

ANALYSIS OF STOCK MARKET USING COMPLEX NETWORKS AND MACHINE LEARNING

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Abstract

ANALYSIS OF STOCK MARKET
USING COMPLEX NETWORKS
AND MACHINE LEARNING

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for the degree of Master of Science, 2018

Due to the complexity of financial market and the interconnect- edness and inter-dependencies of industry sectors in the economy, the price returns of each coupling stocks might have certain underlying economic link. Such behaviours can hardly be explained by traditional financial models and theories. This project combines machine learning techniques, individual stock features, and empirical data of Industry Economic Accounts (IEAs) from Bureau of Economic Analysis (BEA) in the US to predict Granger causality of coupling US stocks. Limited Granger causalities are calculated as a small sample set compared to the target date set. A directed weighted complex network (DWCN) is constructed by considering companies as nodes, correlations of abnormal stock returns (α) as weights of links, and predicted Granger causalities indicate directions of links. The generated DWCN is visualised and its topological properties, sta- bility, and effects on individual stocks and industries are researched in this paper. Suggestions towards financial market investment are provided based on the results of this research.

Declaration

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Chapter 1

Introduction

1.1 Motivation

Financial markets are complex systems, the interconnectedness and interdependencies of industry sectors in the economy are highly inter-coupled with strong correlations with stock price fluctuations, i.e., the price returns of each coupling stocks underlying certain economic link, e.g. two companies that manufacture similar products, or both in one supply chain. Such behaviours can hardly be explained by traditional financial models and theories.

During recent times, weighted but undirected complex network models have been applied to study the correlations of stock prices. Prevailing approach is using companies as nodes, and correlations between each pair of stock price series, return series, or fluctuation patterns as links, e.g., much of the previous research have proved the represented complex networks of worldwide stock markets are scale-free and small-world [1, 2].

Theoretically, directed complex network for stock market can be achieved therefore more potential information can be produced which is helpful for investment decision and financial market supervision. Conducting Granger causality test between stock pairs is straightforward but not feasible due to the heavy-precondition and time-complexity in programme. Compared to the large order of magnitude of total stock pairs, manually calculated Granger causalities are too less to be used as training samples. Enlightened by the recent work by Jean et al. [3] which uses transfer learning and noisy proxy information performed very well at predicting poverty, demonstrating that machine learning techniques is powerful to be applied in a setting with limited training data, so an exploration towards the directed network of stock market

is motivated in this project, combines machine learning techniques, transfer learning, individual stock features, and empirical data of Industry Economic Accounts (IEAs) from Bureau of Economic Analysis (BEA) in the US to predict Granger causality of coupling US stocks. Therefore, a directed weighted complex network (DWCN) is constructed by considering companies as nodes, correlations of abnormal stock returns (alpha) as weights of links, and predicted Granger causalities as the indications of directions of links.

The goal of this project is to reveal the Granger causality of price return series and utilise them into the topological analysis and visualisation of DWCN as so far no previous work has attempted to construct a directed network about stock price. In addition, suggestions for stock market are provided according to the results and findings.

The outline of this document is as follows. In Section 2, specific objectives and deliverables are listed. In Section 3, relevant previous researches on financial market, complex networks, and machine learning are reviewed. Section 4 describes the analytical methods. Ethics and professional considerations and risk considerations are respectively discussed in Section 5 and 6. Section 7 describes project evaluation approaches and finally, planning Gantt chart is presented in Section 8.

1.2 Objectives

1.3 Proposed methodology

1.3.1 Construction of the stock network

EIO (Economic Input-Output) table

The Bureau of Economic Analysis (BEA) in the US publishes Economic Input-Output (EIO) tables each year, which are the transaction matrices of all purchases and sales between sectors in a certain industry group level of a year, i.e. depict how industries provide input to, and use output from, each other to produce Gross Domestic Product (GDP).

This paper uses the use table of 2016. Among the transaction matrix (Z) there are Total Industry Input (I) row at the bottom and the Total Industry Output (O) column at the right are the statistics of total purchase by each sectors and total sales from each sectors respectively.

$$a_{ij} = -\log_{10}(z_{ij}/I_j)^{-1} \quad (1.1)$$

$$b_{ij} = -\log_{10}(z_{ij}/O_i)^{-1} \quad (1.2)$$

1.3.2 Logarithmic return of stock prices

$$r_i(\tau) = \ln P_i(\tau) - \ln P_i(\tau - \Delta t)$$

$$c_{i,j} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{(\langle r_i^2 \rangle - \langle r_i \rangle^2)(\langle r_j^2 \rangle - \langle r_j \rangle^2)}} \quad (1.3)$$

Correlation coefficient

1.3.3 Directed Watts–Strogatz small-world network

1.3.4 Directed random network

1.3.5 Topological properties of directed networks

Degree, out-degree, and degree distribution

The degree of a node k represents the number of its neighbours. In terms of the directed stock price return network, this paper mainly focuses on the out-degree analysis on the nodes.

Out-degree k_{out} is the number of edges which start from the given node and end at others, while in-degree k_{in} is the number of edges which end at the given node and start from others. In directed graph, there is relationship between k_{in} and k_{out}

$$k = k_{in} + k_{out}. \quad (1.4)$$

The degree distribution of stock price return network $p(k)$ can be defined as:

$$p(k) = \frac{N_k}{N}, \quad (1.5)$$

while N_k represents the number of nodes whose out-degree value is k .

Path length

Clustering coefficient

Clustering coefficient is a measure of the degree to which nodes in a network tend to cluster together. Concerning the clustering coefficient of the complex networks, it is defined as:

$$C_i = \frac{2E_i}{(k_i(k_i - 1))}, \quad (1.6)$$

where k_i is the degree of a given node v_i , E_i is the real existing edges among the nearest neighbour nodes of the given node v_i , and $k_i(k_i - 1)/2$ means the maximum possible edges existing between its nearest neighbours of the node v_i . Besides, the clustering coefficient of a node accounts for the extent to which the transmission relationship between the given node and its neighbours also exists between its neighbours, and the clustering coefficient may be given by:

$$C = \frac{3 \times \text{number of triangles in the networks}}{\text{number of connected triples of nodes}}. \quad (1.7)$$

This measure gives an indication of the clustering in the whole network, and can be applied to both undirected and directed networks.

Degree centrality

Degree centrality can be used to determine the critical nodes among the entire network and to recognise the most associated firms in the chosen stock market. When it comes to directed network, two separate measures to calculate degree centrality are defined, which are in-degree and out-degree. In-degree represents the number of edges incoming to a node and out-degree represents the number of edges outgoing from a node.

As one of the most widespread measures to calculate network centrality, degree centrality can be described as the number of direct links that relate to a specific node [?]. While the degree of centrality has generally been accumulated to the sum of weights to form the weighted networks. The equation of this measure is shown as bellow:

$$C_D^W(i) = \sum_j^N w_{ij} \quad (1.8)$$

where W represents the matrix of weighed adjacencies, and w_{ij} represents the weight of the link between node i and j .

1.3.6 Robustness test

1.4 Summary of results

1.5 Outline of the thesis

Chapter 2

Background and state of the art

The revolutionary who pioneered the theory of portfolio, Markowitz [?] proposed the mean-variance model and established a clear mathematical definition of the two vague concepts of risk and return. Sharp [?] and Linter [?] added two key assumptions based on the mean-variance model to enable the portfolio mean-variance valid, forming a capital asset pricing model (CAPM) with the support of economic theories. The CAPM believes that only non-dispersible systemic risks can be compensated off, while non-systematic risks can be eliminated by effectively decentralised investments. Investors could only assume systemic risks through decentralised investment. The systematic risk of a single security or portfolio can be characterised by beta, which represents the extent to which a single security or portfolio is affected by the overall market volatility.

