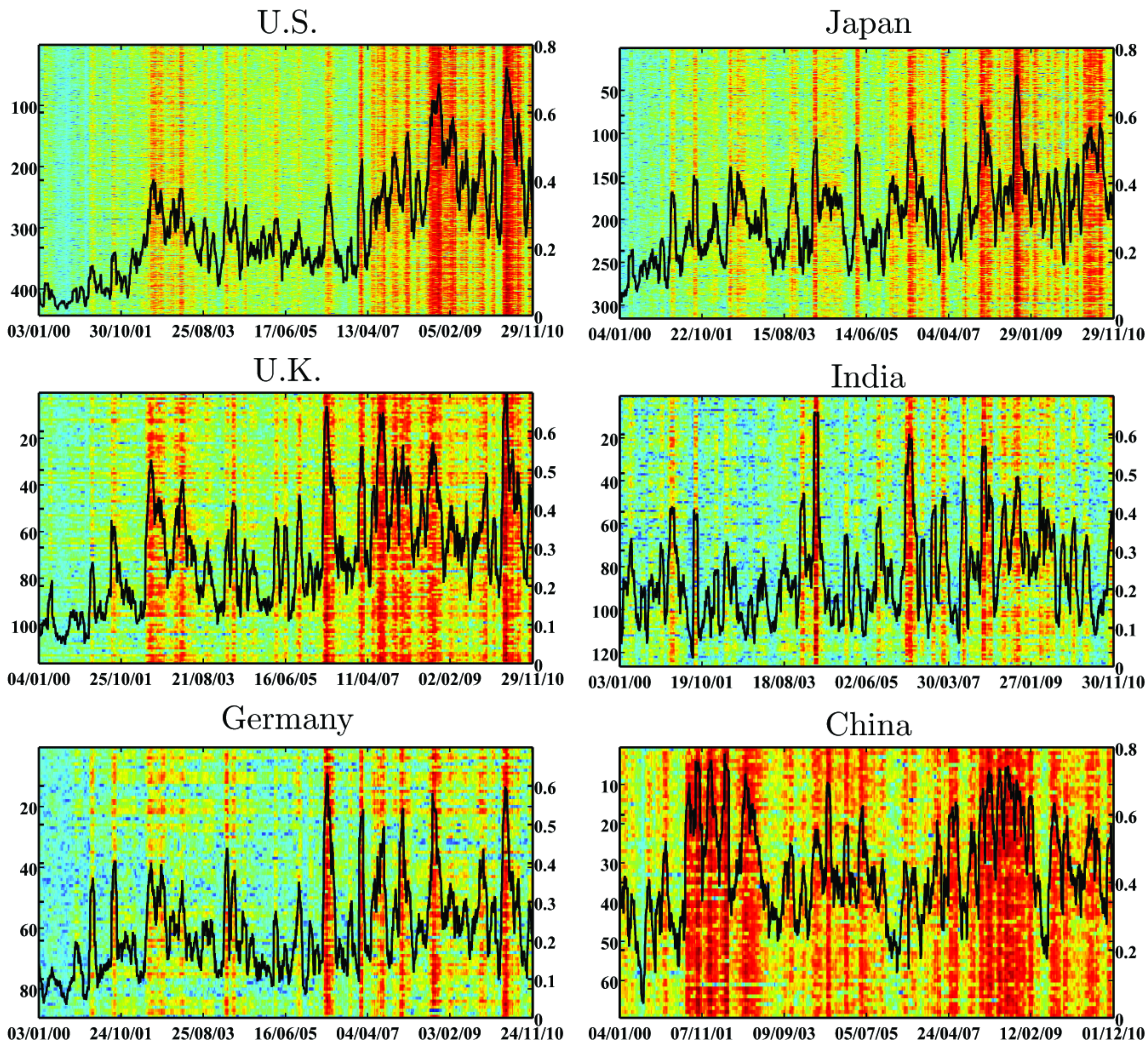
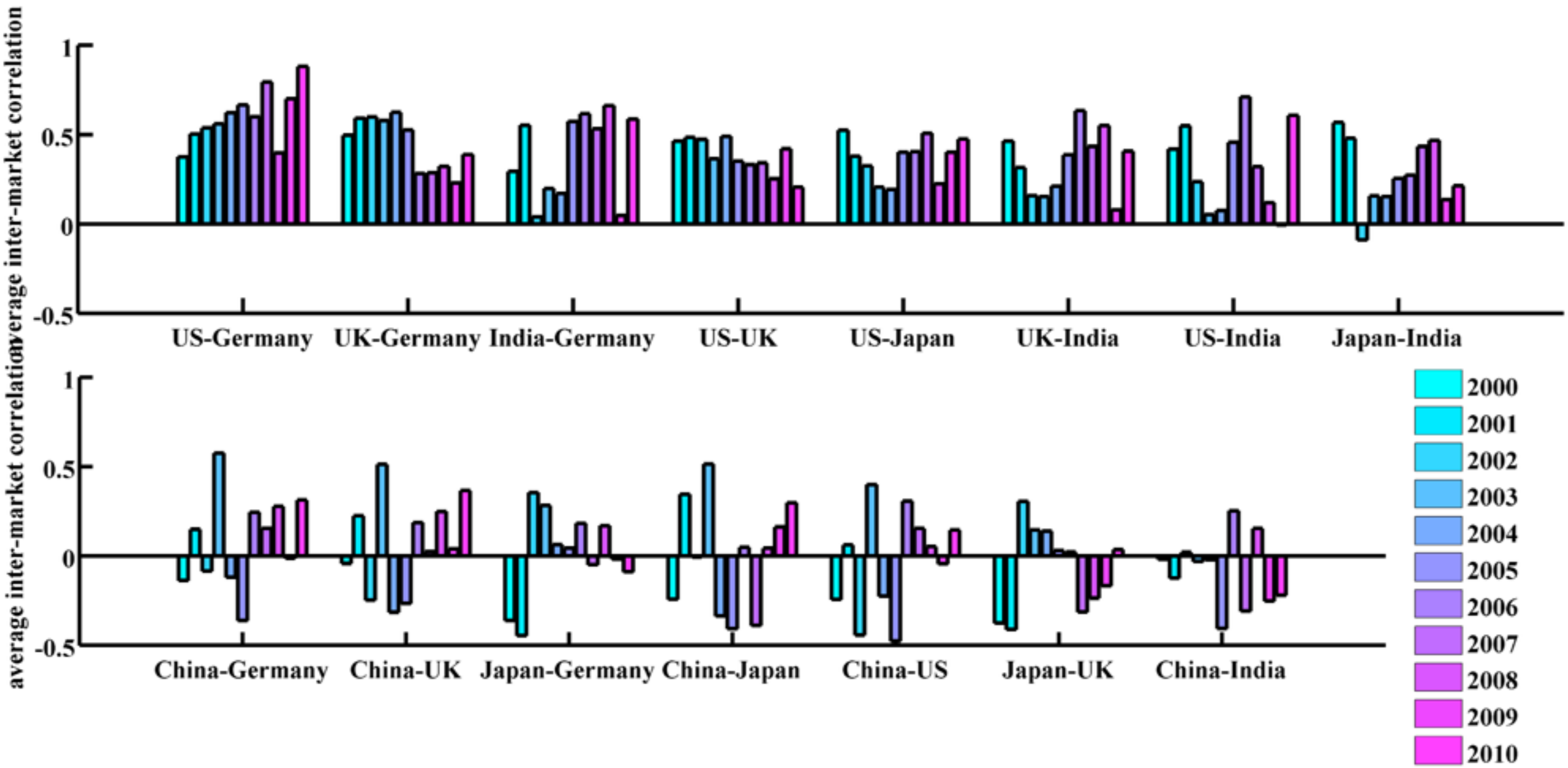




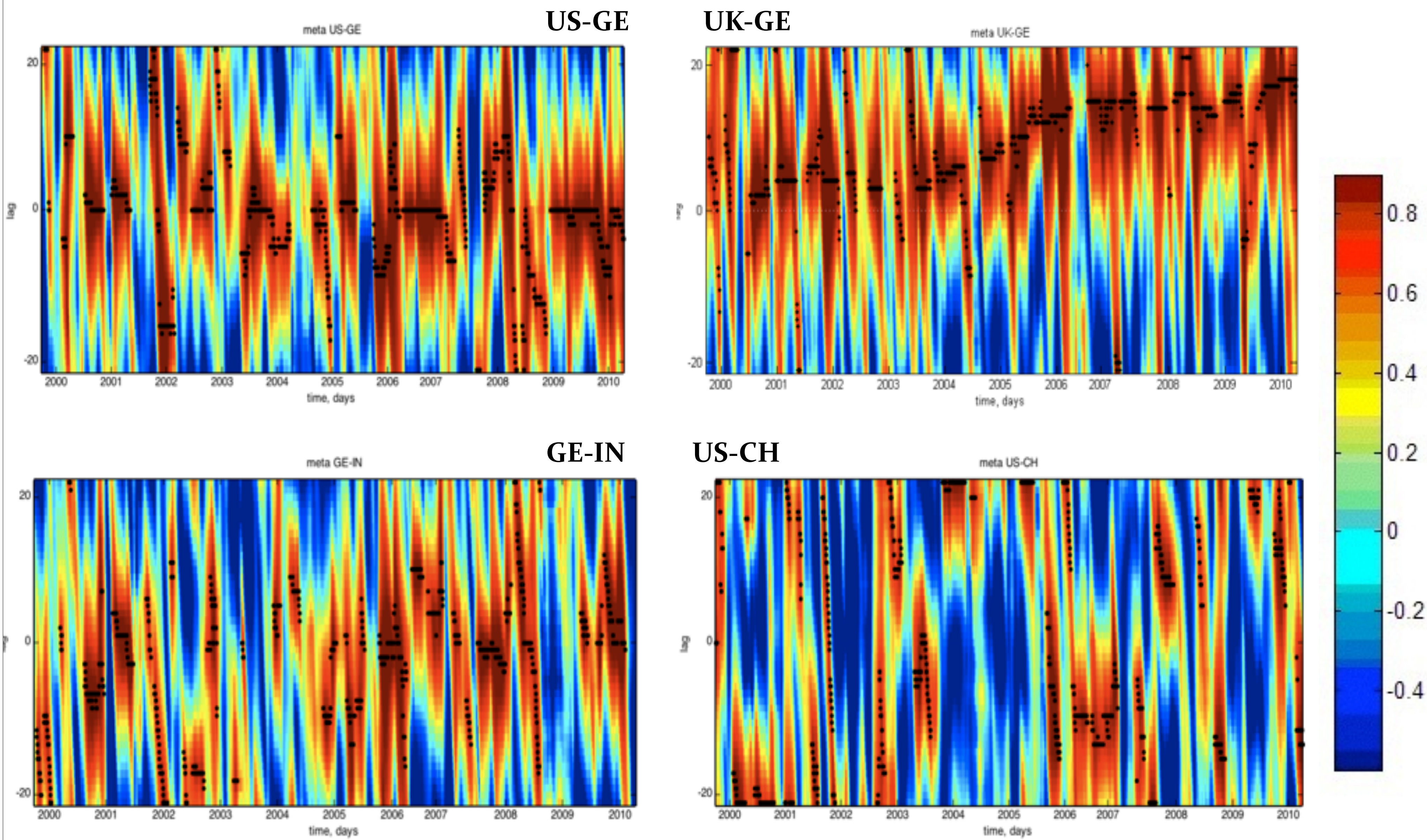
Stock market Correlations



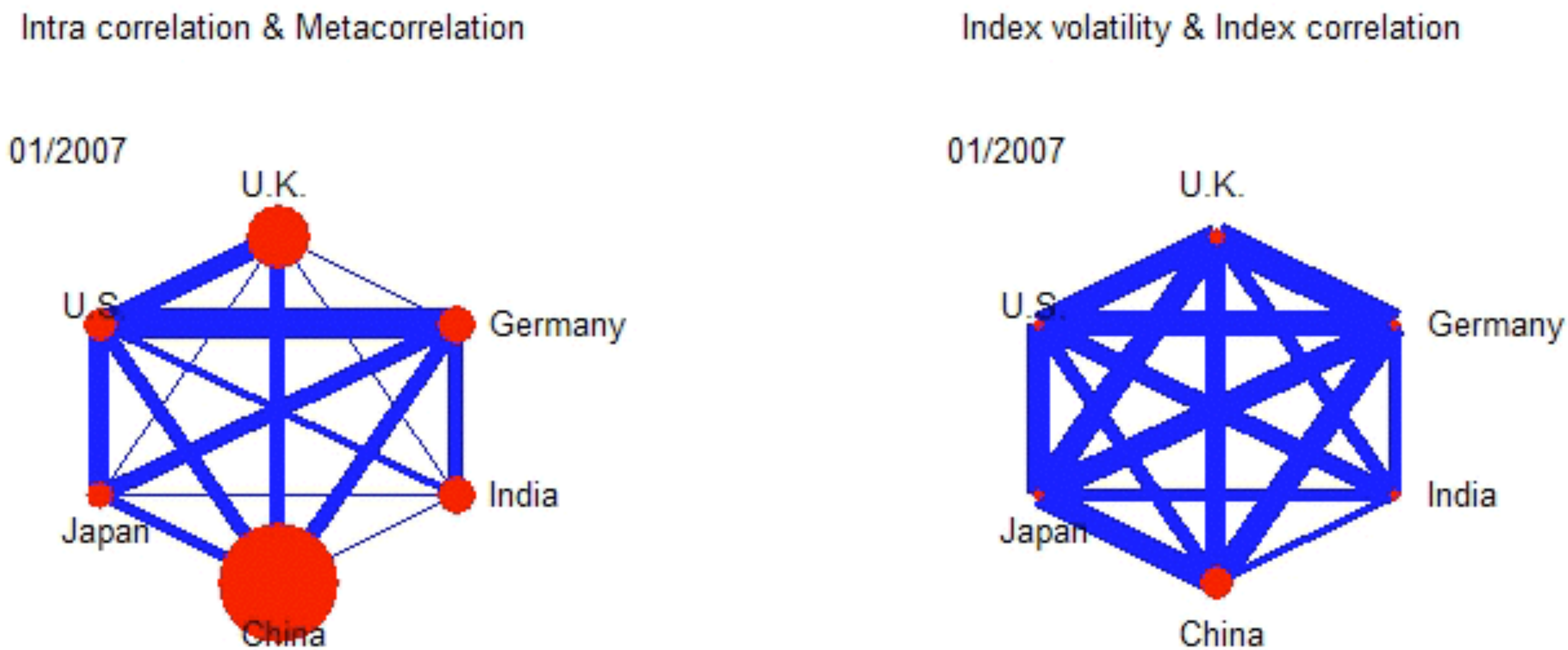
Market Meta-Correlation



Question: Can correlations in one market predict correlations in a second market?



