Turning Crisis into Opportunity:

Analyzing the Network Structure and Dynamic Changes of Major Financial Market Before and After Economic Crises

JAYWOONG JEONG, HYEONGMIN PARK, JUCHAN LEE, MINKYUNG CHOI
Industrial & Systems Engineering Department
KAIST

Background (1): Economic Crisis

- Economic downturns are an inevitable cyclical occurrence throughout history. The financial world has witnessed numerous crises over time, each providing invaluable data and lessons.
- In fact, crises present opportunities for those able to identify and capitalize on inherent market inefficiencies. During every economic downturn when everyone else is crumbling, **there are those who seize opportunities from within and rise up.**

Goals: "모두가 손해를 볼 때 이익을 얻거나 **최소한 손해를 줄일 수 있는 전략**이 필요하다!"

Background (2):Related Works

Literature review (1): Economic Networks

- Understanding and analyzing the **complexity of financial systems has emerged as an important research topic**.
- Moreover, if there are signs of systemic risk, it is necessary to have a macro-management system not only for the financial sector but also for the real sector.
- Ultimately, since the financial system is difficult to predict or control and relies on highly interdependent connections, exploring and identifying approaches to understand the complexity of the network is a crucial research topic.

Frank Schweitzer, Giorgio Fagiolo, Didier Sornette, Fernando Vega-Redondo, Douglas R. White:
Economic Networks: What do we know and what do we need to know?
Working Paper. To appear in *ACS - Advances in Complex Systems*, vol 12, no 4 (2009).

Economic Networks: What do we know and what do we need to know?

Frank Schweitzer,[1*] Giorgio Fagiolo,[2] Didier Sornette,[1,3] Fernando Vega-Redondo,[4,5] Douglas R. White[6]

[1] ETH Zurich, Department of Management, Technology and Economics, Kreuzplatz 5, 8032 Zurich, Switzerland
[2] Laboratorio di Economia e Management (LEM), Scuola Superiore Sant'Anna, Piazza Martiri della Liberta 33, 56127 Pisa, Italy
[3] Swiss Finance Institute, c/o University of Geneva, 40 blvd. Du Pont d' Arve, 1211 Geneva 4, Switzerland
[4] Economics Department, European University Institute, Via della Piazzuola 43, 50133 Firenze, Italy
[5] Instituto Valenciano de Investigaciones Economicas C/ Guardia Civil 22 esc. 2 no 1, 46020 Valencia, Spain
[7] Institute of Mathematical Behavioral Sciences, University of California, 3151 Social Science Plaza, Irvine, California 92697, USA

*To whom correspondence should be addressed; E-mail: fschweitzer@ethz.ch

Abstract

We examine the emergent field of economic networks and explore its ability to shed light on the global and volatile economy where credit, ownership, innovation, investment, and virtually every other economic activity is carried at a scale and scope that respects no geographical, organizational, or political boundaries. In this context, the study of economic networks and their dynamics must reflect the vast complexity of the interaction patterns and integrate it with a realistic account of the incentives and information that govern agents' behavior. The interplay of both has been shown to produce metastabilities, system crashes, and emergent structures in ways that are yet only poorly understood. Meeting this exciting scientific challenge requires a combination of time series analysis, complexity theory, and simulation with the analytical tools that have been developed by game theory, as well as graph and matrix theories. We argue that this will help achieving a better integration of theory and data models and provide a better understanding of the potentials and risks of modern economic systems.

1 Motivation

The current economic crisis illustrates a critical need for new and fundamental understandings of the structure and dynamics of economic networks. Economic systems are increasingly built on interdependencies of both behavior and information, leading to a global economy where credit and investment, trade and input-output flows, research and innovation all occur at a truly world scale

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Source: Schweitzer F, Fagiolo G, Sornette D, Vega-Redondo F, Vespignani A, White DR. Economic networks: the new challenges. Science. 2009 Jul 24;325(5939):422-5. doi: 10.1126/science.1173644. PMID: 19628858.