Worldwide scholars had been actively conducting empirical tests towards the practicality of the CAPM then, while early results show that beta is able to explain return movements of stocks. However, in the late 1970s, some empirical studies upon the CAPM began to show that a large part of the changes in the stock returns cannot be explained by beta, with increasingly market return anomalies were found.

Researchers had proposed models and theories considering the individual stock features to explain. For instance, Fama and French [?, ?] proposed a three-factor model based on the inter-temporal capital asset model (ICAPM) [?] and the arbitrage pricing theory (APT) [?], which reveals a large part of the cross-section of the stocks' average return that cannot be explained by CAPM, can be explained using firm size, book-to-market equity ratio, and overall market return.

While traditional stock pricing models still capture limited forms of financial behaviour, the premises of standard financial theory contradict the modern notion of financial markets are complex systems [?], by which many statistical niceties such as stationarity no longer can be taken for granted. Recent researches have implemented the network theory to reveal the underlying factors of price movements. Huang et al. [?] implemented the threshold method to build 's correlation network in China's A-Share stock market and studied the networks topological properties and topological stability. Namaki et al. [?] utilised Random Matrix Theory (RMT) to specify the biggest eigenvector in the complex network of price correlations. Yu [?] studied the evolution of gold price from a network perspective using the visibility network approach. Chopra and Khanna [?] developed a framework which associates the economic input–output (EIO) model with techniques for understanding interdependencies and interconnectedness in the economy of US, based on complex networks theory. Boginski et al. [?] identified cliques and independent groups among stock networks. Chen et al. [?] studied the inter-stock and inter-industry effects towards stock returns based on the topological properties of a complex network of correlations.

In a nutshell, prevailing complex network approaches to analyse stock markets are almost all about investigating weighted or unweight but undirected networks. To the best knowledge of mine, no previous work has attempted to construct a directed network so far.

Chapter 3

Pre-processing of stock market and industrial data

This paper considers 1,418 stocks of listing US companies that traded consecutively in the NYSE and NASDAQ stock market of US on the trading days from January 4, 2016 to December 30, 2016 and uses daily closing price during this period.

The economical use table data from the Industry Economic Accounts (IEAs) of year 2016 in a summary-level of industrial sectors are collected from the official website of Bureau of Economic Analysis [oEA18], US Department of Commerce.

Chapter 4

Topological properties of directed complex networks

Chapter 5

Community detection

This paper considers an approach to detect possible communities in directed networks based on modularities [LN08].

Algorithm 1 Community detection

```

1: procedure COMMUNITY( $G, nNode, nEdge, EntireModMat, EntireNodeSpace$ )
2:   procedure CALDELTAQ( $s, \mathbf{B}$ )
3:     return  $Q \leftarrow 1 / (4 * nNode) * s^T (\mathbf{B} + \mathbf{B}^T) s$ 
4:   procedure UPDCOMMUNITYASSIGNMENT( $NodeSpace, UpdAssign$ )
5:      $Mark1, Mark2 \leftarrow \max(Assignment) + 1, \max(Assignment) + 2$ 
6:     for each  $node \in NodeSpace$  do
7:       if  $node \in UpdAssign > 0$  then node of Assignment  $\leftarrow Mark1$ 
8:       if  $node \in UpdAssign < 0$  then node of Assignment  $\leftarrow Mark2$ 
9:     return Assignment
10:    procedure SUBDIVIDECOMMUNITY( $\mathbf{B}$ )
11:       $SymmetricMatrix \leftarrow \mathbf{B} + \mathbf{B}^T$ 
12:       $eigv \leftarrow$  eigenvector as  $\max(eigenvalues)$  in  $SymmetricMatrix$ 
13:      return sign( $eigv$ )
14:    procedure CALMODULARITY( $assignment$ )
15:      for each  $node1 \in Nodes of G$  do
16:        for each  $node2 \in Nodes of G$  do
17:          if assignment of  $node1 \leftarrow$  assignment of  $node2$  then
18:             $Q \leftarrow Q + HasEdge - (nIn(node1)) * (nOut(node2)) / (nEdge)$ 
19:      return  $Q / (nEdge)$ 
20:    procedure GENMODULARITYMATRIX( $NodeSpace, ModMat$ )
21:      for each  $node1 \in NodeSpace$  do
22:        for each  $node2 \in NodeSpace$  do
23:           $B \leftarrow HasEdge - (nIn(node1)) * (nOut(node2) / nEdge)$ 
24:          if Assignment of  $node1 =$  Assignment of  $node2$  then
25:            for each  $node \in NodeSpace$  do  $C \leftarrow C + HasEdge1 +$ 
26:             $HasEdge2 - (nIn(node1) * nOut(node) + nIn(node) * nOut(node1)) / nEdge$ 
27:    procedure INTERATEBISECTION( $ModMat, NodeSpace$ )
28:       $UpdAssign \leftarrow$  SubdivideCommunity( $ModMat$ )
29:       $DeltaQ \leftarrow$  CalDeltaQ( $UpdAssign, ModMat$ )
30:      if  $DeltaQ > 0$  then
31:        Assignment  $\leftarrow$  UpdCommunityAssignment( $NodeSpace, UpdAssign$ )
32:        for each  $side \in UpdCommunityAssignment$  do
33:           $ModMat \leftarrow$  GenModularityMatrix( $NodeSpace$ )
34:          InterateBisection( $ModMat, NodeSpace$ )
35:      return Assignment
  
```

Chapter 6

Benchmarking networks generation

Numerous literatures support the idea that undirected stock networks have small-world features. It is helpful that examine whether the directed one is a small-world network or not by comparing it with known and conventional small-world networks like Watts-Strogatz model [WS98], as well as conventional random networks like Erdős–Rényi model [ER59].

6.1 Directed Watts-Strogatz small world network

The Watts-Strogatz (WS) model is a randomly generated graph with small world network properties such as high clustering coefficient and small average short path lengths.

In the Complex Networks science, a network with both a small average path length and a large average clustering coefficient feature is called a small world network. In the WS model, when the random reconnection probability p of the connected nodes is gradually increased from 0 to 1, it can be observed that the initial regular network will go through the following three phases: regular network, small-world network, and eventually random network.

This paper uses an alternative method based on WS model [SW14]. Specify the number of nodes N , the mean degree K (assumed to be an even integer), and a special parameter β , satisfying $0 \leq \beta \leq 1$ and $N \gg K \gg \ln N \gg 1$, the model constructs an undirected graph with N nodes and $NK/2$ edges as the following algorithm depicts:

Algorithm 2 WattsStrogatzSmallWroldNetwork

```

1: procedure GENERATESMALLWORLDNETWORK( $nNodes, p0, beta$ )
2:    $Dmax \leftarrow nNodes \% 2$ 
3:    $R \leftarrow range from 1 to Dmax$ 
4:    $D \leftarrow$  circulant matrix of  $R/Dmax$ 
5:    $p \leftarrow beta * p0 + ((D \leq p0) * (1 - beta))$ 
6:    $A \leftarrow 1 * (\text{randomised matrix } p < p)$ 
7:   fill diagonal of matrix  $A$ 
8:   return  $A$ 

```

6.2 Directed Erdős–Rényi random network

The Erdős–Rényi (ER) model generates a graph that winded randomly between N nodes in the network with probability p . The degrees of nodes comply with a Poisson distribution, indicating that most nodes have approximately same number of edges.