Goal: Financial Seismograph



Financial Seismograph: Analysis and visualization of how correlations in one market can propogate and influence correlations in a different market

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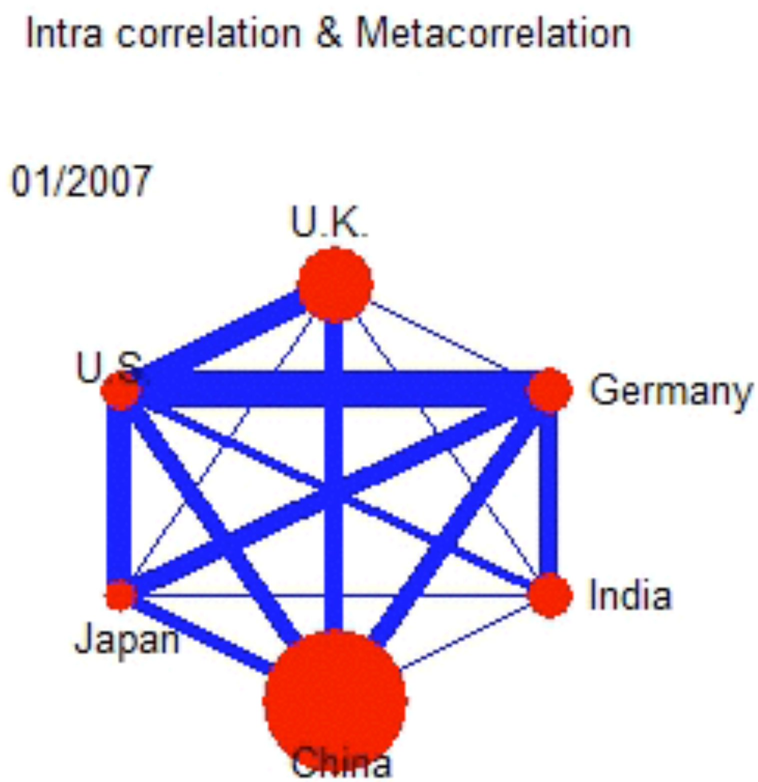

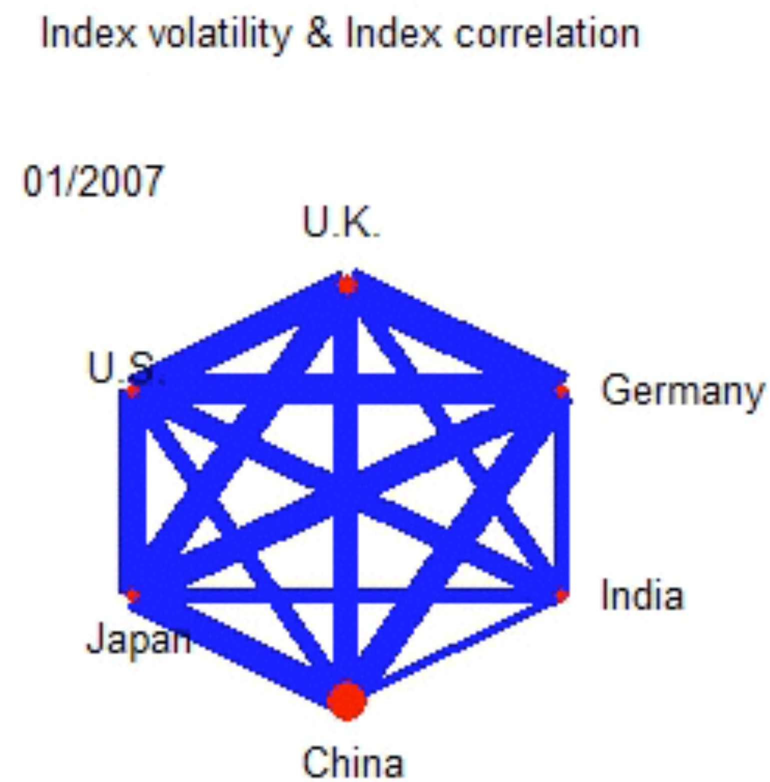

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(5) Discussion

What is a network?

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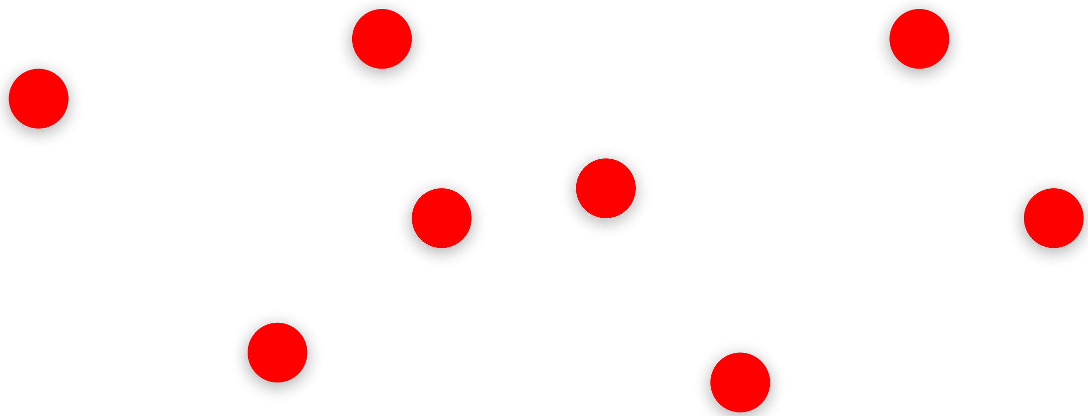

- **components**: nodes, vertices N

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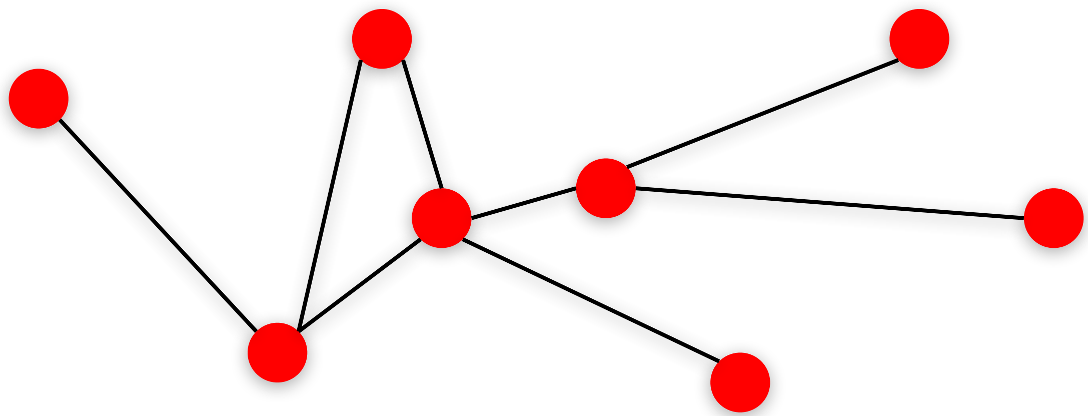
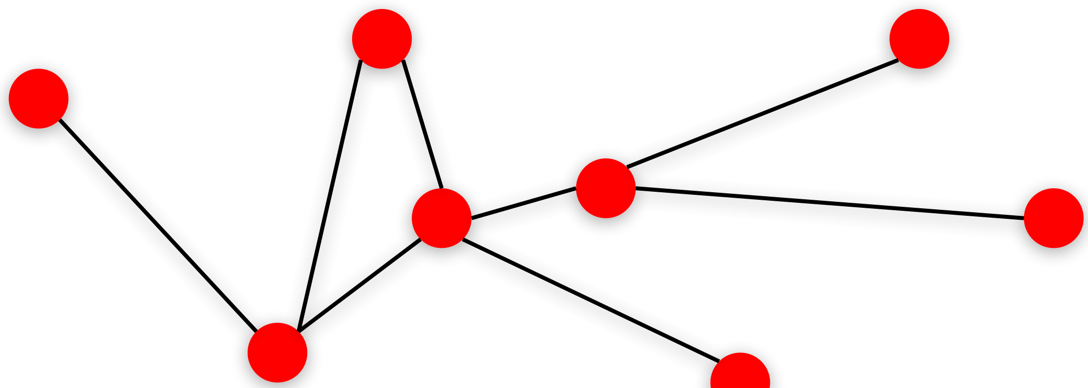
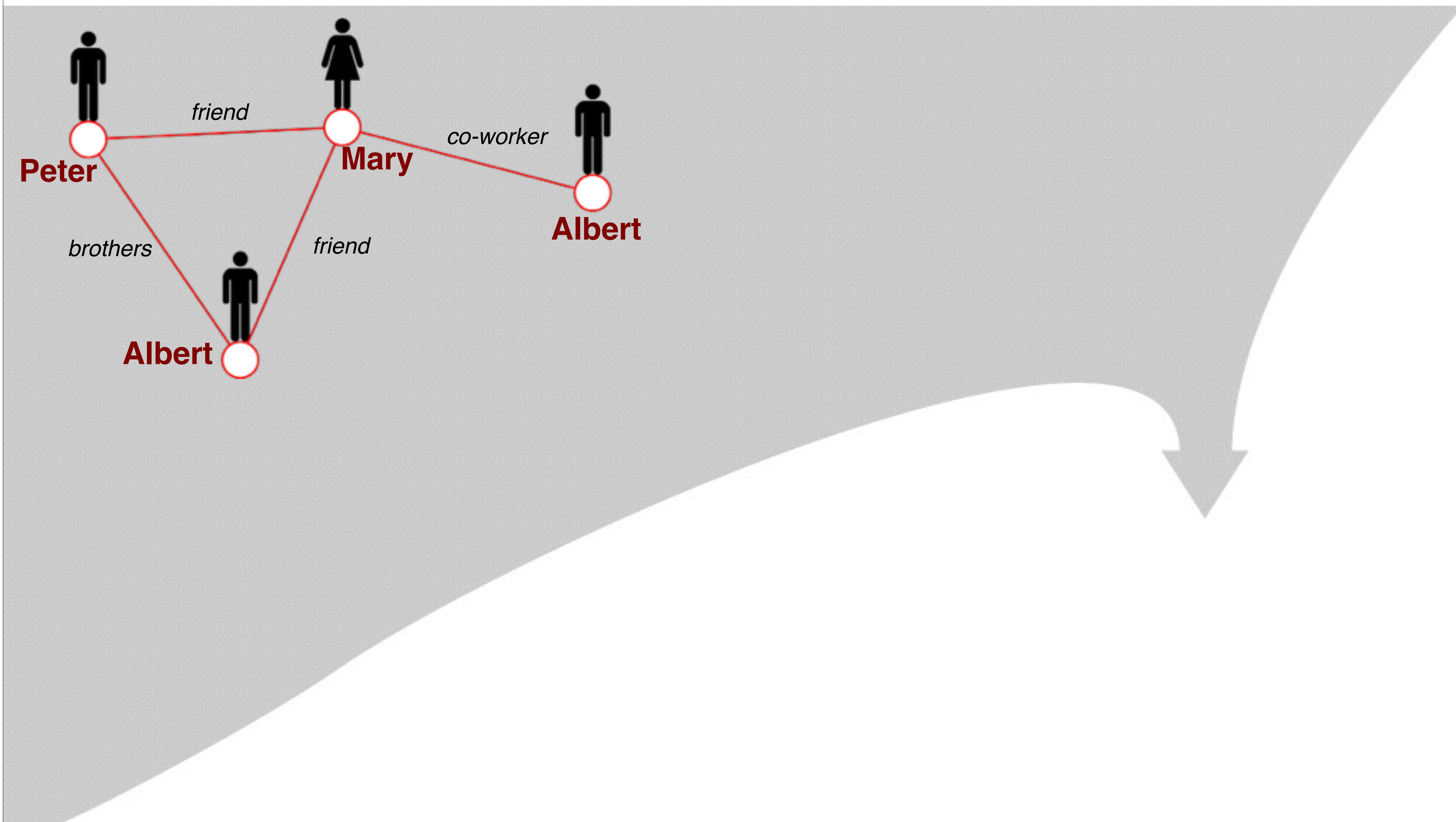