Literature review (2):
주식 네트워크를 통한 코로나19 충격의 금융산업 시스템 위험에 대한 영향: 경제 충격과의 비교

- This study observes the impact of the COVID-19 shock on the interconnection between stocks in the financial industry from a network perspective.
- The market collapse caused by the COVID-19 shock shows time series characteristics very similar to those of economic shocks.
- In the stock network of the minimum spanning tree, while economic shocks weaken through market adjustments after the event and show connections between different stocks, the COVID-19 shock maintains the connection structure among similar stocks despite active market adjustments, due to continuous unexpected shocks.

https://doi.org/10.26588/kdic.2021.22.1.002

주식네트워크를 통한 코로나19 충격의 금융산업 시스템 위험에 대한 영향: 경제충격과의 비교*

엄철준**

〈요 약〉

본 연구는 코로나19 충격이 금융산업의 주식들 간 연결 관계에 미치는 영향을 네트워크 관점에서 관찰한다. 코로나19 충격에 기인한 시장붕괴는 경제충격의 경우와 매우 유사한 시계열 특징을 보인다. 최소 신장 트리의 주식네트워크에서, 경제충격은 사건일 후에 시장 조정을 통해 그 효과가 약화되고 다른 구조의 주식들 간 연결 관계를 보이는 반면에, 코로나19 충격은 적극적 시장 조정에도 불구하고, 예상치 못한 충격이 계속 발생함에 따라 유사한 주식들 간의 연결 구조를 계속 유지한다. 그랜저 인과관계의 주식네트워크에서, 경제충격은 사건일 전에 전조증상의 유의적 정보흐름을 보이고 사건일 후의 상승추세는 점진적으로 사라지는 반면에, 코로나19 충격은 사건일 전에 전조증상의 유의적 정보흐름이 없고 사건일에 갑자기 증가하는 정보흐름의 추이를 보이고, 특히 이후기간에 유의적 정보흐름의 상승 추이가 지속되는 시계열 특징을 보인다. 결국, 향후 금융산업의 시스템 위험에 관련된 연구들에 있어서, 코로나19와 같은 비경제적 사건들에 기인한 시장충격은 차별적 접근법이 필요하다.

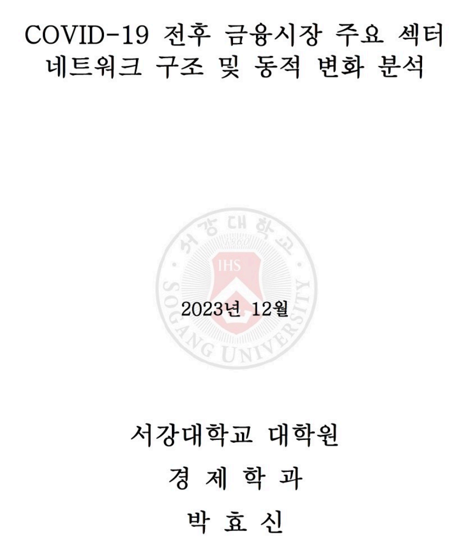
핵심주제어: 코로나19, 시스템 위험, 주식네트워크, 최소 신장 트리, 그랜저 인과관계
JEL 분류번호: G01, G29, C02, C51

접수일(2021년 1월 25일), 수정일(2021년 4월 6일), 게재확정일(2021년 5월 20일)

* 본 논문은 예금보험공사의 2020년 외부연구지원을 받아 작성된 2020 외부연구지원 공모논문집(통권 제17호)에 수록된 연구보고서의 내용을 정리·보완한 것입니다. 금융안정연구의 연구논문 심사과정에서 질적 개선을 위해 유익한 비평을 해주신 익명의 2명 심사위원께 감사드립니다.
** 부산대학교 경영대학 교수. 주소: 46241 부산광역시 금정구 부산대학로63번길 2 (장전동) 부산대학교 경영대학;

Literature review (3):
COVID-19 전후 금융시장 주요 섹터 네트워크 구조 및 동적 변화 분석

- This paper aims to analyze the **<u>impact of COVID-19 on the interconnections between stocks</u>** in key sectors of the KRX300 index.
- Using methods such **<u>as Minimum Spanning Tree, node centrality, and community detection algorithms</u>**, the study identifies changes in network structures and key nodes before and after COVID-19.
- The findings indicate that the financial sector maintains significant influence throughout, with a notable shift in importance from the consumer discretionary sector to the information technology sector post-COVID-19, highlighting the utility of GAT models in capturing these dynamic market changes.