Erdős and Rényi has found that as the number of edges M gradually increases from a small value, the random graph will evolve from a fragmented graph with many independent components to a fully connected one [Str01].

Chapter 7

Empirical study and results

7.1 Network construction

This paper first calculated normalised direct requirement and normalised direct demand values for every sectors using formula 1.1 and formula 1.2 and cross-correlation coefficients between every stock pairs using formula 1.3.

According to the figure 7.1, the transaction densities decrease as threshold of normalised direct requirement and normalised direct demand increase, and their patterns are exactly similar with the same inflection point at around $threshold = 0.136$ where the densities begin to decline. Therefore, the values of thresholds for normalised direct requirement and normalised direct demand are set to be equal, i.e., $\theta_{EIO} = \theta_{DD} = \theta_{DR}$, to filter the directed edges among the stock network.

Figure 7.2 shows the distribution of stock price correlation coefficients has a shape complies to the normal distribution with long tails. The correlation coefficients are vary from -0.687 to 0.977 with the mean of 0.265. It implies that the prices of most stocks traded in NYSE and NASDAQ usually fluctuate to the same direction, but the patterns are less similar.

Figure 7.4 shows the number of directed edges remain at the conditions of different value combinations of $\{\theta_{EIO}, \theta_{corr}\}$. When both of the thresholds set to be minimal at their own value range, i.e., $\theta_{EIO} = 0$ and $\theta_{corr} = -1$, the number of directed edges is $N \times (N - 1) = 2,009,306$, while N indicates the total number of nodes, which is 1418. According to the figure 7.4, the number of edges will be less than 100,000, in which case the network has a density of lower than 5%, if $\theta_{EIO} \geq 0.3545$ or $\theta_{corr} \geq 0.5020$.

It is obvious that the larger values assigned to θ_{EIO} and θ_{corr} , the more significant will be for the weights and directions of the remaining edges. But if the network