- **components**: nodes, vertices N
- **interactions**: links, edges L

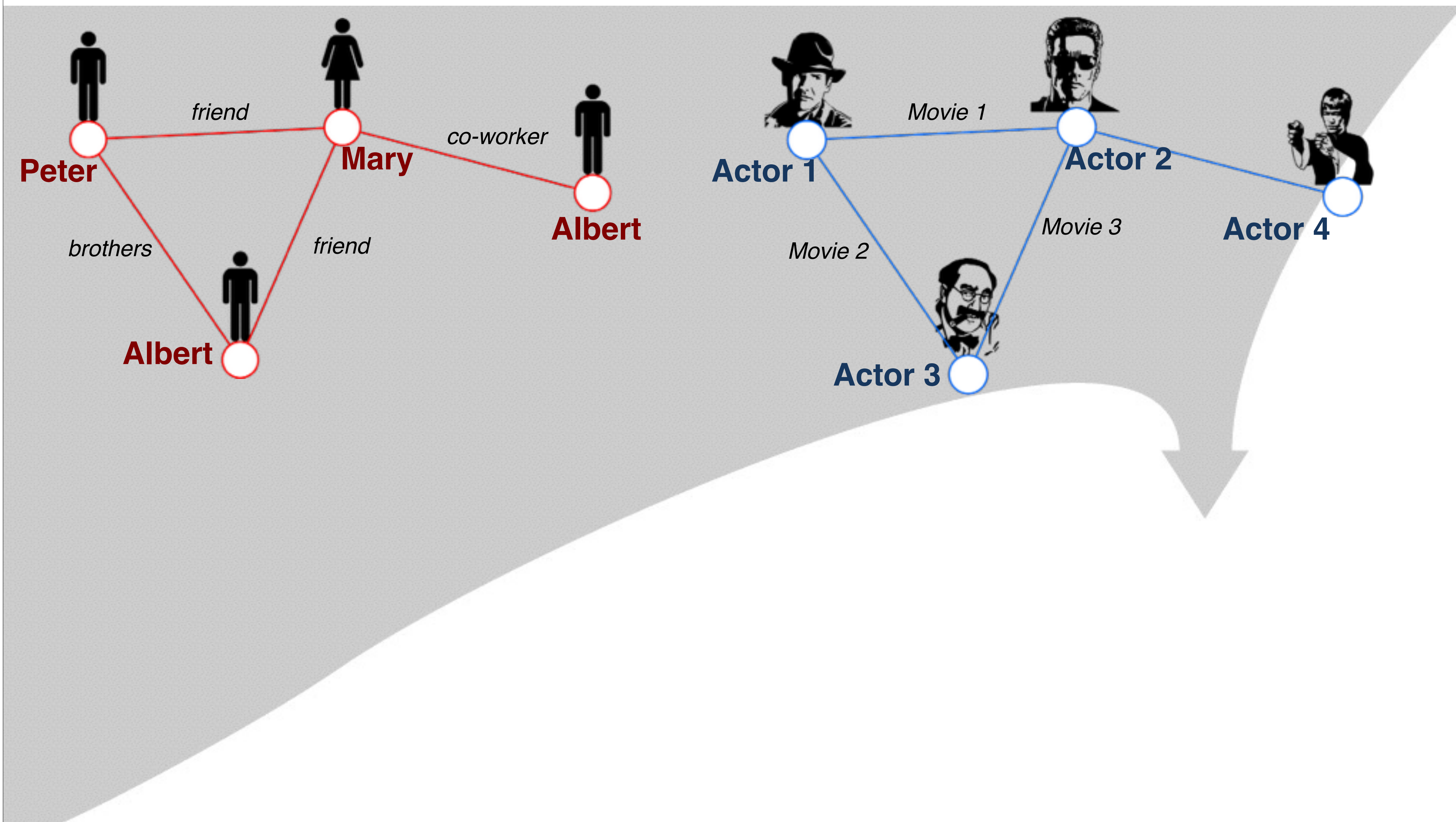
What is a network?



- **components**: nodes, vertices N
- **interactions**: links, edges L
- **system**: network, graph (N,L)



friend
co-worker
Peter
Mary
Albert
brothers
friend
Albert



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Peter
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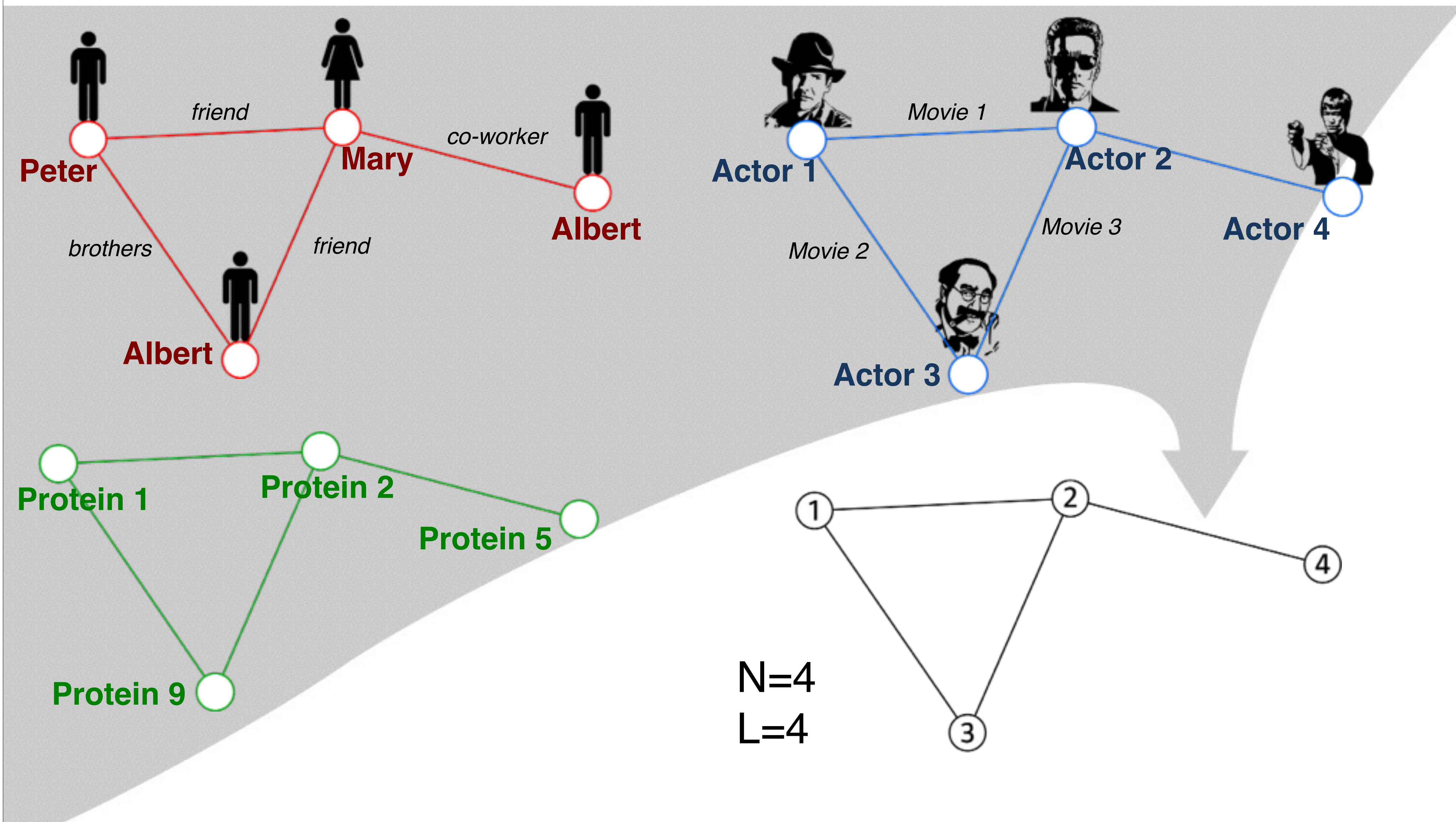
friend
Albert
Movie 1
Actor 1
Actor 2
Movie 3
Actor 4
Movie 2
Actor 3



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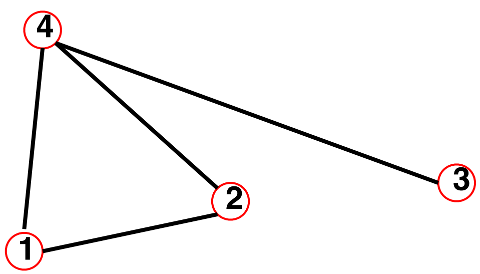
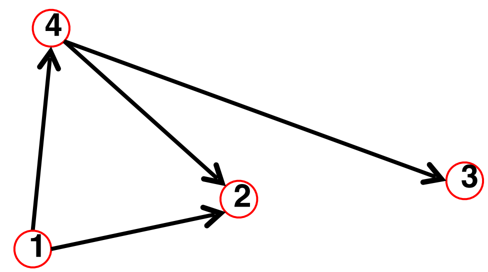
friend
Albert
Movie 1
Actor 1
Actor 2
Actor 4
Movie 3
Movie 2
Actor 3
Protein 1
Protein 2
Protein 5
Protein 9
1
2
3
4
N=4
L=4

The Adjacency Matrix





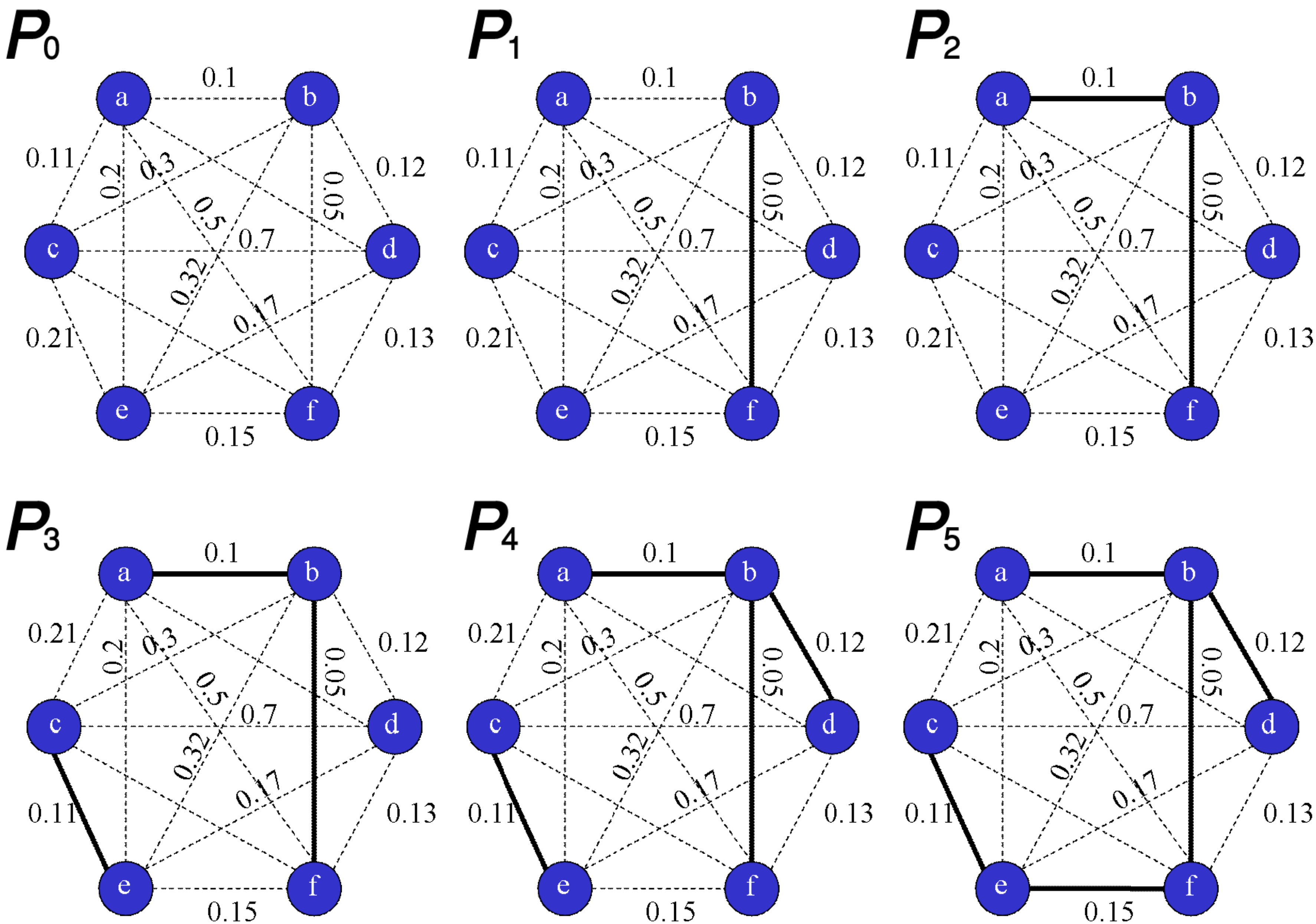
$\mathbf{A_{ij}=1}$ if there is a link between node *i* and *j*

$\mathbf{A_{ij}=0}$ if nodes *i* and *j* are not connected to each other.

$$A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \qquad A_{ij} = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Note that for a directed graph (right) the matrix is not symmetric.

	a	b	c	d	e	f
a	0	0.1	0.11	0.4	0.2	0.5
b	0.1	0	0.3	0.12	0.32	0.05
c	0.11	0.3	0	0.7	0.21	0.5
d	0.4	0.12	0.7	0	0.17	0.13
e	0.2	0.32	0.21	0.17	0	0.15
f	0.5	0.05	0.5	0.13	0.15	0



P_0
a
b
c
d
e
f
0.1
0.11
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.21
0.13
0.15
P_1
a
b
c
d
e
f
0.1
0.11
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.21
0.13
0.15
P_2
a
b
c
d
e
f
0.1
0.11
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.21
0.13
0.15
P_3
a
b
c
d
e
f
0.1
0.21
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.11
0.13
0.15
P_4
a
b
c
d
e
f
0.1
0.21
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.11
0.13
0.15
P_5
a
b
c
d
e
f
0.1
0.21
0.2
0.3
0.12
0.05
0.5
0.7
0.32
0.17
0.11
0.13
0.15