COVID-19 전후 금융시장 주요 섹터
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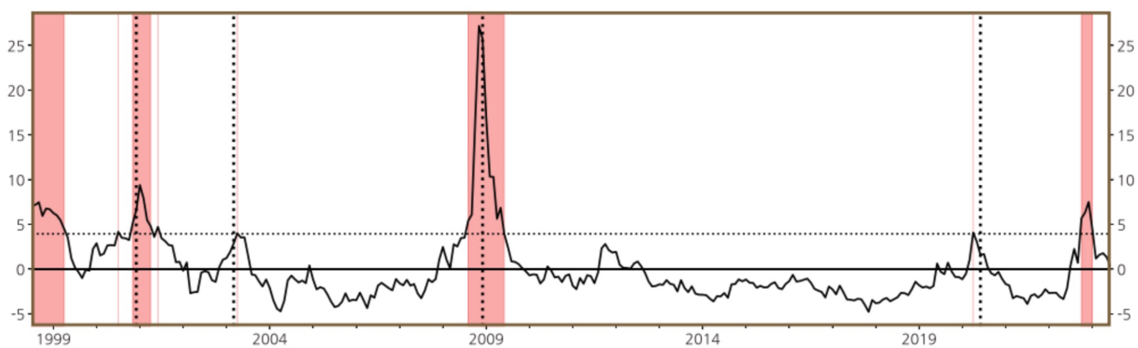
2023년 12월

서강대학교 대학원
경 제 학 과
박 효 신

Literature review (4): BoK Report on Defining Crisis

- Bank of Korea made an index Composite Financial Pressure Index (CFPI), which reflects **market instability** in banking, bonds, stocks, and foreign exchange
- It detected the 1997 foreign exchange crisis, the 2008 global financial crisis, and the 2020 COVID-19 pandemic.
- These events can be analyzed as representative cases of **1) internal economic factors, 2) external economic factors, and 3) non-economic factors.**

〈그림 1〉 복합금융압력지수(CFPI) 추이



주: 가로 점선은 CFPI의 1표준편차, 음영은 CFPI가 1표준편차를 상회한 시장불안(market stress) 기간을 표시한다. 세로 점선은 GDP 성장률(전기 대비)이 지난 4분기 평균보다 1표준편차 이상 하락한 시점을 나타낸다.

〈식 1〉 복합금융압력지수(CFPI)

ㅇ 은행부문압력지수
= KRX 은행지수 변동성
+ CD스프레드 (CD수익률 − 통안증권 수익률)

ㅇ 채권 · 주식부문압력지수
= KOSPI 지수 변동성
− KOSPI 지수 수익률(12개월 최대 하락폭)
− 기간프리미엄 (국채3년물 − 통안증권1년물)
+ 회사채 스프레드 (회사채AA − 국채3년)

ㅇ 외환부문압력지수
= USD/KRW 환율 변동성

주: 각 부문별 변수를 표준화한 후 합산하여 CFPI를 산출했다.

Source: 김태완, 박정희, 이현창(2024), "데이터 기반 금융·외환 조기경보모형" BOK이슈노트, 2024(11).
이창훈, 홍지연, 이현창(2024), "빅데이터와 기계학습 알고리즘을 활용한 실시간 인플레이션 전망(real-time inflation forecasting)", BOK이슈노트, 2024(5).

Insight and Problem descriptions

- Insight
  - Research on how these methodologies can be applied to **actual investment strategies remain laking**
  - This study aims to develop an **effective portfolio strategy** for the Korean stock market based on these new methodologies and evaluate it empirically.

- Problem Description
  - Through this research, we aim to contribute to understanding the complexity of financial networks and **developing more efficient and stable investment strategies.**
  - By analyzing the periods before and after the major crises identified by the Bank of Korea's Composite Financial Pressure Index (CFPI). We analyze what investment strategies should be adopted for various situations. such as the 1997 foreign exchange crisis, the 2008 global financial crisis, and the 2020 COVID-19 pandemic.

Data (1): Acquisition

- Our analysis focuses on the daily closing prices of stocks listed on the Korea Composite Stock Price Index (KOSPI). The data includes various attributes for each stock, such as the closing price, volume, and other financial indicators.
- We have defined the data ranges for the IMF, Subprime, and COVID-19 periods based on significant economic events and their impacts on the financial markets.

Crisis Period	Pre-Crisis Period	Post-Crisis Period
IMF	1996-11-01 to 2001-08-23	2001-08-23 to 2011-08-23
Subprime	2000-01-01 to 2006-12-31	2007-01-01 to 2008-12-31
COVID-19	2010-01-01 to 2019-12-31	2020-01-01 to 2022-12-31

Table 1. Data Ranges for IMF, Subprime, and COVID-19 Crisis Periods

Data (2): Preprocessing for Graph Structure of KOSPI Data

2.2.1 Log Returns Calculation. First, we calculated the daily log returns for each stock to normalize the data and mitigate the effects of scale differences. The log return $r_{i,t}$ for stock i on day t is given by:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{1}$$

where $P_{i,t}$ is the adjusted closing price of stock i on day t.