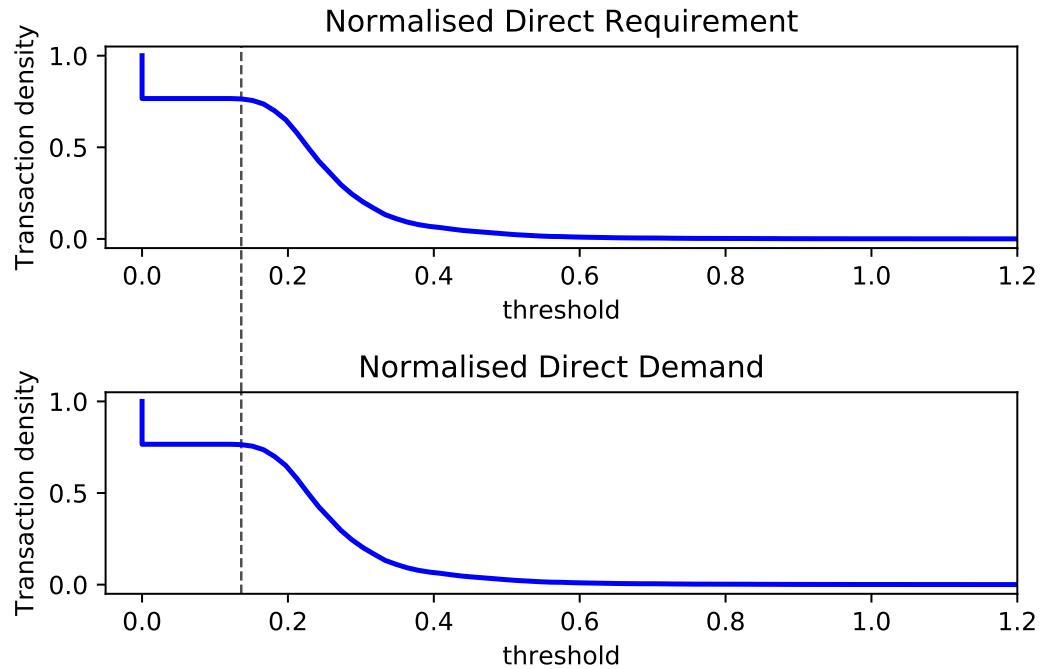


Figure 7.1: Transaction densities

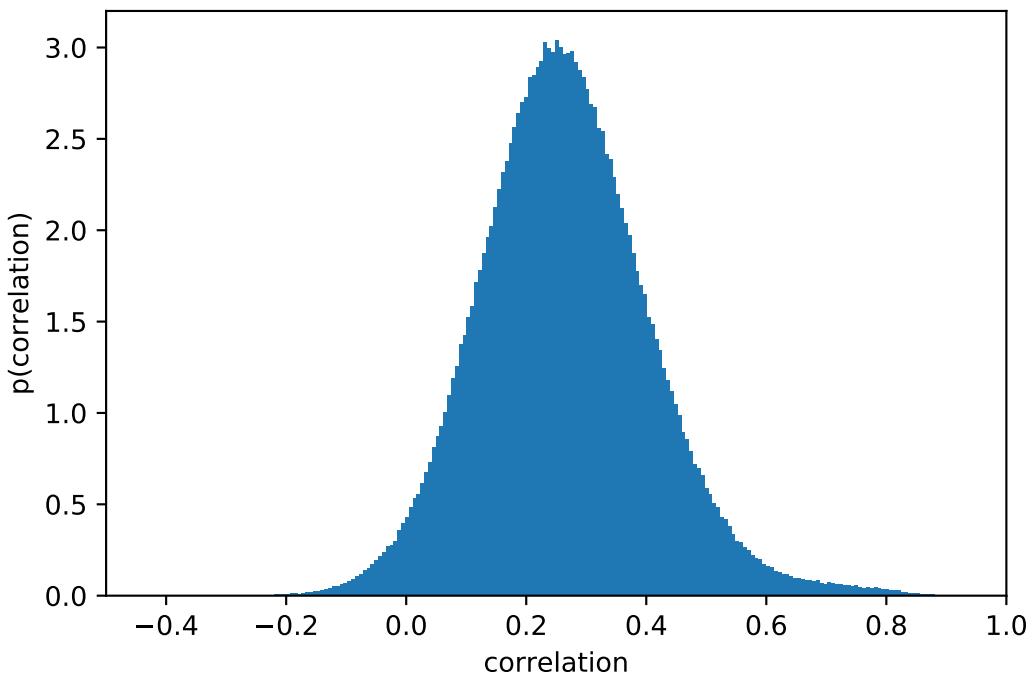


Figure 7.2: Stock price return correlation coefficient distribution

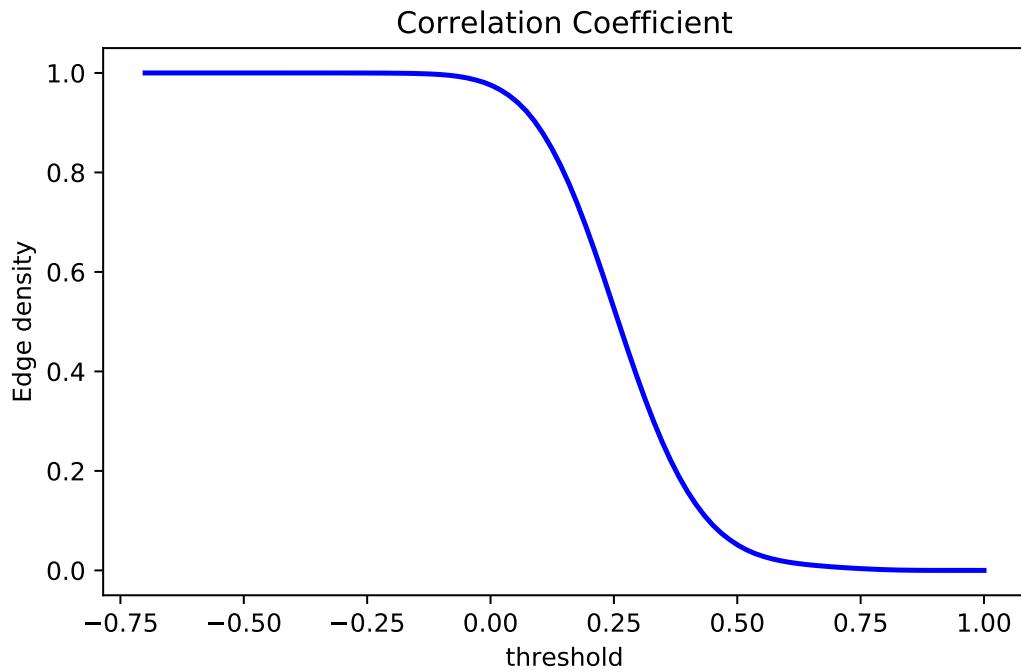


Figure 7.3

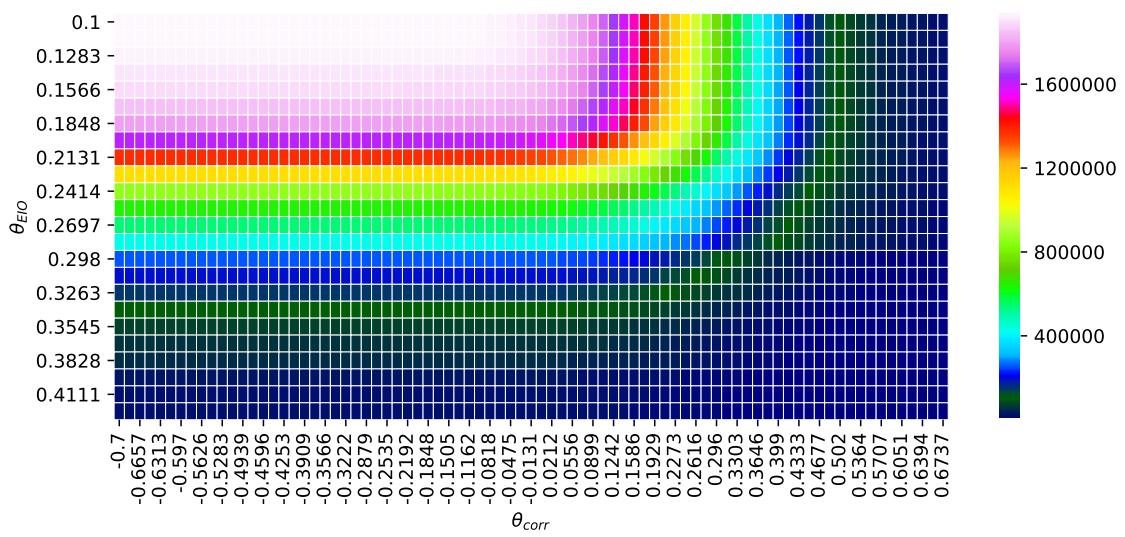


Figure 7.4: Numbers of directed edges per EIO-threshold and correlation-coefficient-threshold

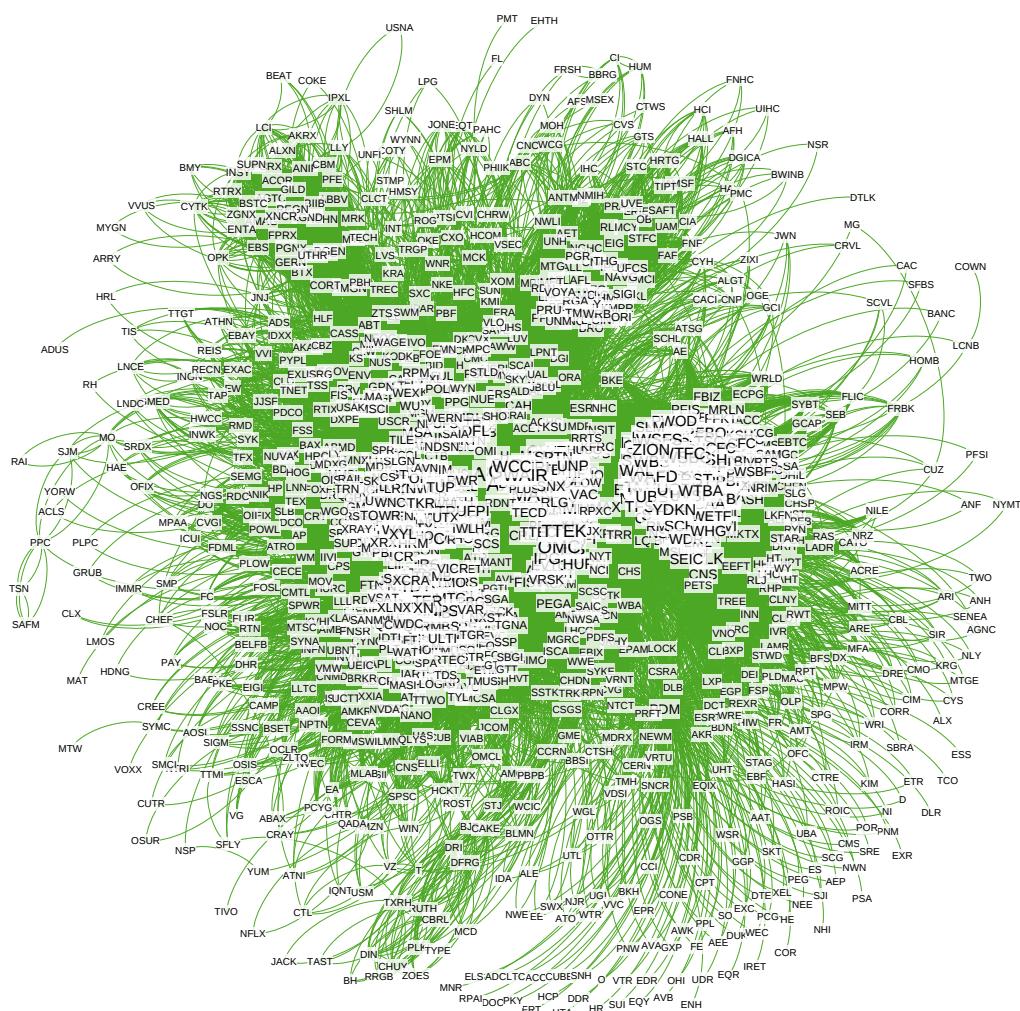


Figure 7.5: Transaction densities

Directed networks	Stock network	Small-world network	Random network
Number of nodes	1418	1418	1418
Number of edges	102051	102088	102097
Out-degree distribution	Power-law	Normal	Normal
Average out-degrees	143.94	143.99	144.00
Average path length	2.775	2.005	1.973
Clustering coefficient	0.4675	0.1367	0.05105
Global efficiency	0.2563	0.5161	0.5216
Local efficiency	0.6276	0.5027	0.4456
Assortativity	0.02004	-0.002180	0.001452

Table 7.1: Main properties of stock network, small-world network, and random network

becomes too sparse, it can not be strongly or even weakly connected and there would be many independent cliques, hence the network becomes too inefficient to be a sensible network. As a result, this paper selects the threshold-value-pair $\{\theta_{EIO} = 0.292, \theta_{corr} = 0.379\}$ to construct a directed unweighted network and a directed weighted network for the 2016 US stock market.