Stock Dependency Networks

1. Calculate partial correlation $PC(i,k \mid j) \quad j = 1,2,\ldots,N$

2. Correlation Influence

$$D(i,k \mid j) \equiv C(i,k) - PC(i,k \mid j)$$

3. Stock Dependency $d(i \mid j) = \frac{1}{N-1} \sum_{k \neq j,i}^{N-1} D(i,k \mid j)$

4. Construct Planar Graph (PMFG, Tumminello *et al., PNAS 2005)*

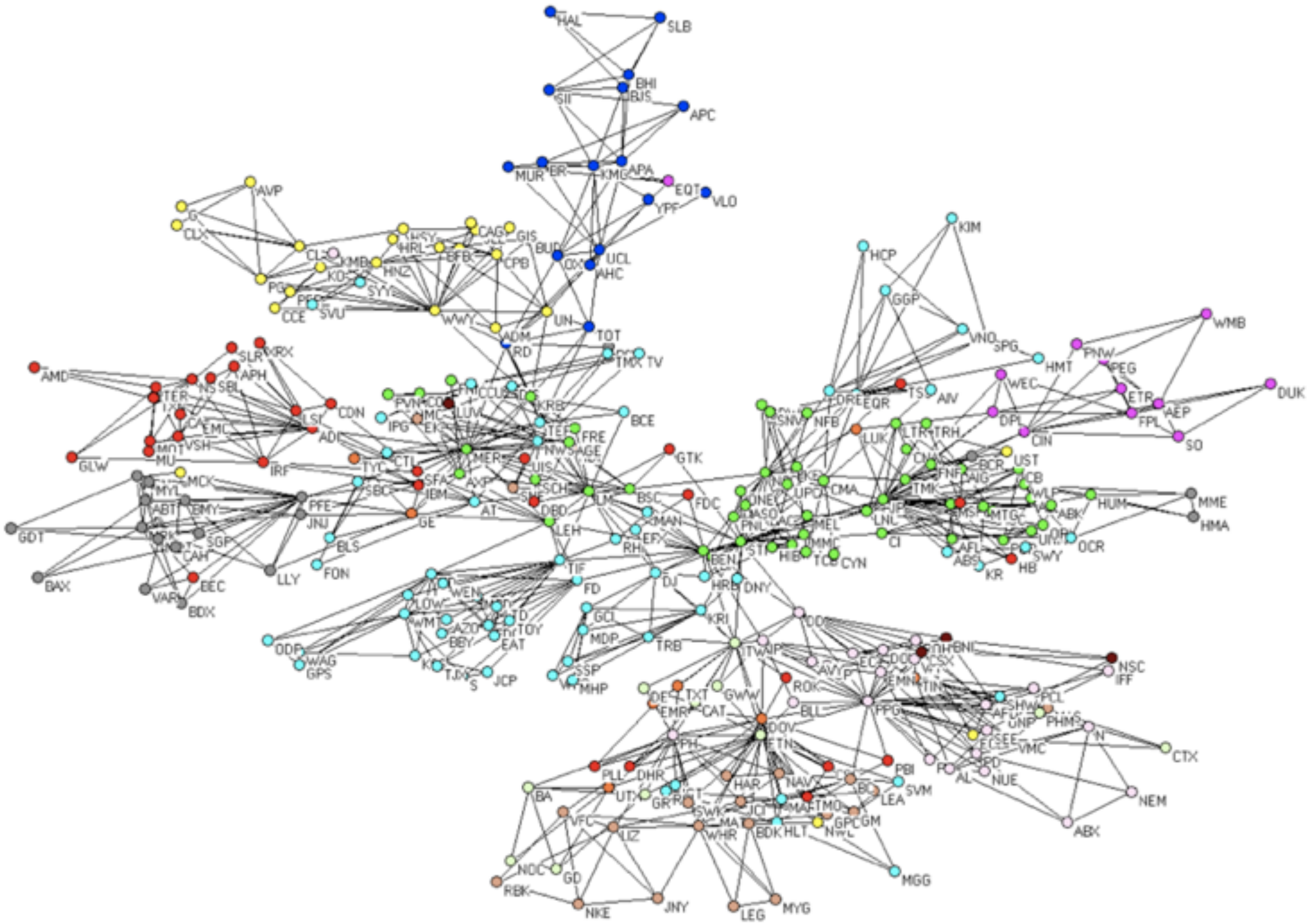
Dror Y. Kenett, Michele Tumminello, Asaf Madi, Gitit Gur-Gershgoren, Rosario N. Mantegna, and Eshel Ben-Jacob (2010), Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market, PLoS ONE 5(12), e15032

Data

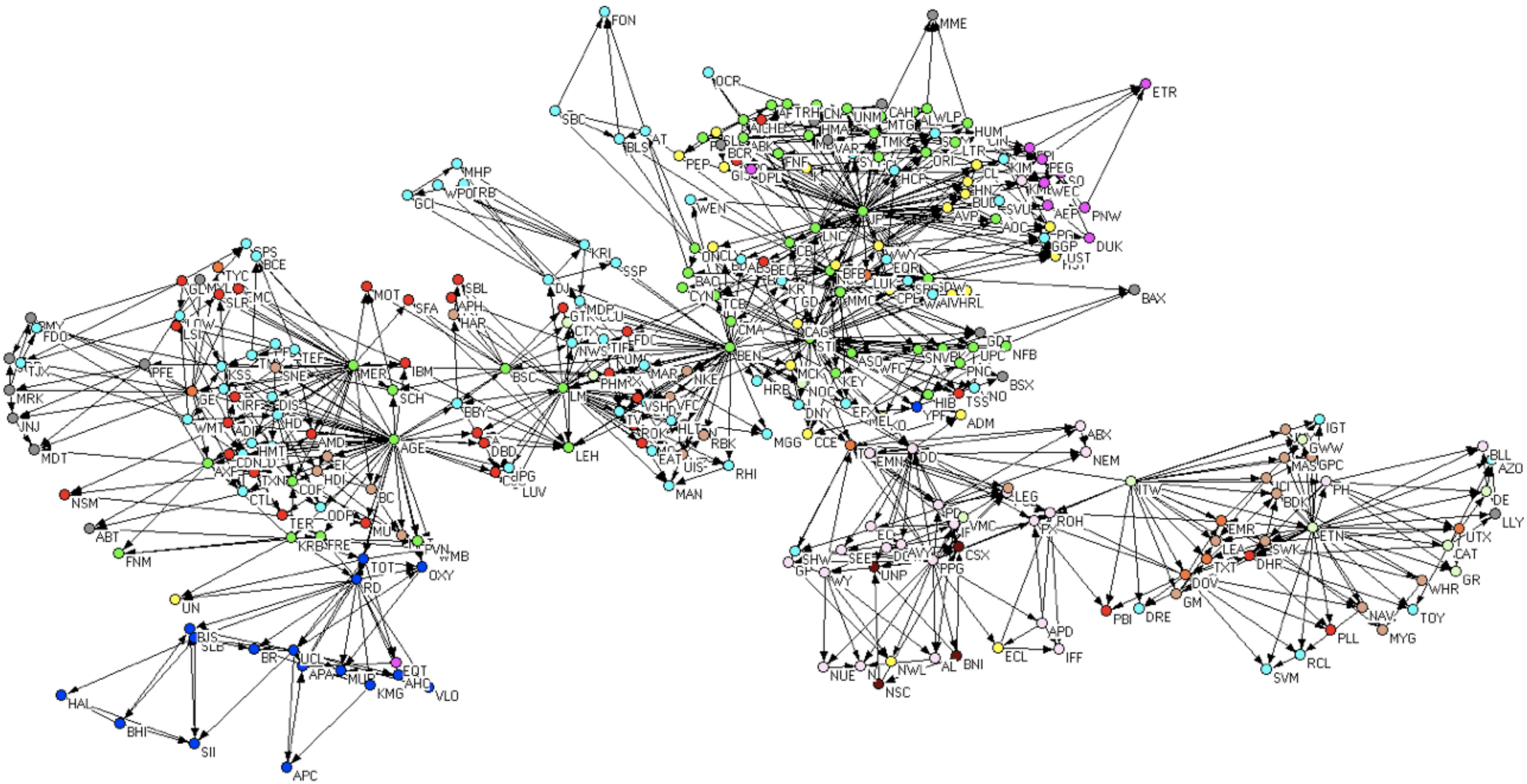
$N = 300 \qquad T = 748$

Index	Sector	# stocks
1	Basic Materials	24
2	Consumer Cyclical	22
3	Consumer Non Cyclical	25
4	Capital Goods	12
5	Conglomerates	8
6	Energy	17
7	Financial	53
8	Healthcare	19
9	Services	69
10	Technology	34
11	Transportation	5
12	Utilities	12

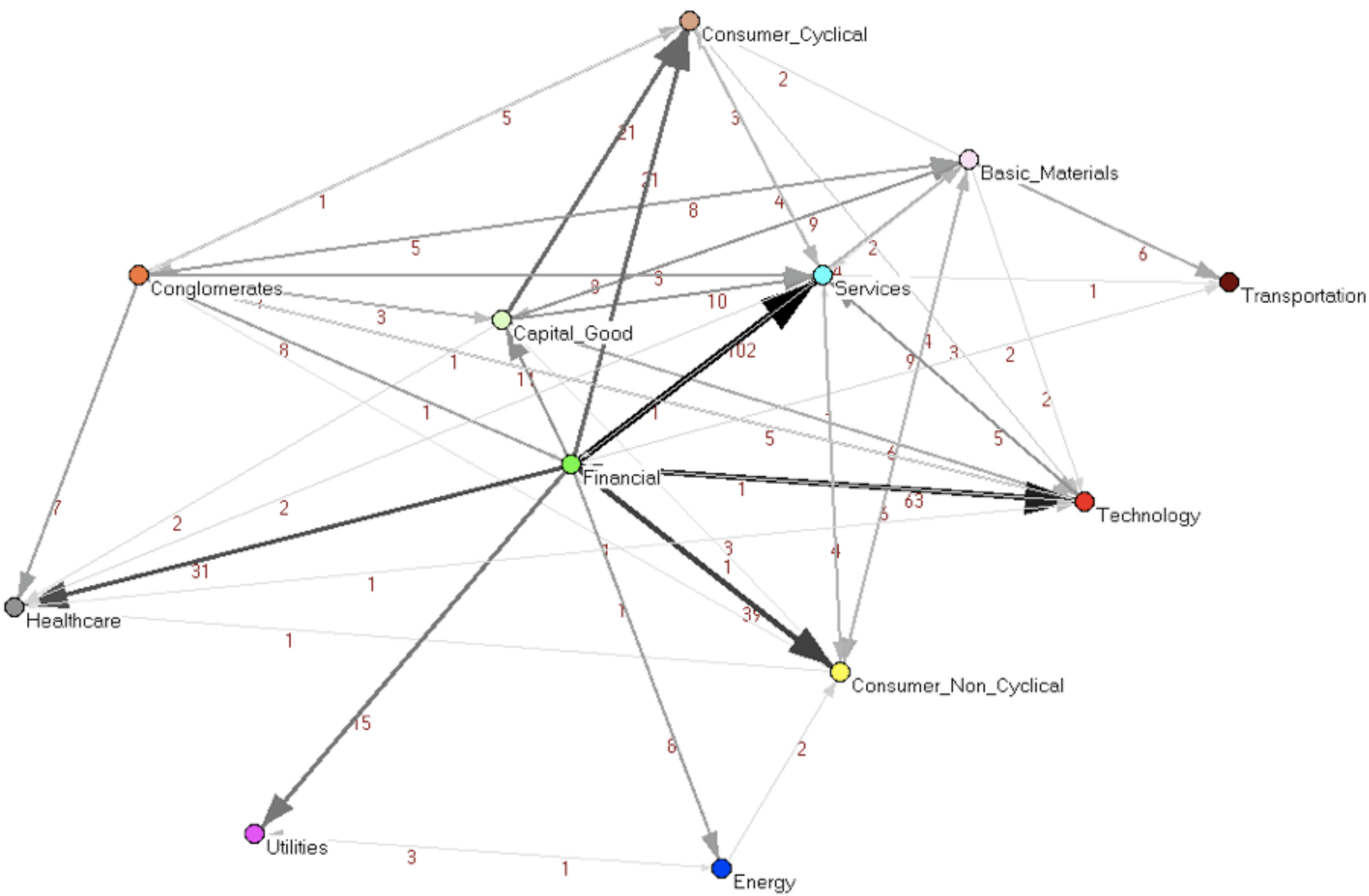
Stock Dependency Network: S&P Stocks



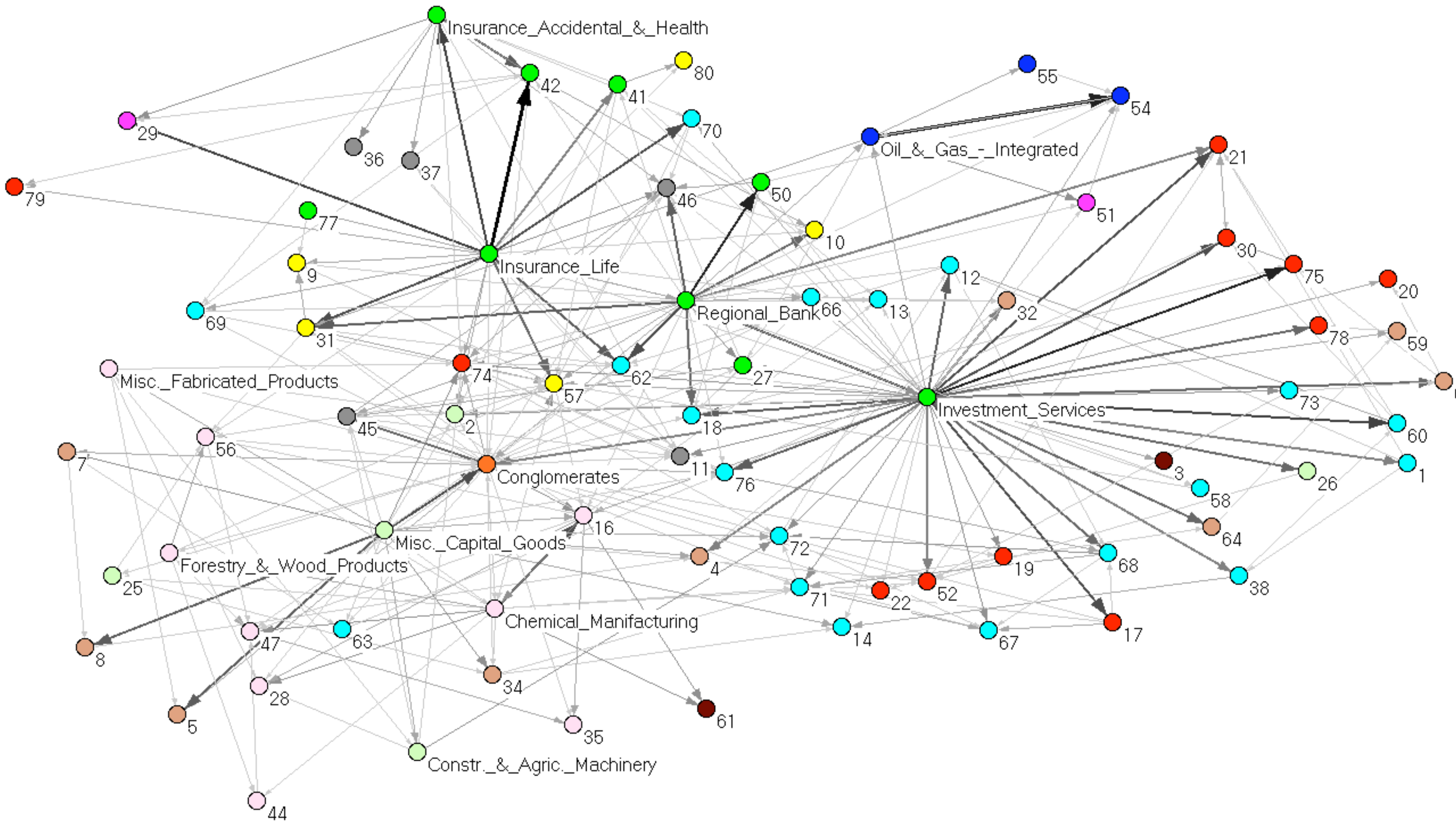
Stock Dependency Network: S&P Stocks



Sector Dependency Network



Sector Dependency Network



Theoretical Models

Simple Index

$$r_i = \gamma_i f + \sqrt{1-\gamma_i^2 f}\,\varepsilon_i, \qquad i = 1,\ldots,N,$$

$$\left\langle r_i f \right\rangle = \gamma_i \left\langle f^2 \right\rangle = \gamma_i,$$