2.2.2 Correlation Matrix and Distance Matrix. We then computed the correlation matrix C using the daily log returns. The correlation coefficient ρ_{ij} between stocks i and j is calculated as:

$$\rho_{ij} = \frac{\text{Cov}(r_i, r_j)}{\sigma_i \sigma_j}, \tag{2}$$

where $\text{Cov}(r_i, r_j)$ is the covariance between the returns of stocks i and j, and σ_i and σ_j are the standard deviations of r_i and r_j, respectively.

To construct the graph, we transformed the correlation matrix into a distance matrix D, where the distance d_{ij} between stocks i and j is defined as:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}. \tag{3}$$

Methodologies (1): MST

3.1 Minimum Spanning Tree (MST)

3.1.1 Graph Construction for MST. To perform MST analysis, we constructed the graph using a correlation distance matrix. The process involved the following steps:

(1) **Data Collection and Filtering**: We collected daily closing prices for all KOSPI-listed stocks and filtered out those with insufficient data within the specified date range. This ensured consistency and completeness in the dataset.
(2) **Identifying Common Date Range**: We standardized the analysis period by identifying a common date range across all stocks, ensuring accurate time series analysis.
(3) **Filtering Stock Prices by Common Dates**: We filtered stock prices to include only data within the common date range, excluding stocks with insufficient data points.
(4) **Selecting Top 100 Stocks by Market Capitalization**: We focused on the top 100 stocks based on market capitalization, ensuring the analysis centered on the most significant stocks in the KOSPI index.
(5) **Constructing the Correlation Matrix**: We calculated the correlation coefficients between the closing prices of each pair of stocks and converted these correlations into distances using the formula:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}, \tag{4}$$

Methodologies (2): Centrality and Community Detection

3.2 Centrality and Community Detection

3.2.1 Graph Construction for Centrality and Community Analysis. For centrality and community detection, we constructed the graph using a weighted correlation matrix. The process included the following steps:

(1) **Data Collection and Filtering**: Similar to the MST analysis, we collected daily closing prices for all KOSPI-listed stocks and filtered out those with insufficient data.
(2) **Identifying Common Date Range**: We identified a common date range to standardize the analysis period across all stocks.
(3) **Filtering Stock Prices by Common Dates**: Stock prices were filtered to include only data within the common date range.
(4) **Selecting Top 100 Stocks by Market Capitalization**: We focused on the top 100 stocks based on market capitalization.
(5) **Constructing the Correlation Matrix**: We calculated the correlation coefficients between the closing prices of each pair of stocks and used these coefficients as edge weights in the graph.
(6) **Filtering Significant Connections**: We retained only the top 10% of edges with the highest correlation coefficients, highlighting the most significant relationships.
(7) **Adding Nodes and Edges to the Graph**: Nodes represented stocks, and edges represented significant correlations, with correlation coefficients as edge weights.
(8) **Removing Isolated Nodes**: We removed nodes not connected to others to maintain a meaningful network structure.

3.2.2 Centrality Analysis. Centrality measures help identify the most influential nodes within a network. In our stock market network, we used the following centrality metrics:

Methodologies (3): Centrality Analysis

- **Degree Centrality**:

$$C_D(v) = \frac{\deg(v)}{n-1}, \tag{6}$$

where $\deg(v)$ is the degree of node v, and n is the number of nodes in Graph.

- **Closeness Centrality**:

$$C_C(v) = \frac{n-1}{\sum_{t \neq v} d(v,t)}, \tag{7}$$

- **Betweenness Centrality**:

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{8}$$

where V is the set of nodes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|v)$ is the number of those paths passing through some node v other than s,t. If $s=t$, $\sigma(s,t)=1$, and if $v \in \{s,t\}$, $\sigma(s,t|v)=0$.

- **Eigenvector Centrality**:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j, \tag{9}$$

where A is the adjacency matrix, x is the eigenvector, and λ is the eigenvalue.