7.2 Analysis of the directed unweighted network

A directed Watts Strogatz small-world network and a random network with the same number of nodes and edges with the stock directed unweighted network are generated. Table 7.1 compares the main topologies of the three different networks.

7.2.1 Power-law distribution

According to the table 7.1, the values of average out-degrees of stock network, small-world network and random network are almost the same due to the similar number of nodes and edges, but in terms of the distributions of out-degrees, stock network is different from the others.

Figure 7.10 and 7.11 show clearly that the out-degree distribution of small-world network and random network follow the normal distribution, i.e, most degree numbers of nodes fall in the middle range, while figure 7.9a illustrates that for the stock network, only a few number of nodes show higher out-degree, while most nodes are in the positions of low out-degree level. The distribution of the directed stock price return

networks follows power-law distribution with the exponent of 4.057.

7.2.2 Small-world property

The average path length of small-world network and random network are both close to 2, indicates that taking any node in the network, it can expect to reach any other nodes just through one node as medium. For stock network, the expectation number of medium nodes is 1.775, which is also a small number for connection, so like small-world and random networks, stock network also has the small-world property.

Although the assortativity values for the three networks are all non-significant,

7.2.3 Community feature

The larger value of clustering coefficient for stock network than the other two networks indicating that the nodes in stock network tend to cluster together. Therefore, communities of stock network will be identified implementing the *algorithm 1* for directed networks in this section. According to the composition of industrial sectors of each community, as figure 7.8 shows, the following five communities are identified: (1) Production (2) Finance (3) Livelihood (4) Insurance and chemical products (5) Utilities and financial vehicles.

The communities of production (purple) and livelihood (blue) are sparsely distributed while there are some large-sized nodes acting as hubs of the overall network. The hubs not only connect to the nodes of same communities, but also the externals. These two communities are partially intertwined due to the high relevancy of production industry and livelihood industry.

Unlike the above two communities, it can be seen from figure 7.6 that the community of finance (green) is decentralised, i.e., there is no obvious hubs and the degrees of each node distribute evenly. It also has a very dense structure, connected closely inside and completely exclusive from other nodes or communities. This means the co-movements among financial stocks are incredibly strong and economically they rely tightly to each other.

The other two communities are more interesting because of their peculiar structural features. Every industrial sectors of individual stocks in community are identified to investigate the properties of the community of insurance and chemical products (yellow). As figure 7.7d illustrates and through the investigation, almost all firms in the upper and lower clusters are in the sectors of "chemical products" and "insurance

	Undirected stock network
Degree distribution	Power-law
Average out-degrees	Power-law
Average path length	2.775
Clustering coefficient	0.4675
Global efficiency	0.2563
Local efficiency	0.6276
Assortativity	0.02004

Table 7.2: Main topologies of conventional stock price network

carriers and related activities” respectively, while firms between the two big clusters, like ”MCK” (McKesson) and ”CAH” (Cardinal Health), are large medical supplier, pharmaceutical and healthcare service companies with high out-degrees to both of the two clusters. Apart from that, there are also a considerable number of links from the nodes in upper cluster to the hubs of chemical companies. Thus, it is reasonable to infer that the prices of medicines have significant influence to medical insurance industry, additionally the purchases of chemical products of pharmaceutical firms and the sales of chemical products have made pharmaceutical and chemical companies influence to each other.

Another investigation towards the community of utilities and financial vehicles (orange) is conducted by the same measure. As figure 7.7e illustrates, there is only one huge hub (PDM) which is the company ”Piedmont Office Realty Trust” among the whole community while all the others are one-degree nodes located remotely. There are more links from the hub to the rest than the opposite direction, and also the weights of the former links are generally higher. The hub, ”Piedmont Office Realty Trust”, is a real estate investment trust company, and the rest in the community contains 59 ”funds, trusts, and other financial vehicles” firms and 44 ”utilities” firms. For a big realty trust enterprise, demand for financial trust business is extremely high, and its successes of investments upon real estates will promote the development of utilities companies. It depicts that the major realty trust enterprise alone has significant influence to all of these financial trust and utilities companies.

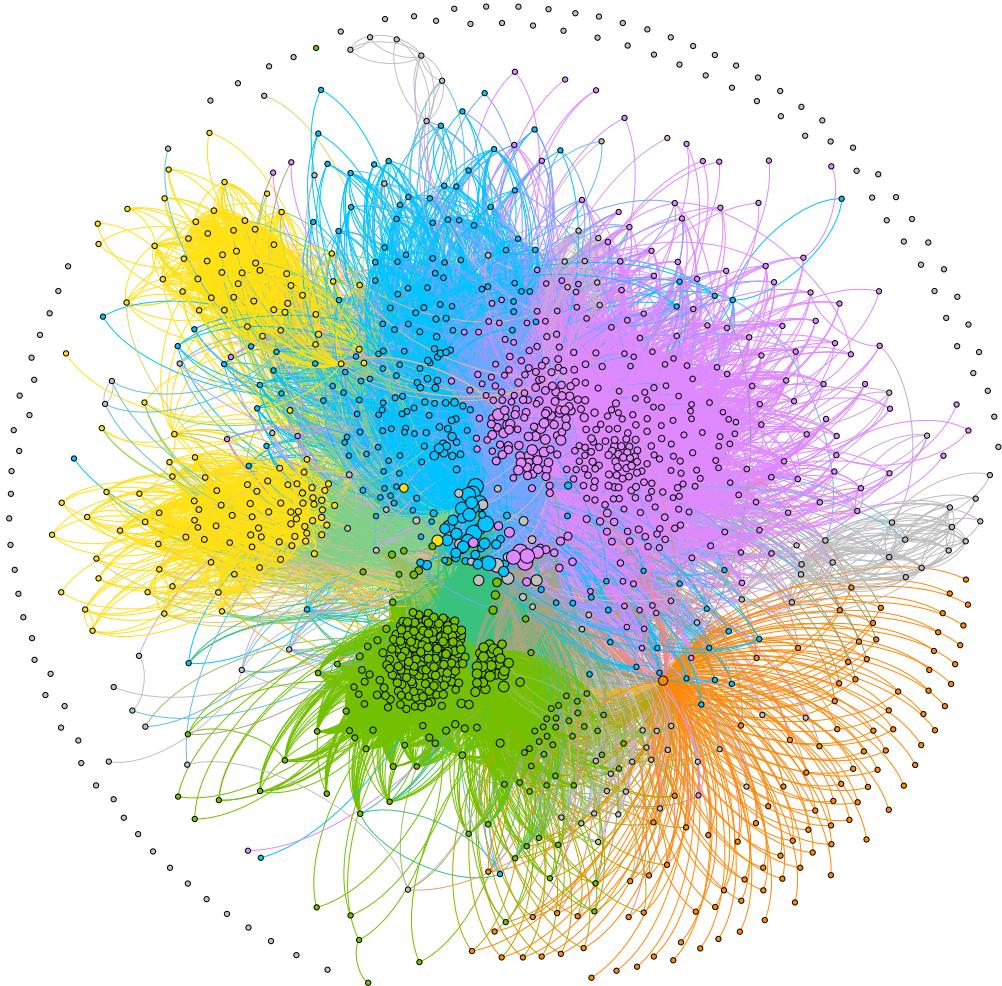
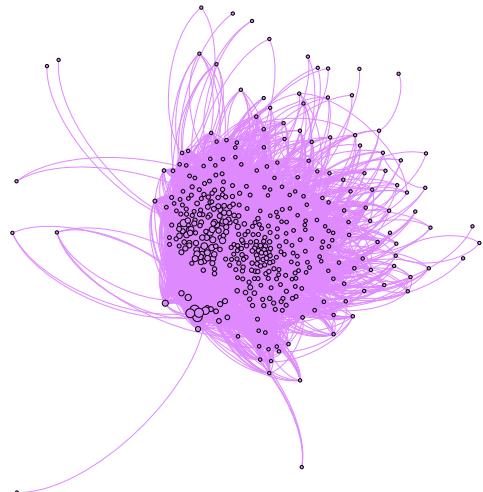
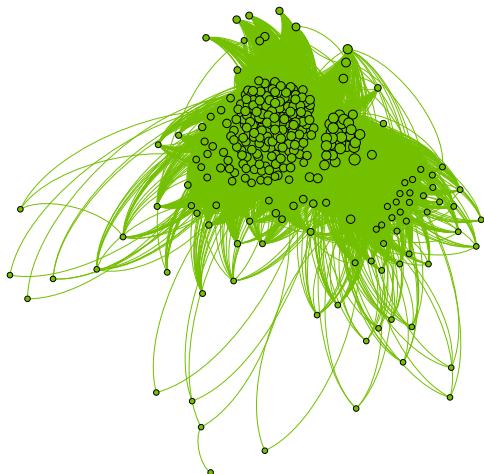