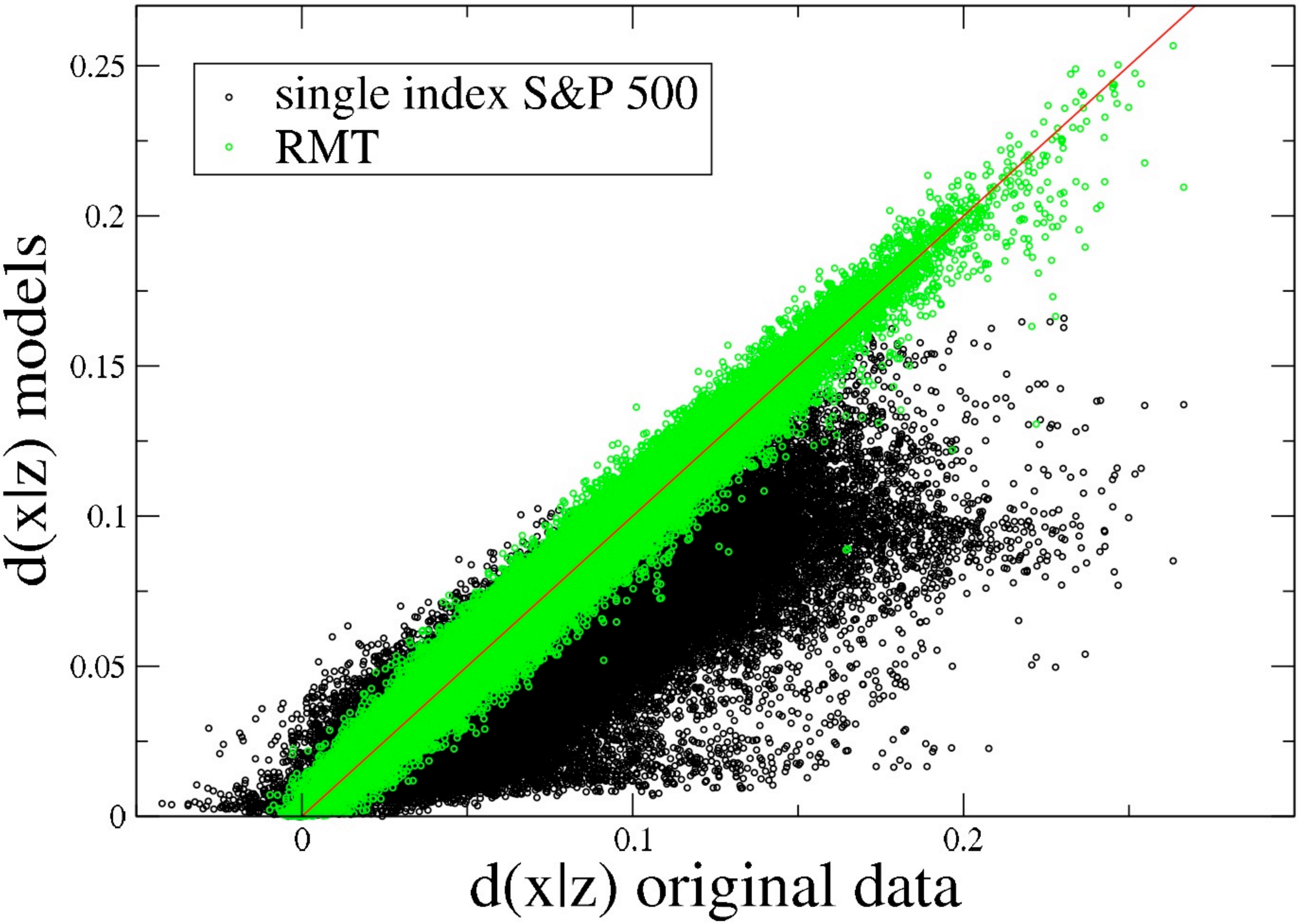
$$\rho_{i,j}(SI) = \left\langle r_i\, r_j \right\rangle = \gamma_i\, \gamma_j$$

RMT

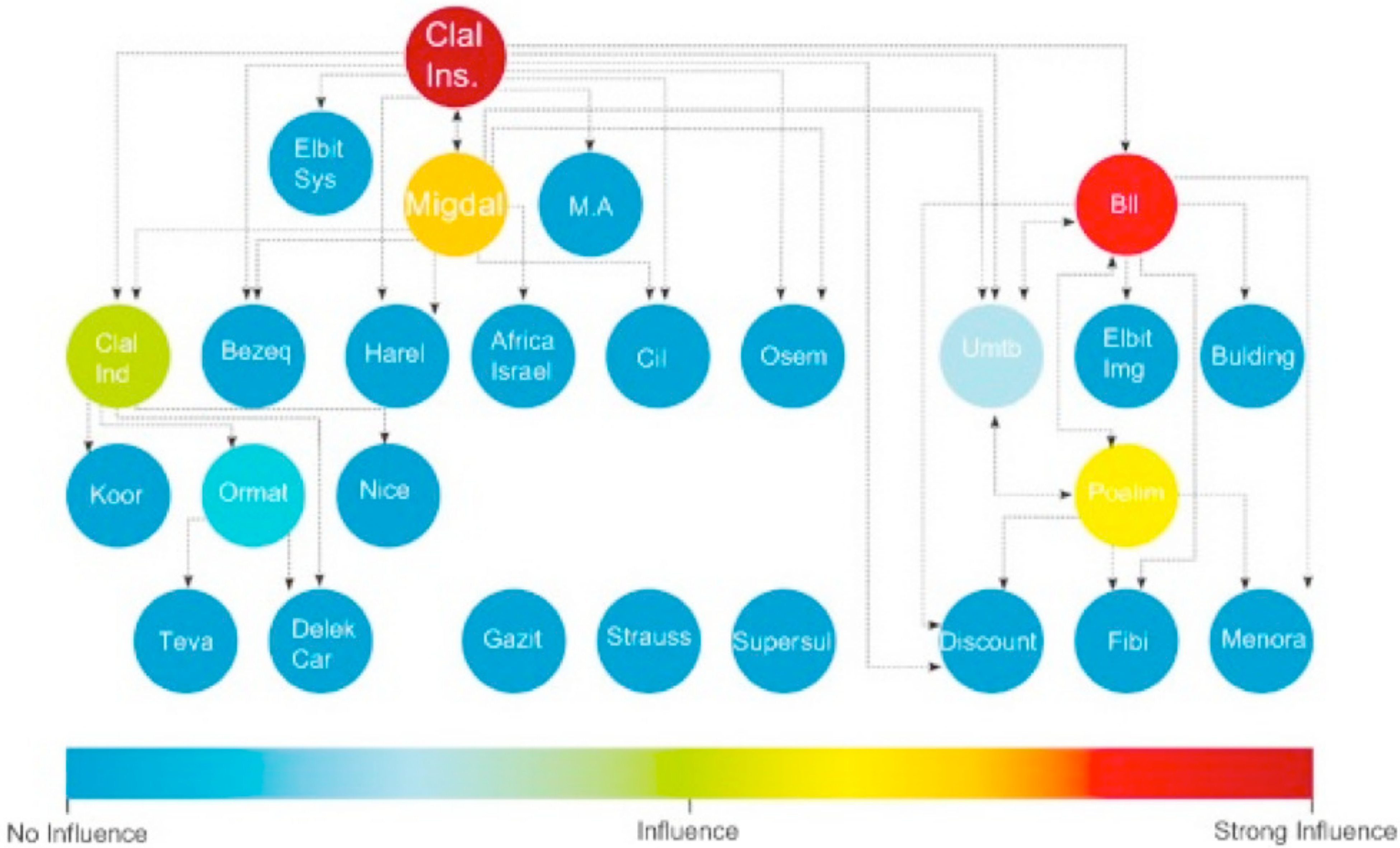
$$r_i = \sum_{h=1}^{K} \gamma_{i,h} \sqrt{\lambda_h} f_h + \sqrt{1 - \sum_{h=1}^{k} \gamma_{i,h}^2 \lambda_h \varepsilon_i} \qquad i = 1,\ldots,N,$$

$$\lambda_{\max} = \left(1 - \frac{\lambda_1}{N}\right)\left(1 + \frac{N}{T} + 2\sqrt{\frac{N}{T}}\right)$$

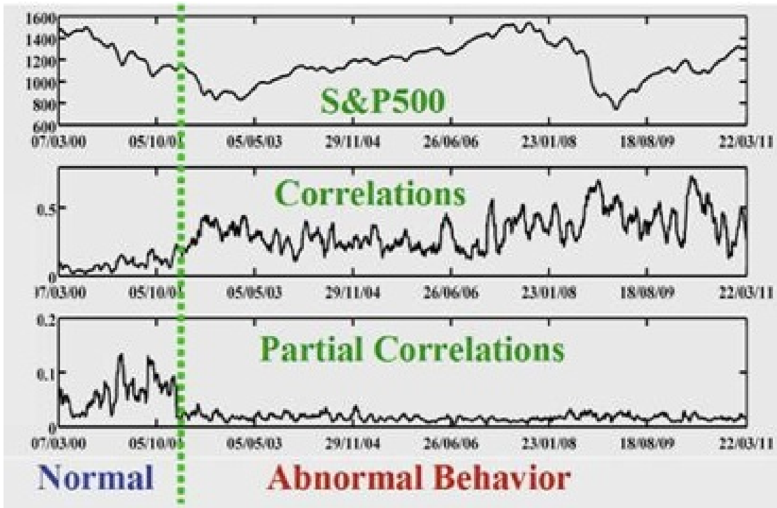
$$\rho_{i,j}(RMT) = \left\langle r_i\, r_j \right\rangle = \sum_{h=1}^{K} \gamma_{i,h} \gamma_{j,h} \lambda_h$$

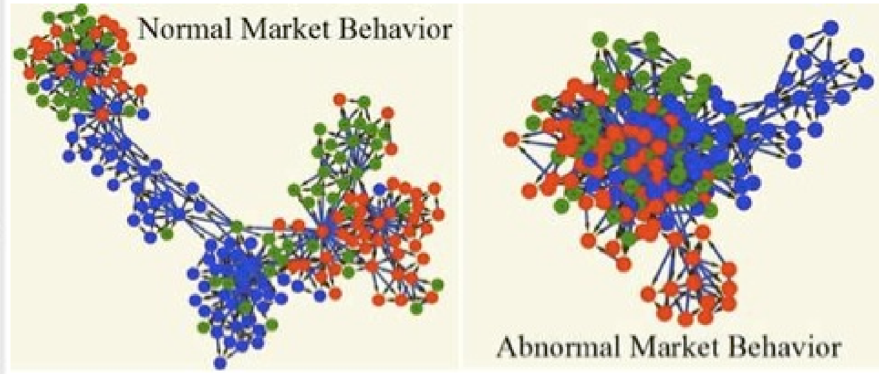

single index S&P 500
RMT
d(x|z) models
d(x|z) original data
0
0.05
0.1
0.15
0.2
0.25
0
0.1
0.2

