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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(5) Discussion
\[ r_i(t) = \log \left[ P_i(t) \right] - \log \left[ P_i(t-1) \right] \]
Stock correlations

\[ C(i, j) = \frac{\langle (r_i - \langle r_i \rangle) \cdot (r_j - \langle r_j \rangle) \rangle}{\sigma_i \cdot \sigma_j} \]
Stock correlations

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Stock correlations

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Dynamics of stock correlations

days = 1-101

Dow Jones Stocks
Dynamics of stock correlations

days = 1-101

Dow Jones Stocks
Dynamics of stock correlations

\[
C(i, j)
\]
Example: Tel-Aviv market
Example: Tel-Aviv market
Quantifying functional relationships

Correlation

\[
C(i, j) = \frac{\langle (r_i - \langle r_i \rangle)(r_j - \langle r_j \rangle) \rangle}{\sigma_i \cdot \sigma_j}
\]
Quantifying functional relationships

**Correlation**

\[
C(i, j) = \frac{\langle (r_i - \langle r_i \rangle) \cdot (r_j - \langle r_j \rangle) \rangle}{\sigma_i \cdot \sigma_j}
\]

**Partial Correlation**

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

**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**

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

**Partial Correlation**

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

**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.
Partial Correlations Example

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

<table>
<thead>
<tr>
<th>Market</th>
<th>Stocks used</th>
<th>Index used</th>
<th># before</th>
<th># filtered</th>
</tr>
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<tbody>
<tr>
<td>US</td>
<td>S&amp;P 500</td>
<td>S&amp;P 500</td>
<td>500</td>
<td>403</td>
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<tr>
<td>UK</td>
<td>FTSE 350</td>
<td>FTSE 350</td>
<td>356</td>
<td>116</td>
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<tr>
<td>Germany</td>
<td>DAX Composite</td>
<td>DAX 30 Performance</td>
<td>605</td>
<td>89</td>
</tr>
<tr>
<td>Japan</td>
<td>Nikkei 500</td>
<td>Nikkei 500</td>
<td>500</td>
<td>315</td>
</tr>
<tr>
<td>India</td>
<td>BSE 200</td>
<td>BSE 100</td>
<td>193</td>
<td>126</td>
</tr>
<tr>
<td>China</td>
<td>SSE Composite</td>
<td>SSE Composite</td>
<td>1204</td>
<td>69</td>
</tr>
</tbody>
</table>

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
Stock correlations

\[ C(i, j) = \frac{\langle (r_i - \langle r_i \rangle) \cdot (r_j - \langle r_j \rangle) \rangle}{\sigma_i \cdot \sigma_j} \]
Example: Dynamics of correlations of S&P500 stocks, in the US market

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

\[ ICF(\tau) \equiv \frac{\langle C(i,j) \rangle_\tau}{\langle PC(i,j | m) \rangle_\tau} \]
Financial States and Transitions
Financial States and Transitions
Financial States and Transitions
Financial States and Transitions
Financial States and Transitions
Financial States and Transitions
Stock market Correlations

U.S. [Graph]

Japan [Graph]

U.K. [Graph]

India [Graph]

Germany [Graph]

China [Graph]
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 propagate and influence correlations in a different market.
Goal: Financial Seismograph

Intra correlation & Metacorrelation

Index volatility & Index correlation

Financial Seismograph: Analysis and visualization of how correlations in one market can propagate and influence correlations in a different market
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(5) Discussion
What is a network?
What is a network?

- **components**: nodes, vertices
What is a network?

- **components**: nodes, vertices

- **interactions**: links, edges
What is a network?

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

Mary

Albert

friend

co-worker

brothers

friend
The Adjacency Matrix

Undirected

\[ A_{ij} = \begin{cases} 1 & \text{if there is a link between node } i \text{ and } j \\ 0 & \text{if nodes } i \text{ and } j \text{ are not connected to each other.} \end{cases} \]

\[
A_{ij} = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}
\]

Directed

\[
A_{ij} = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}
\]