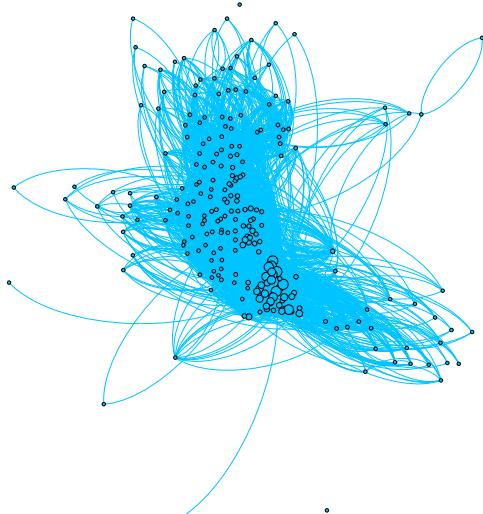
Figure 7.6: Community structure of the 2016 US stock price return network. Five distinct communities are detected represented by different colours of nodes. The direction of edge is clockwise. The size of nodes and thickness of edges are related to the value of degrees and weights. The grey nodes do not belong to any communities and most of them have zero degree.



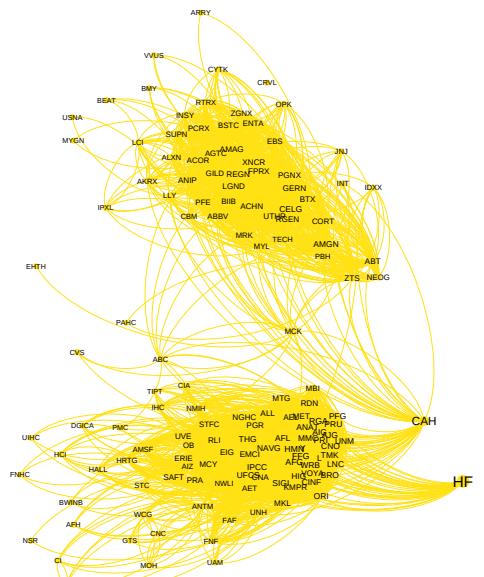
(a) Production



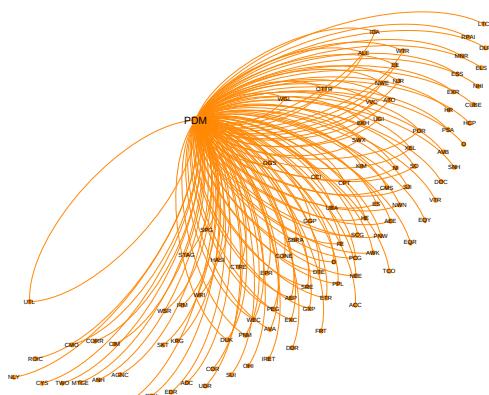
(b) Finance



(c) Livelihood



(d) Insurance and chemical products



(e) Utilities and financial vehicles

Figure 7.7: Community sole views of the directed stock network. Stock tickers are displayed for the sparsely distributed communities.

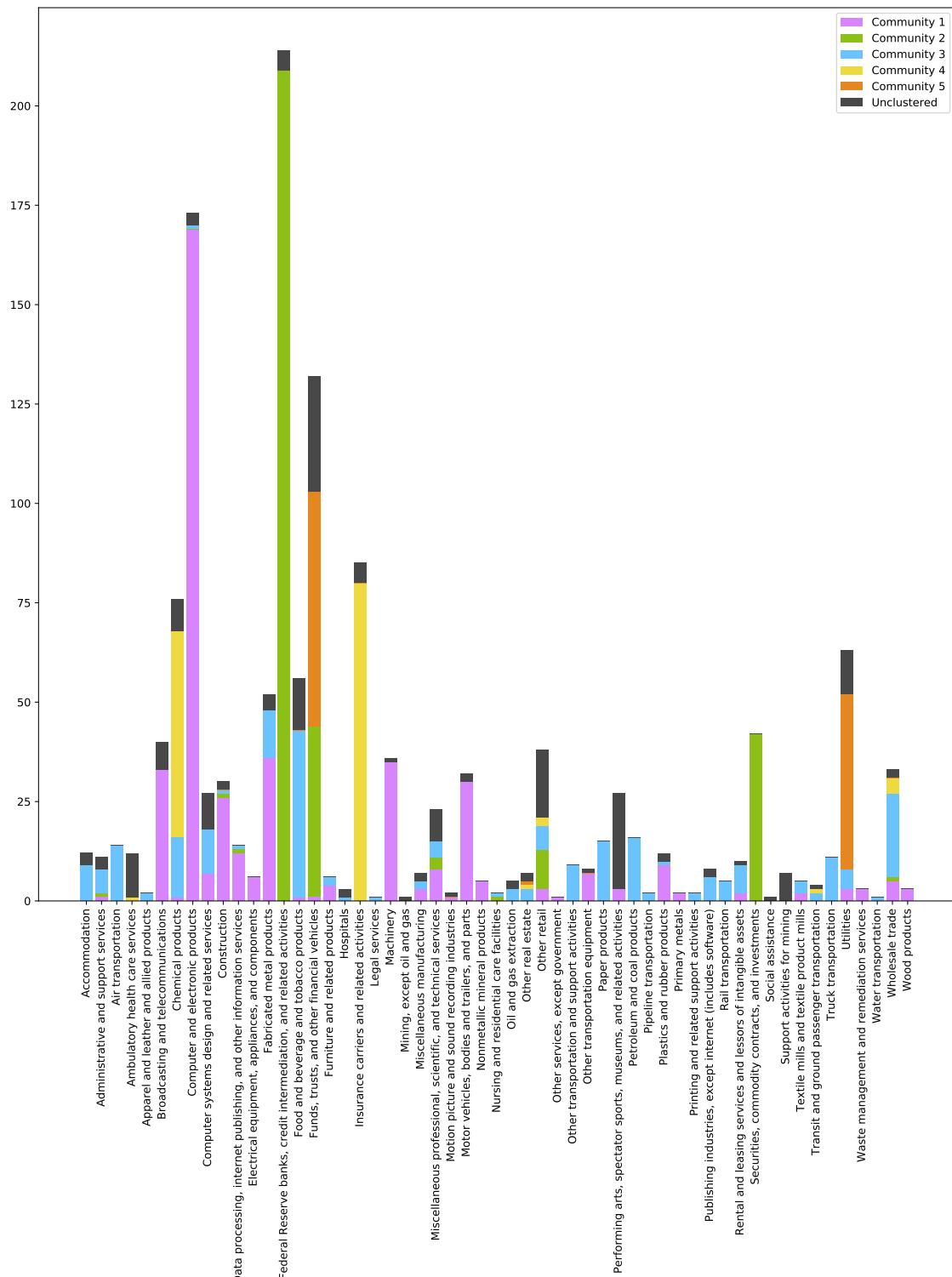


Figure 7.8: Stacked bar chart about the distribution of communities upon industrial sectors. Colours of stacks correspond to the colours of communities in figure 7.6 and figure 7.7, except the black stack indicating the nodes not belong to any communities. Sectors are arranged alphabetically.