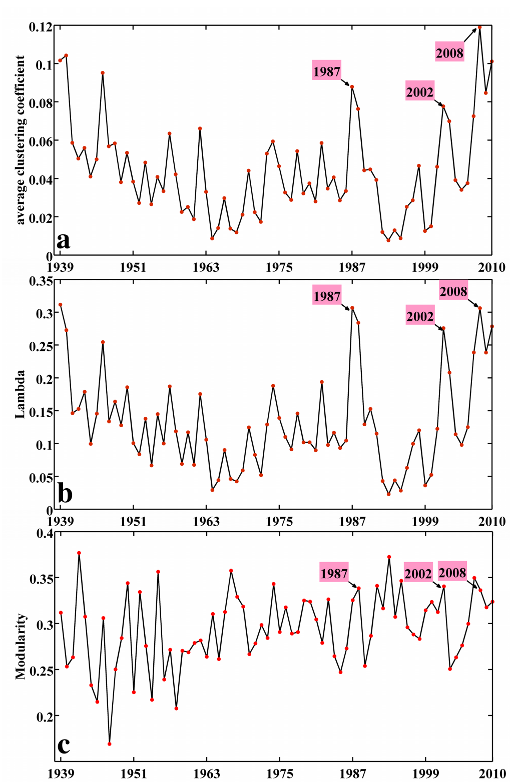
Case study - Tel-Aviv market

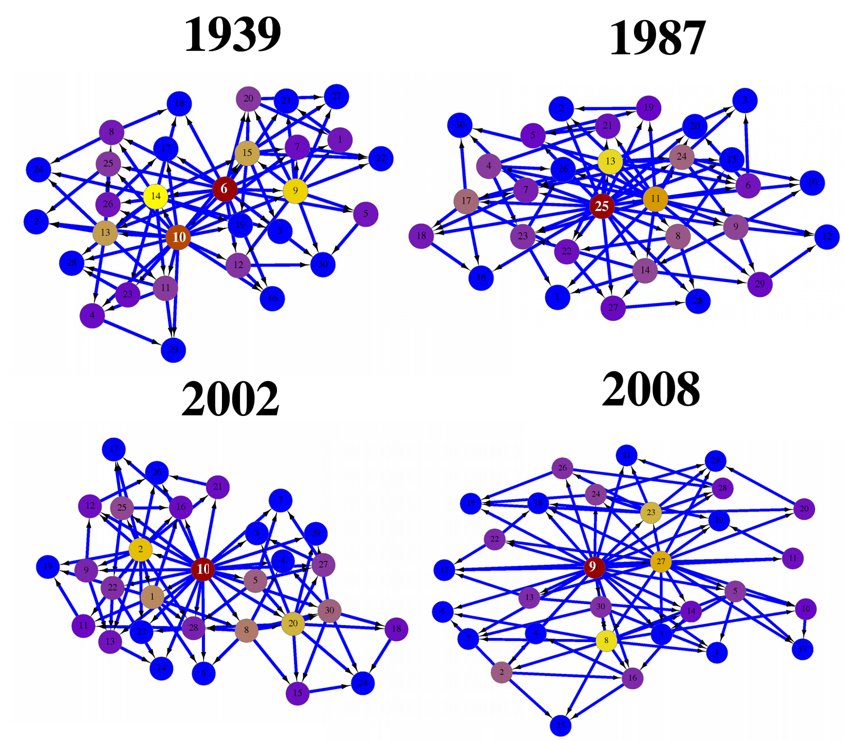


Market states







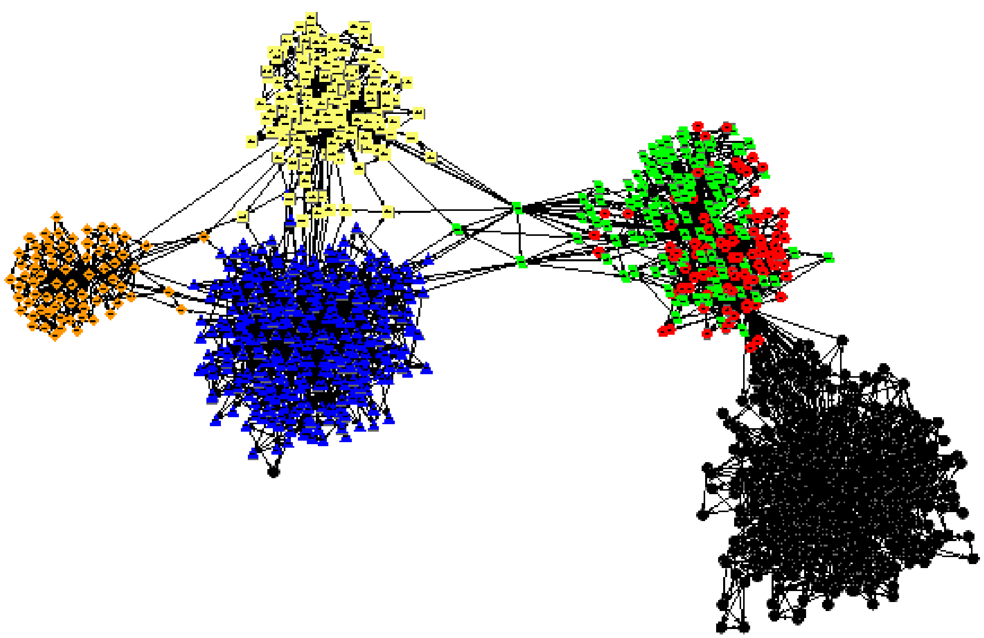


Market dynamics

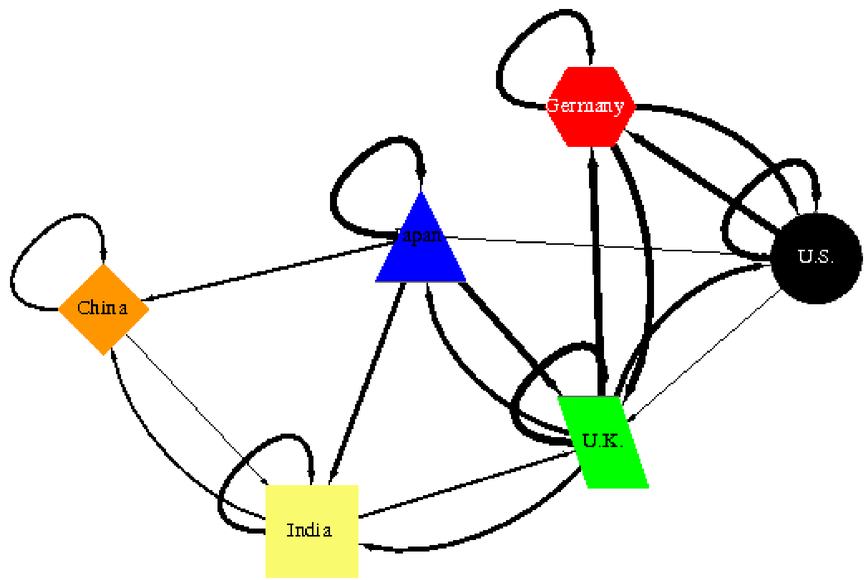
Interdependencies in the global financial village

Network analysis of influence and dependencies between Companies/Countries

Stock dependency network

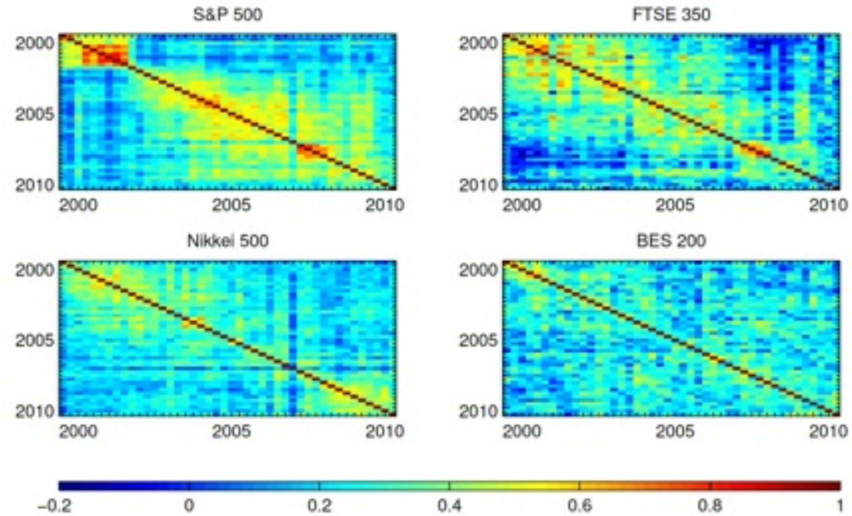


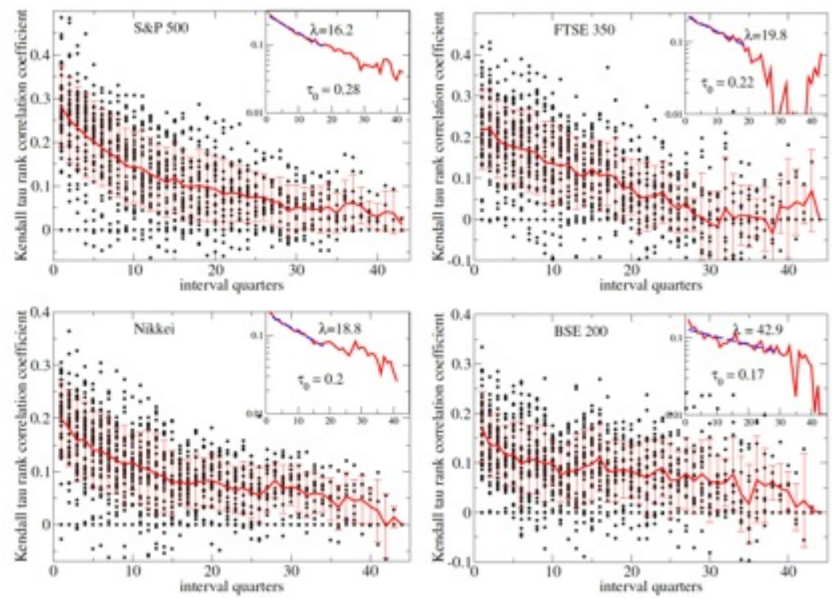
Country dependency network



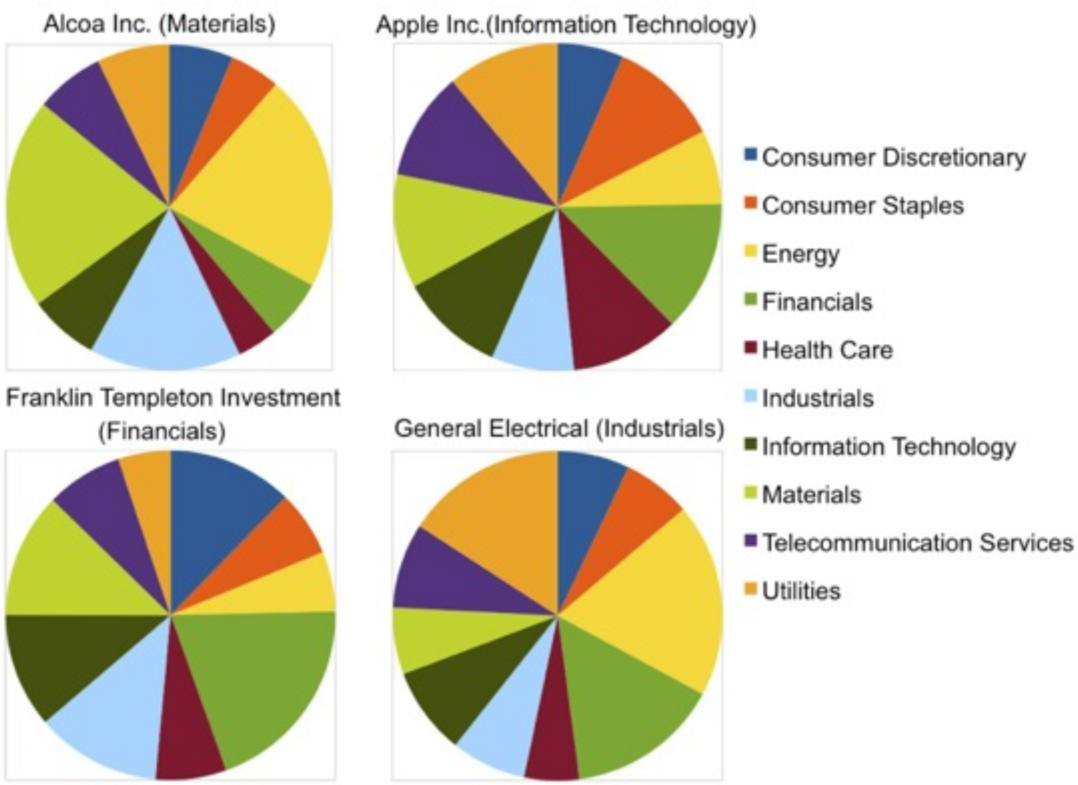
Investigating market structure

2)





1)



Outline

(1) Introduction

- Financial time series
- Stock correlations
- Dynamics of stock correlations

(2) Global financial village

- Market intra and meta correlation
- Financial Seismograph

(3) Dependency and Influence

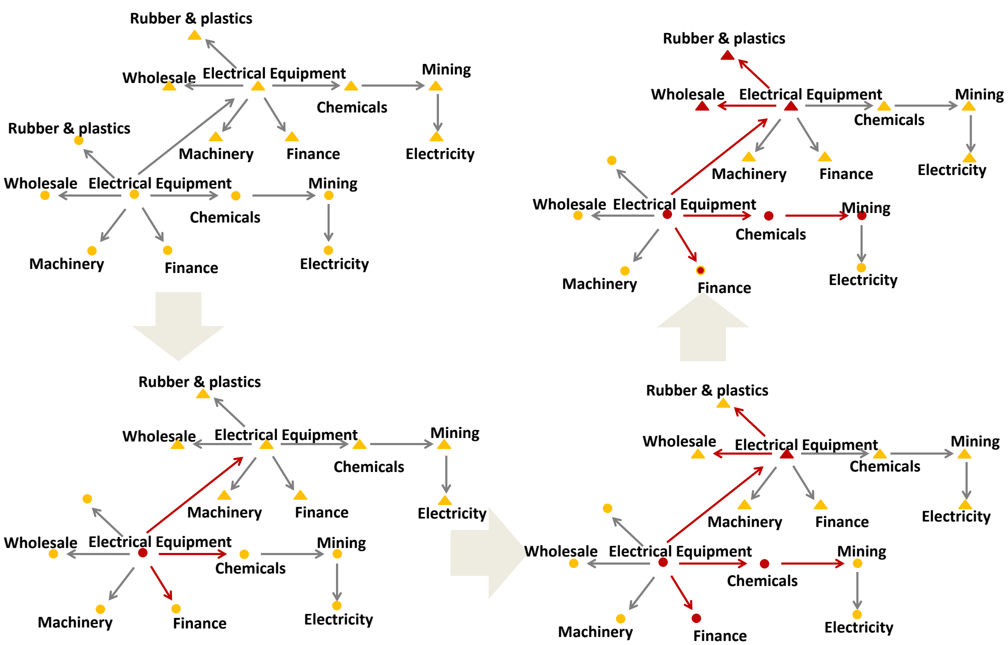
(4) Examples of network projects

I. Cascading failures in industry networks
II. Overlapping communities in networks
III. Failure and recovery in networks
IV. Evolution of networks
V. Cascading failures in the financial system
VI. Interdependent networks