Note that for a directed graph (right) the matrix is not symmetric.
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
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<td>a</td>
<td>0.0</td>
<td>0.1</td>
<td>0.11</td>
<td>0.4</td>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>b</td>
<td>0.1</td>
<td>0.0</td>
<td>0.3</td>
<td>0.12</td>
<td>0.32</td>
<td>0.05</td>
</tr>
<tr>
<td>c</td>
<td>0.11</td>
<td>0.3</td>
<td>0.0</td>
<td>0.7</td>
<td>0.21</td>
<td>0.5</td>
</tr>
<tr>
<td>d</td>
<td>0.4</td>
<td>0.12</td>
<td>0.7</td>
<td>0.0</td>
<td>0.17</td>
<td>0.13</td>
</tr>
<tr>
<td>e</td>
<td>0.2</td>
<td>0.32</td>
<td>0.21</td>
<td>0.17</td>
<td>0.0</td>
<td>0.15</td>
</tr>
<tr>
<td>f</td>
<td>0.5</td>
<td>0.05</td>
<td>0.5</td>
<td>0.13</td>
<td>0.15</td>
<td>0.0</td>
</tr>
</tbody>
</table>
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

\[
N = 300 \quad T = 748
\]

<table>
<thead>
<tr>
<th>Index</th>
<th>Sector</th>
<th># stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Basic Materials</td>
<td>24</td>
</tr>
<tr>
<td>2</td>
<td>Consumer Cyclical</td>
<td>22</td>
</tr>
<tr>
<td>3</td>
<td>Consumer Non Cyclical</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>Capital Goods</td>
<td>12</td>
</tr>
<tr>
<td>5</td>
<td>Conglomerates</td>
<td>8</td>
</tr>
<tr>
<td>6</td>
<td>Energy</td>
<td>17</td>
</tr>
<tr>
<td>7</td>
<td>Financial</td>
<td>53</td>
</tr>
<tr>
<td>8</td>
<td>Healthcare</td>
<td>19</td>
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<tr>
<td>9</td>
<td>Services</td>
<td>69</td>
</tr>
<tr>
<td>10</td>
<td>Technology</td>
<td>34</td>
</tr>
<tr>
<td>11</td>
<td>Transportation</td>
<td>5</td>
</tr>
<tr>
<td>12</td>
<td>Utilities</td>
<td>12</td>
</tr>
</tbody>
</table>
Stock Dependency Network: S&P Stocks
Sector Dependency Network
Sector Dependency Network
Simple Index

\[ r_i = \gamma_i f + \sqrt{1 - \gamma_i^2} f \varepsilon_i, \quad i = 1, \ldots, N, \]

\[ \langle r_i f \rangle = \gamma_i \langle f^2 \rangle = \gamma_i, \]

\[ \rho_{i,j}(SI) = \langle r_i r_j \rangle = \gamma_i \gamma_j \]

RMT

\[ r_i = \sum_{h=1}^{K} \gamma_{i,h} \sqrt{\lambda_h} f_h + \sqrt{1 - \sum_{h=1}^{K} \gamma_{i,h}^2} \lambda_i \varepsilon_i, \quad i = 1, \ldots, N, \]

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

\[ \rho_{i,j}(RMT) = \langle r_i r_j \rangle = \sum_{h=1}^{K} \gamma_{i,h} \gamma_{j,h} \lambda_h \]
Case study - Tel-Aviv market
Market states

Market dynamics

S&P500

Correlations

Partial Correlations

Normal Market Behavior

Abnormal Market Behavior

1939

1987

2002

2008
Interdependencies in the global financial village

Network analysis of influence and dependencies between Companies/Countries

Stock dependency network

Country dependency network
Investigating market structure

1)

Alcoa Inc. (Materials)

Apple Inc. (Information Technology)

Franklin Templeton Investment (Financials)

General Electric (Industrials)

- Consumer Discretionary
- Consumer Staples
- Energy
- Financials
- Health Care
- Industrials
- Information Technology
- Materials
- Telecommunication Services
- Utilities
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(5) Discussion
I. Cascading failures in industry networks

1) 

2) 
2009 Industry Survived after removing China Chemicals

3) 

4) 
Number of steps after removing China Chemicals 2009
II. Overlapping communities

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

2)
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 \( m \).

Bank \( i \)

Asset \( m \)

\( w_{i,m} \):

\( s_{i,m} \):

\[ 1 - p: \text{ initial shock to an asset} \]

\[ \alpha: \text{liquidity parameter} \]

describes market’s reaction to bank failure
VI. Interdependent networks

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?

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