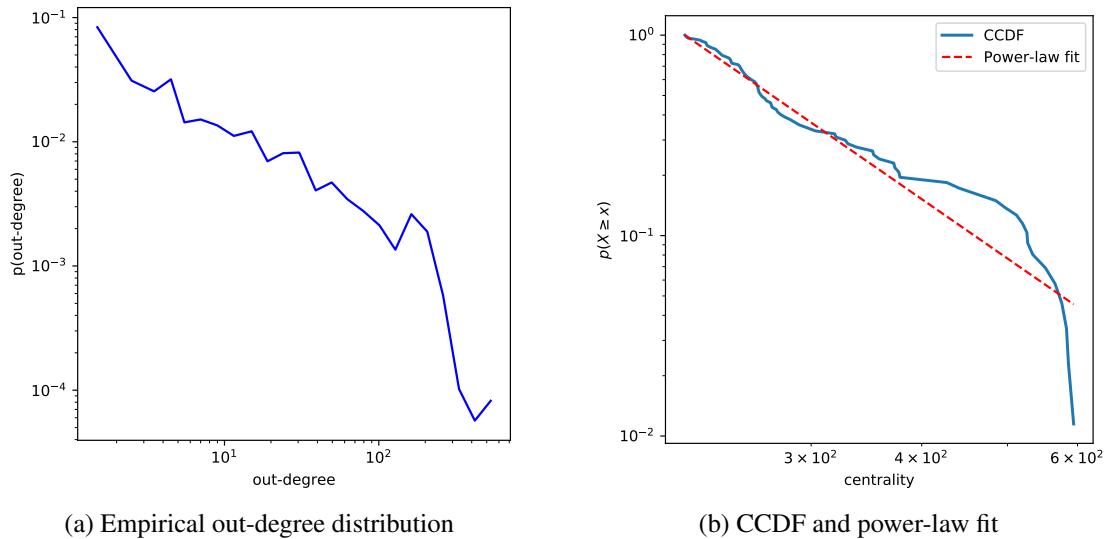


Figure 7.9: Out-degree distribution of stock network

	Undirected stock network
Strength distribution	Power-law
Average centrality	1
Weighted assortativity	0.1244