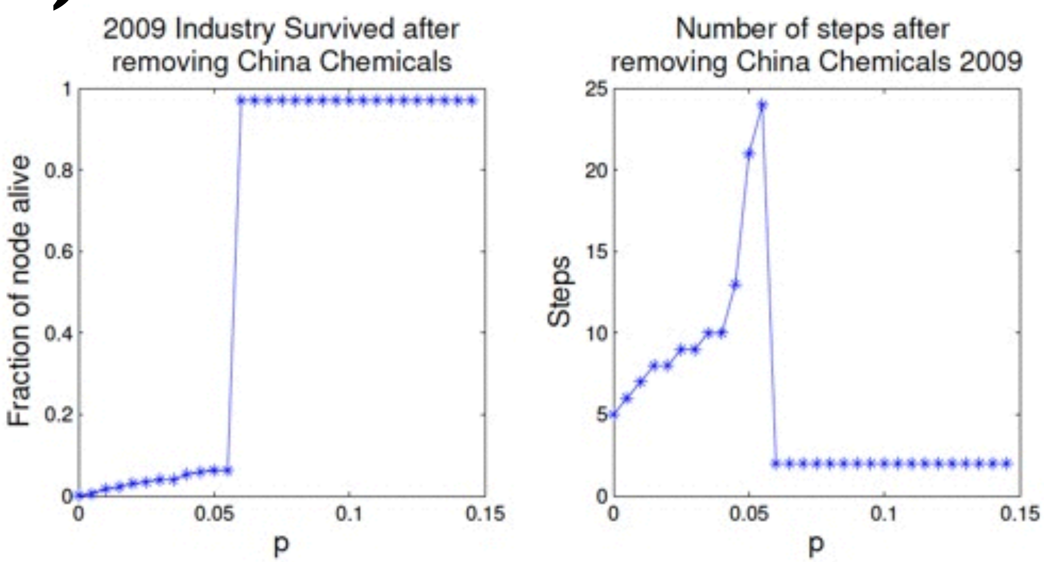
(5) Discussion

I. Cascading failures in industry networks

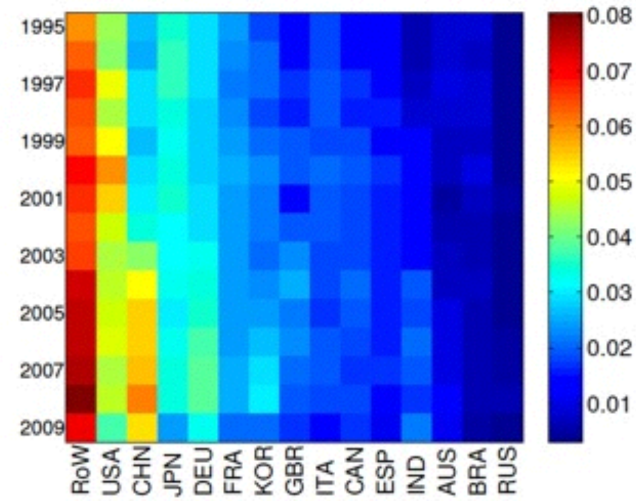
1)



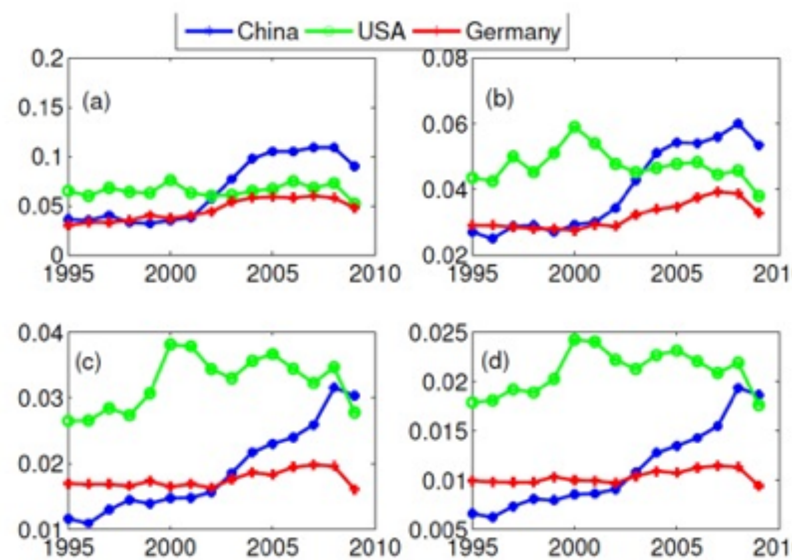
2)



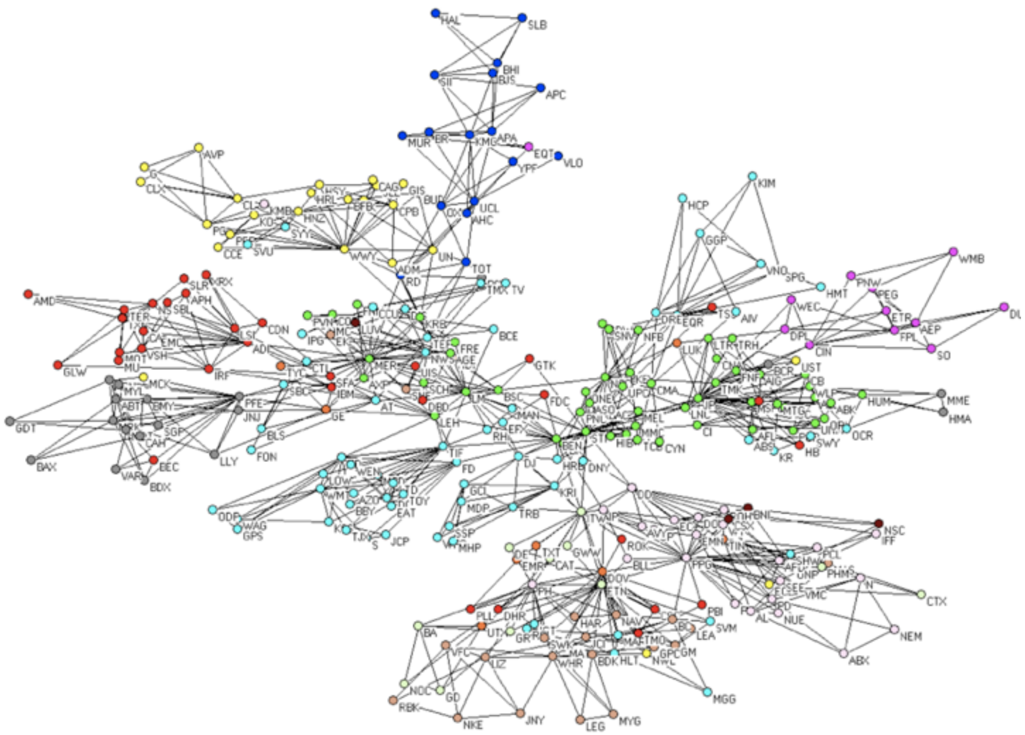
3)

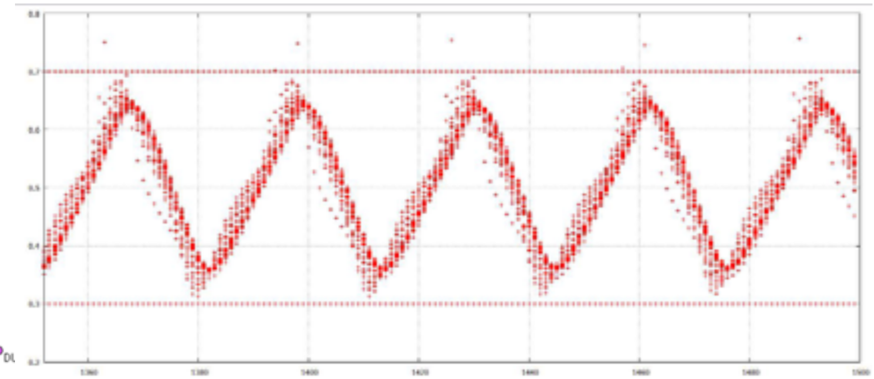


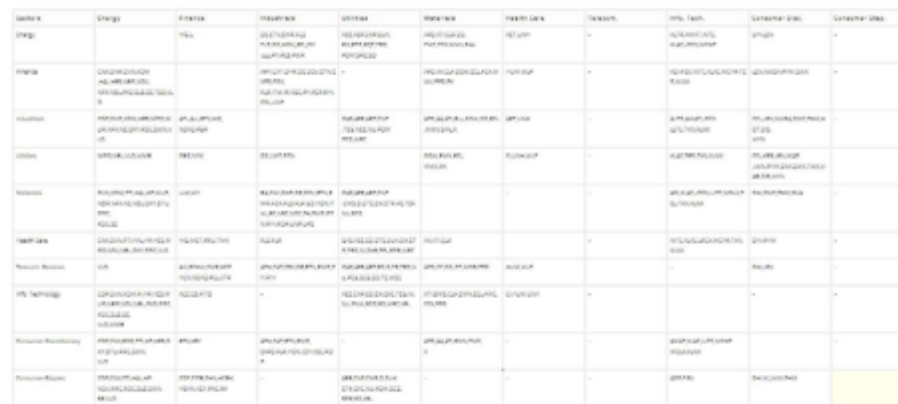
4)



II. Overlapping communities

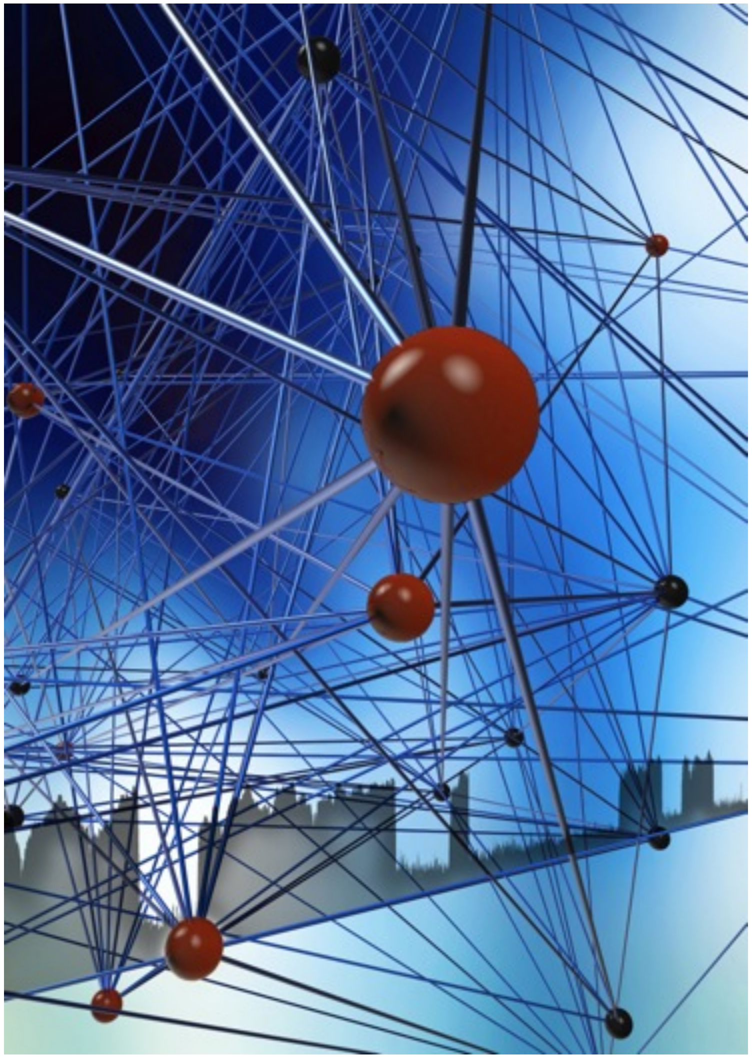


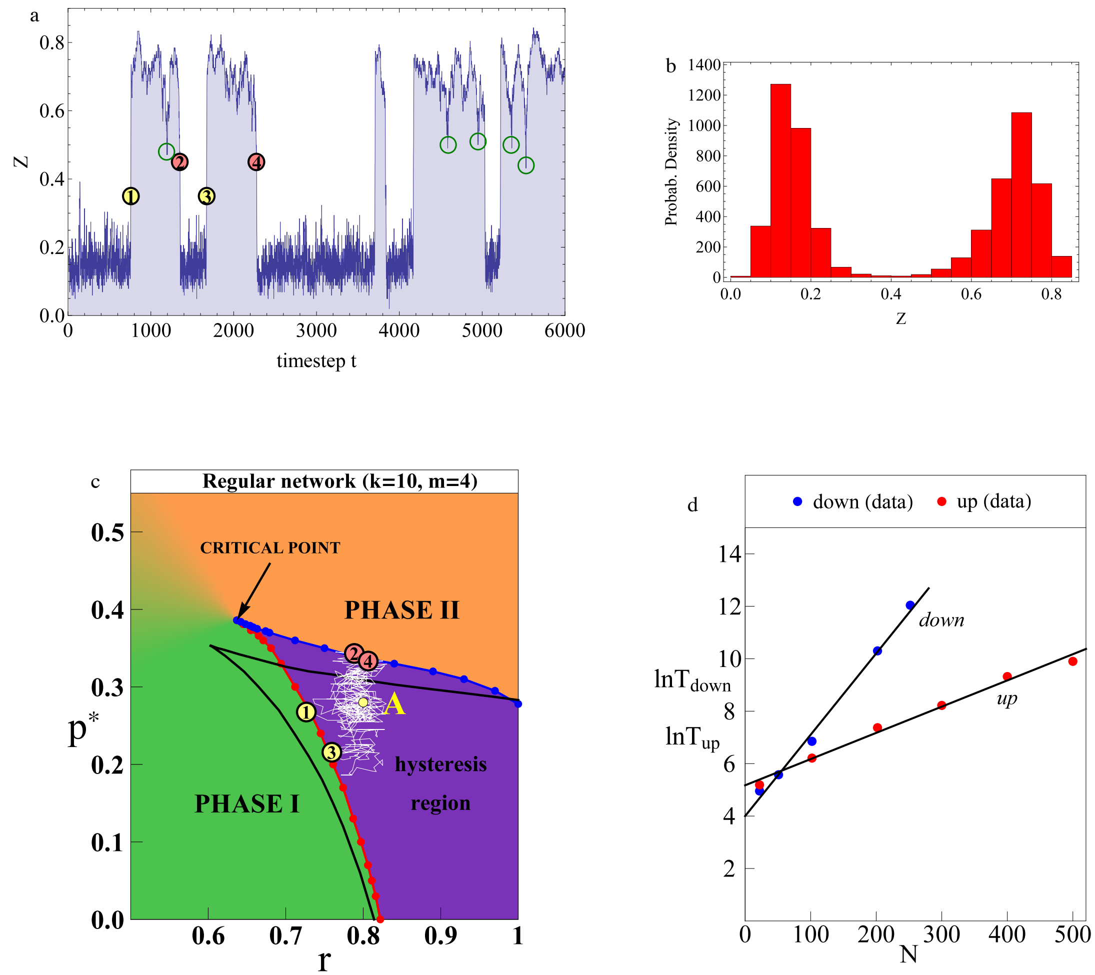




$$\dot{\phi}_i = \omega_i + \frac{d}{k_i + k_{p_i}} \sum_{i=1}^{N} \sin\left(\phi_j - \phi_i\right) + \frac{d_p k_{p,i}}{k_i + k_{p_i}} \sin\left(\phi_{p_i} + \phi_i\right) \qquad i = 1, \ldots, N$$

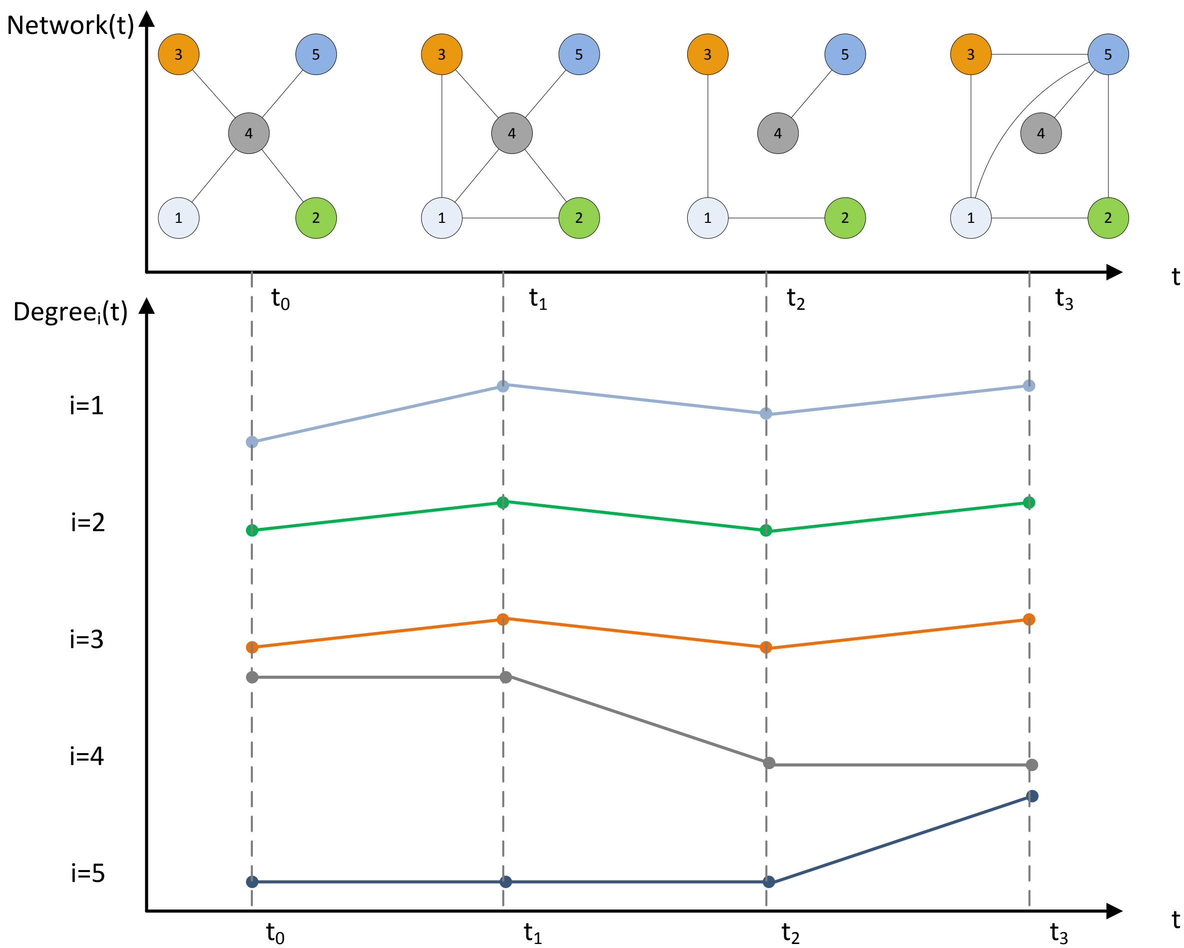
III. Failure and recovery in networks



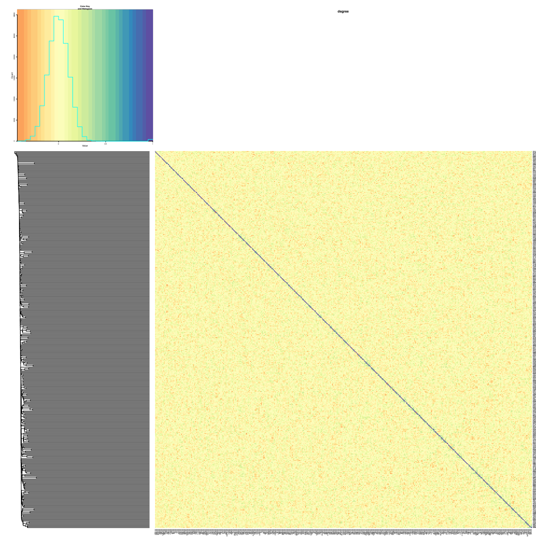


Antonio Majdandzic, Boris Podobnik, Sergey Buldyrev, Dror Y. Kenett, Shlomo Havlin, and H. Eugene Stanley (in press), Macroscopic phase-flipping in Dynamical Networks, Nature Physics

IV. Evolution of networks



1)



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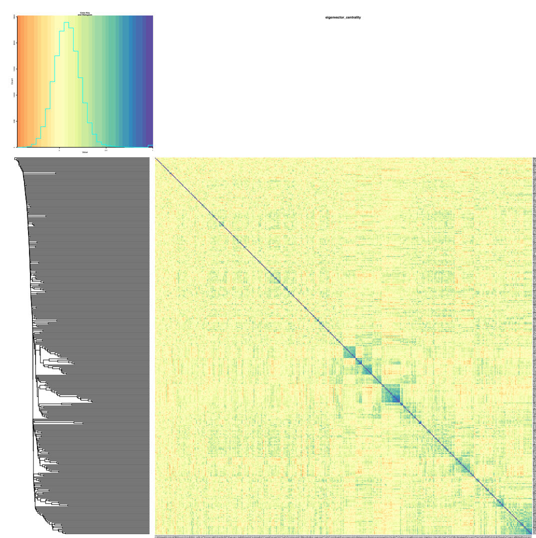
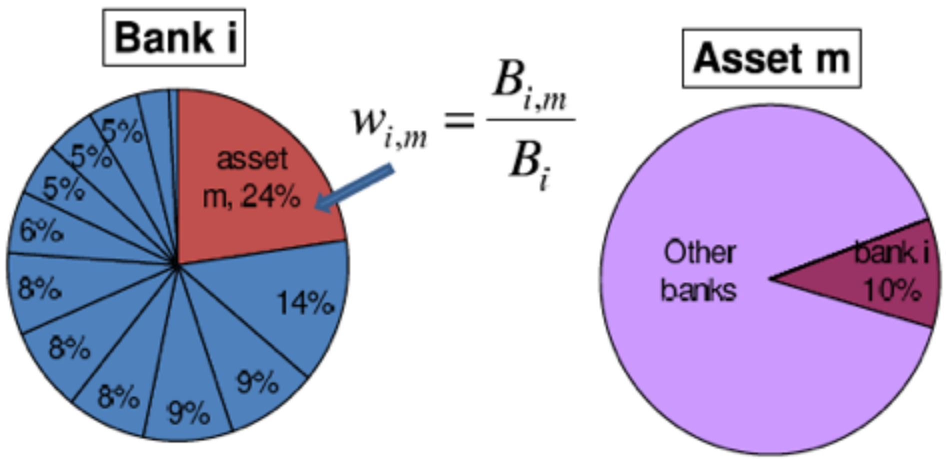


V. Cascading failures in the financial system

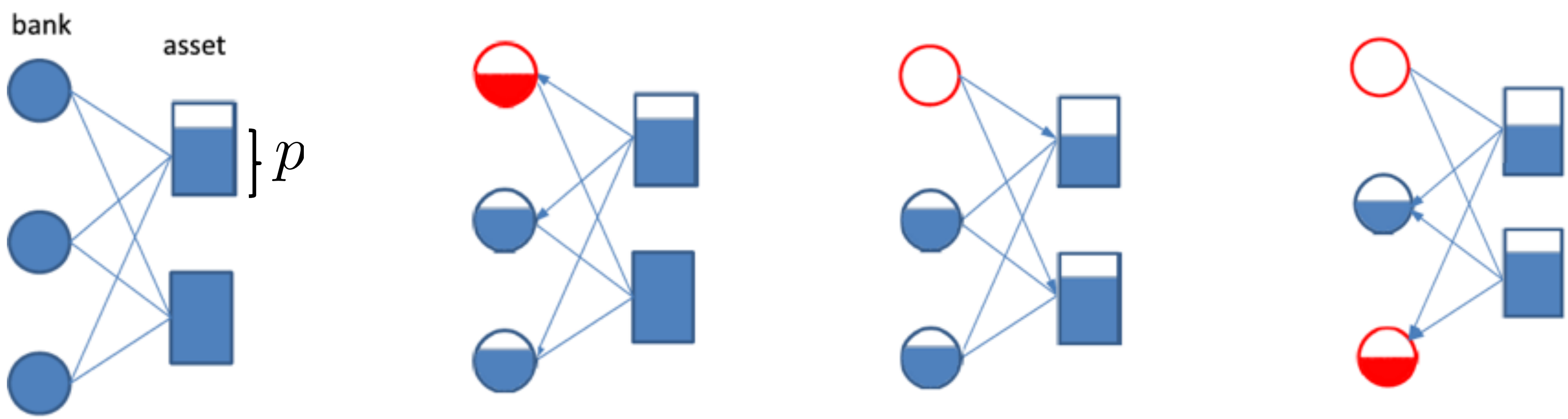
Bipartite Model



$$w_{i,m} = \frac{B_{i,m}}{B_i}$$

$$s_{i,m} = \frac{B_{i,m}}{A_m}$$

B_i: Total asset of bank i.
$B_{i,m}$: The amount of asset m that bank i owns.
A_m: Total market value of asset m.

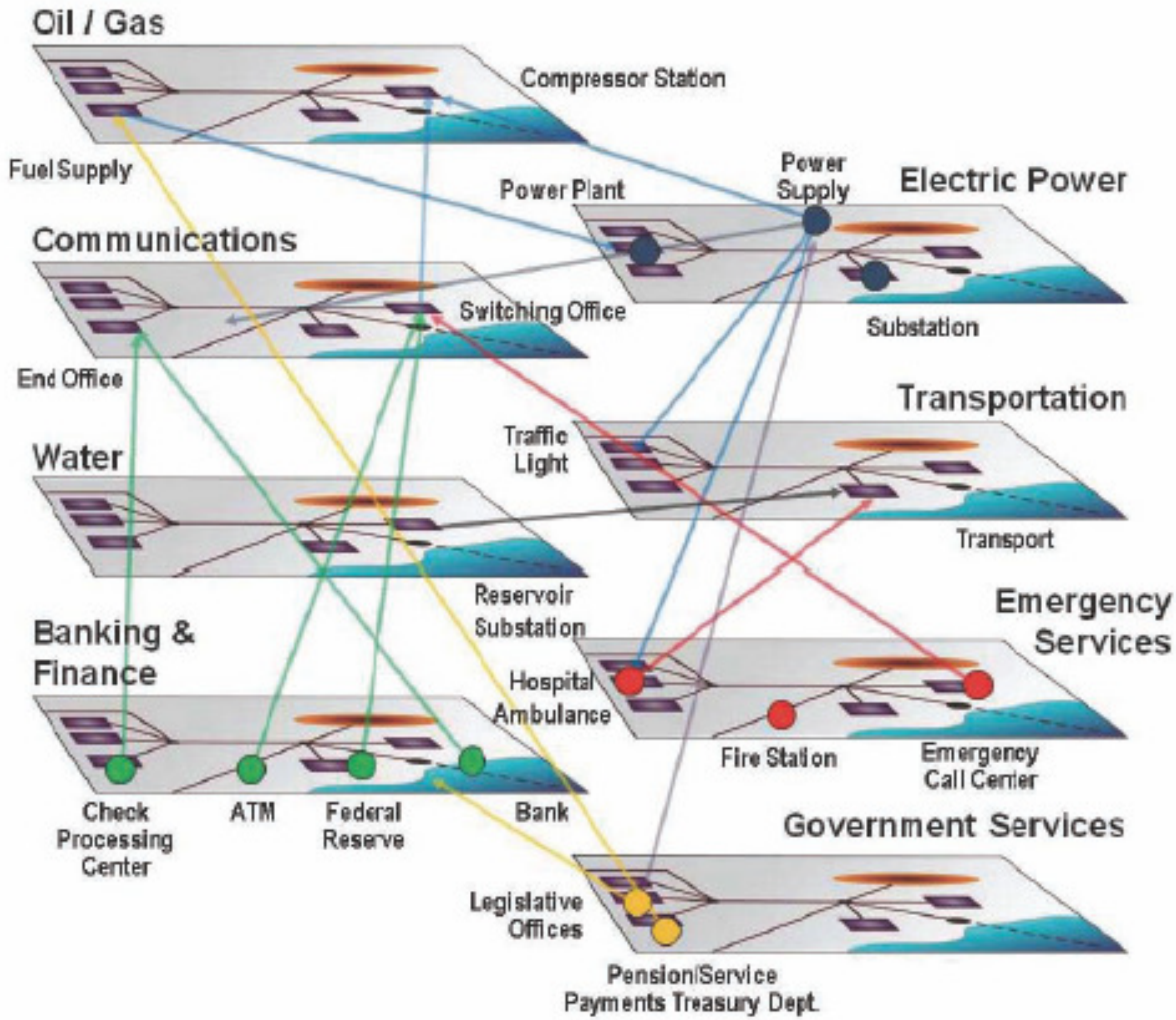


fail when
asset < liability

assets depreciate
$\alpha B_{i,m}$

1-p: initial shock to an asset
α : liquidity parameter
describes market's reaction to bank failure

VI. Interdependent networks



Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., & Havlin, S. (2010). Catastrophic cascade of failures in interdependent networks. Nature, 464(7291), 1025-1028.

Summary

- Correlations in Financial Markets
- Market meta-correlation
- Uniformity and Multiformity of markets
- Bottom-up and Top-down effects
- State dependent correlations

Applications

- Prediction
- Risk management
- Portfolio construction and optimization
- Stability of financial markets
- Financial contagion
- Financial seismograph

Thank You.

Questions?

Email: drorkenett@gmail.com