Table 7.3: Main topologies of directed weighted stock price network

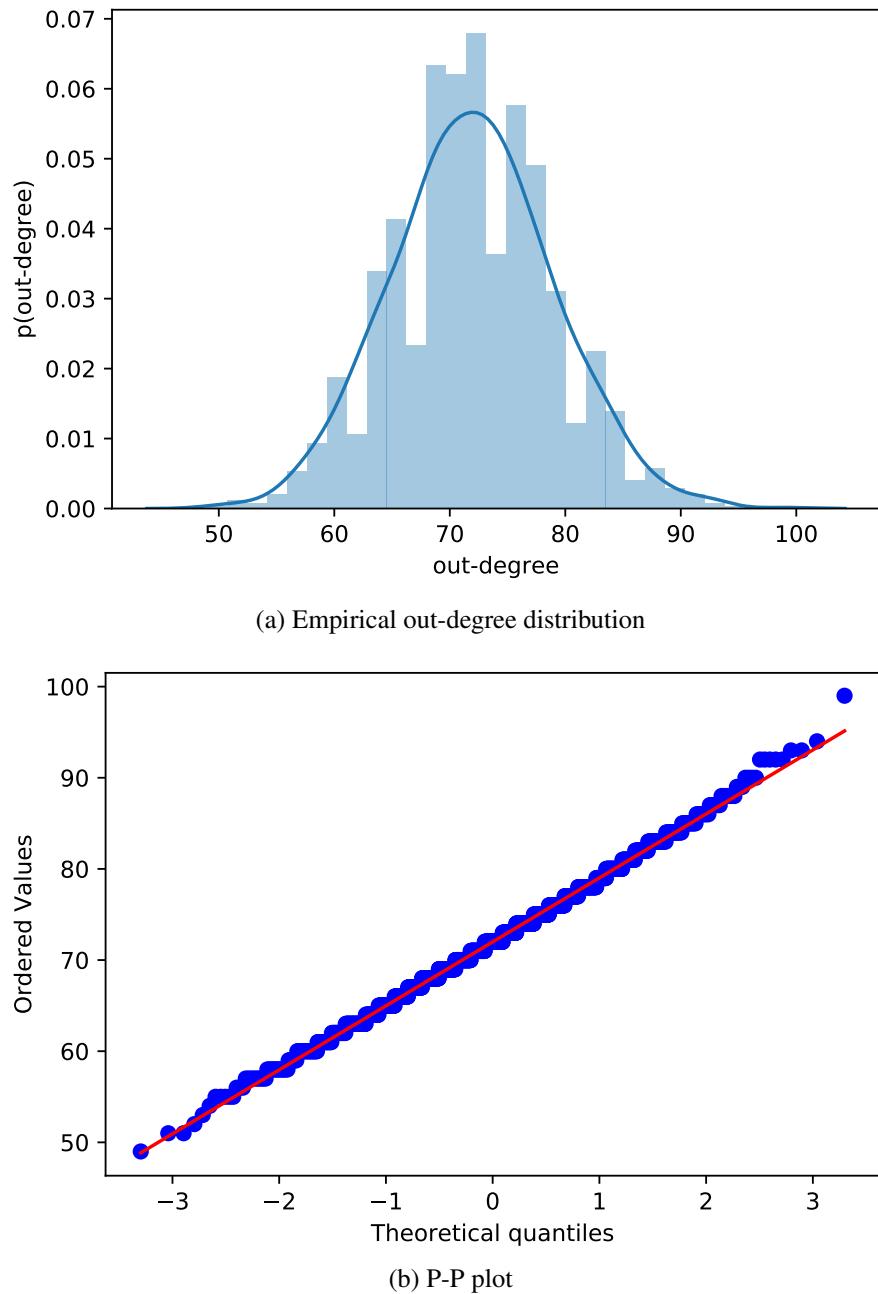


Figure 7.10: Out-degree distribution and P-P plot of small-world network

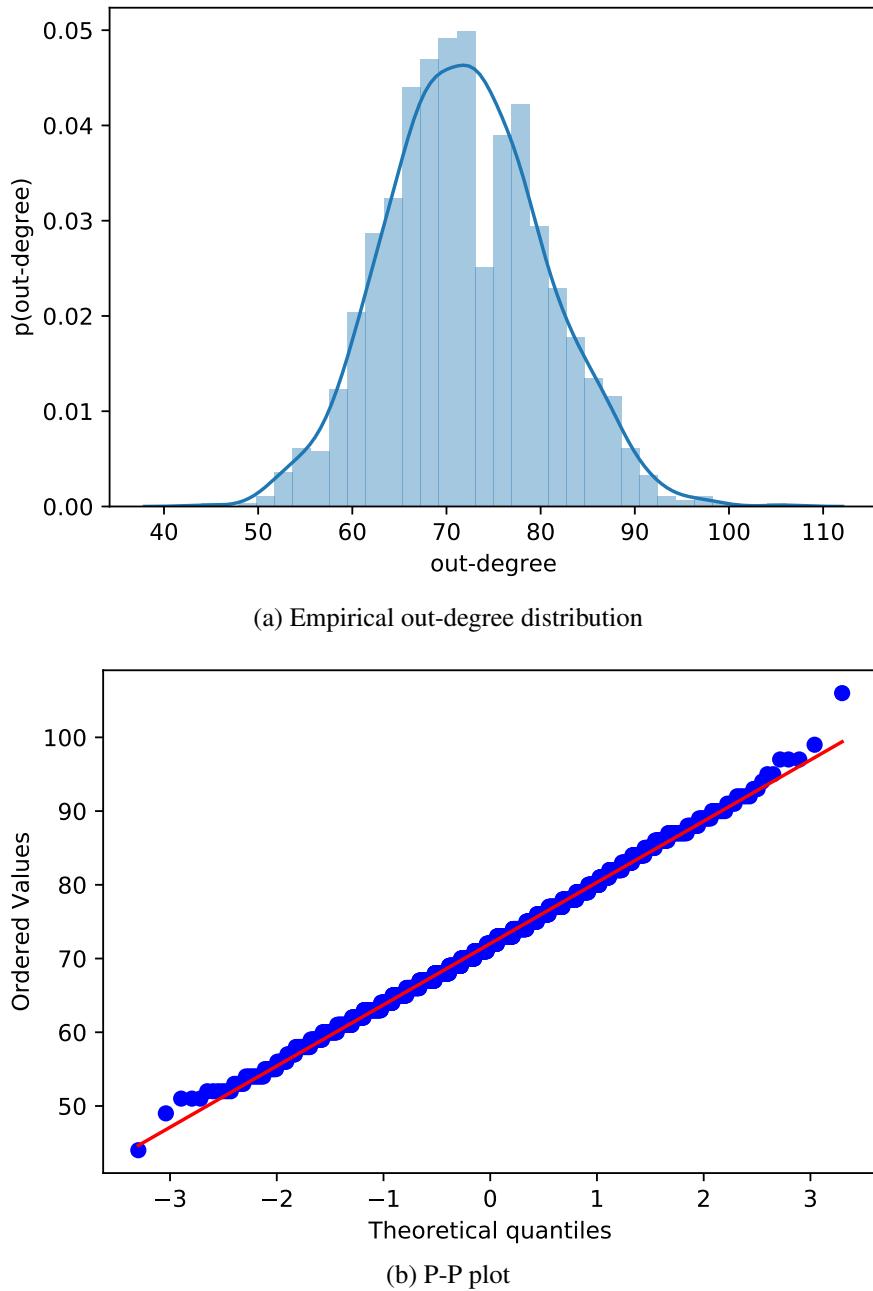


Figure 7.11: Out-degree distribution and P-P plot of random network

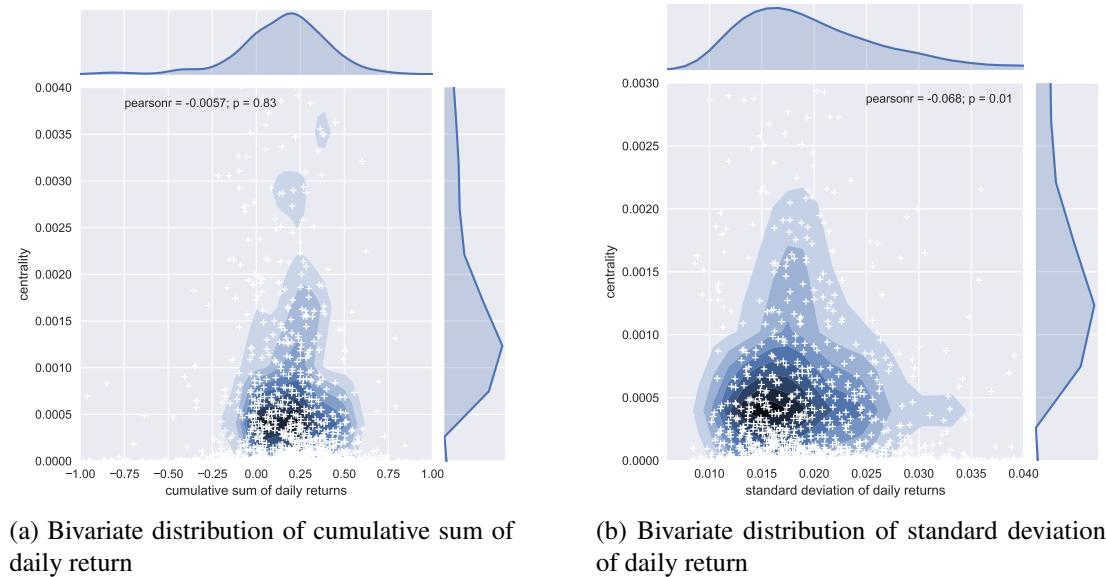


Figure 7.12: Bivariate distribution

7.3 Analysis of the directed weighted network

7.3.1 Analysis on the relationship between price return and clustering coefficient

7.4 Stability of network

Chapter 8

Conclusions and future watch

Hello

Chapter 9

Making a bibliography

Whenever you wish to refer to books or articles relevant to your report you should use a citation such as [?]. You can also force entries to appear in the bibliography without a citation appearing in the document, by using \nocite.

Each document cited must have an entry in a .bib file. For this document we have only one, called `refs.bib`. These files are listed in the \bibliography command at the end of `report.tex`. Note that the .bib files can (and often do) contain many more entries than are actually cited in a particular document; the only ones that appear in the bibliography are those that have been referenced using \cite or \nocite.

In order to generate the appropriate reference entries, you will need to run `bibtex` after `latex` has been run, using the command `bibtex report`. This will generate a file `report.bbl`, which contains the bibliography entries. Once that file is there, you do not need to run `bibtex` again unless you add new citations, but you will probably have to run `latex` twice after running `bibtex` the first time.

The `TEX FAQ` ([?]) gives tips on how to cite URLs.

The file `refs.bib` provides an example of what can be done with Bib`TEX`. You can find much more information in any book on `LATEX`, for example [HZY09, LN08, CK15, CLSW15]

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Appendix A

Example of operation

An appendix is just like any other chapter, except that it comes after the appendix command in the master file.

One use of an appendix is to include an example of input to the system and the corresponding output.

One way to do this is to include, unformatted, an existing input file. You can do this using \verbatiminput. In this appendix we include a copy of the C file hello.c and its output file hello.out. If you use this facility you should make sure that the file which you input does not contain TAB characters, since L^AT_EX treats each TAB as a single space; you can use the Unix command expand (see manual page) to expand tabs into the appropriate number of spaces.

A.1 Example input and output

A.1.1 Input

(Actually, this isn't input, it's the source code, but it will do as an example)

```
/* Hello world program */

#include <stdio.h>

int main(void)
{
    printf("Hello World!\n") ;
    return 0 ;
}
```

```
}
```

A.1.2 Output

Hello World!

A.1.3 Another way to include code

You can also use the capabilities of the `listings` package to include sections of code, it does some keyword highlighting.

```
/* Hello world program */

#include <stdio.h>

int main(void)
{
    printf("Hello_World!\n");
    return 0;
}
```