Methodologies (3): Community Detection

3.2.3 Community Detection. Community detection identifies groups of stocks that are more densely connected to each other than to the rest of the network. We used the Louvain method to maximize modularity:

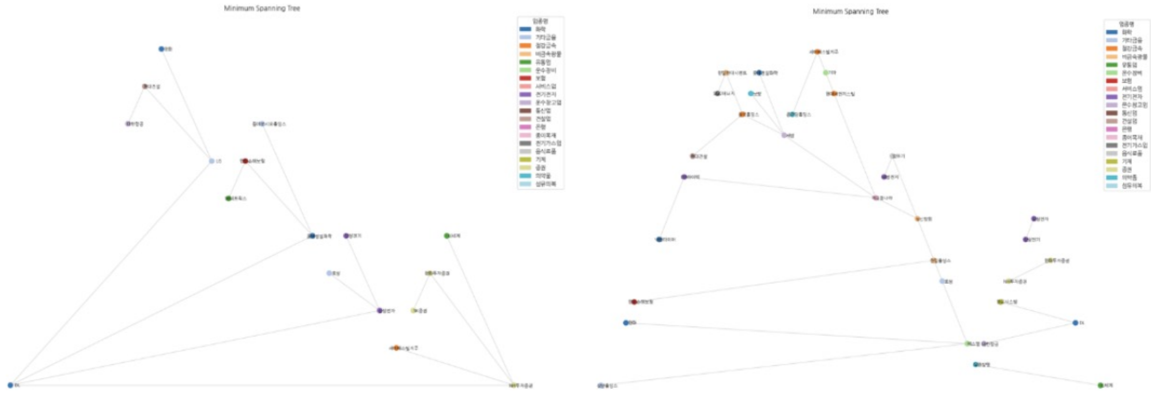
$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j), \tag{10}$$

where A_{ij} is the edge weight, k_i and k_j are the degrees of nodes i and j, m is the total number of edges, and $\delta(c_i, c_j)$ is 1 if nodes i and j are in the same community, and 0 otherwise.

By following these methods, we constructed robust and meaningful graph structures for both MST analysis and centrality/community detection, enabling us to explore the complex relationships and dynamics within the stock market.

Results (1): 1997 IMF Financial crisis

- MST



(a) MST before IMF financial crisis (b) MST after IMF financial crisis

Fig. 1. Comparison of MST before and after the IMF financial crisis

- Interconnections among securities firms weakened and even severed after the crisis. Instead, the center shifted to prominent cement and raw material companies such as Dongkuk Holdings and Sungshin Cement. In addition, the distance between large corporations and their subcontractors increased, as the large corporations faltered, leading subcontractors to reduce their connections and potentially change their business models to focus on other revenue streams for survival.

Results (1): 1997 IMF Financial crisis

- Centrality

Table 2. Degree Centrality before IMF

Item	Industry	Degree Centrality
DL	Chemical	0.324
Shinsegae	Distribution	0.324
SK Securities	Securities	0.297
Korean Air	Transportation warehousing	0.297
Hanhwa InvestmentSecurities	Securities	0.297

Table 3. Degree Centrality after IMF

Item	Industry	Degree Centrality
Sebang	Transportation warehousing	0.378
Donguk Holdings	Steel metal	0.324
Hanil Holdings	Non-metallic minerals	0.297
KleanNara	Paper wood	0.270
SungShin Cement	Non-metallic minerals	0.216

Table 4. Betweenness Centrality before IMF

Item	Industry	Betweenness Centrality
Hanwha General Insurance	Insurance	0.0303
Samsung	Electronics	0.0142
Shinsegae	Distribution	0.0129
Lotte Fine Chemical	Chemical	0.0128
Korean Air	Transportation Warehousing	0.0128

Table 5. Betweenness Centrality after IMF

Item	Industry	Betweenness Centrality
Hanil Holdings	Non-metallic minerals	0.1101
Sebang	Transportation warehousing	0.0937
Donguk Holdings	Steel metal	0.0430
Hanil Hyundai Cement	Non-metallic minerals	0.0358
SeahBesteel	Steel metal	0.0328

- Degree Centrality
  - Before the IMF crisis, security firms such as NH Investment Securities, SK Securities, had a high degree centrality, accounting for the high importance of the network. However, their importance dropped after the crisis, potentially due to significant restructuring and increased regulation in the financial and securities sectors
- Betweenness Centrality
  - Overall betweenness centrality increased significantly after the IMF crisis, rising by approximately four times. This indicates that the market shares a similar response to the economic crisis.

Results (1): 1997 IMF Financial crisis

- Community Detection

4.1.3 Community Detection. The results of community detection before and after the IMF crisis are shown in tables 6 and 7.

Table 6. Community Detection before IMF

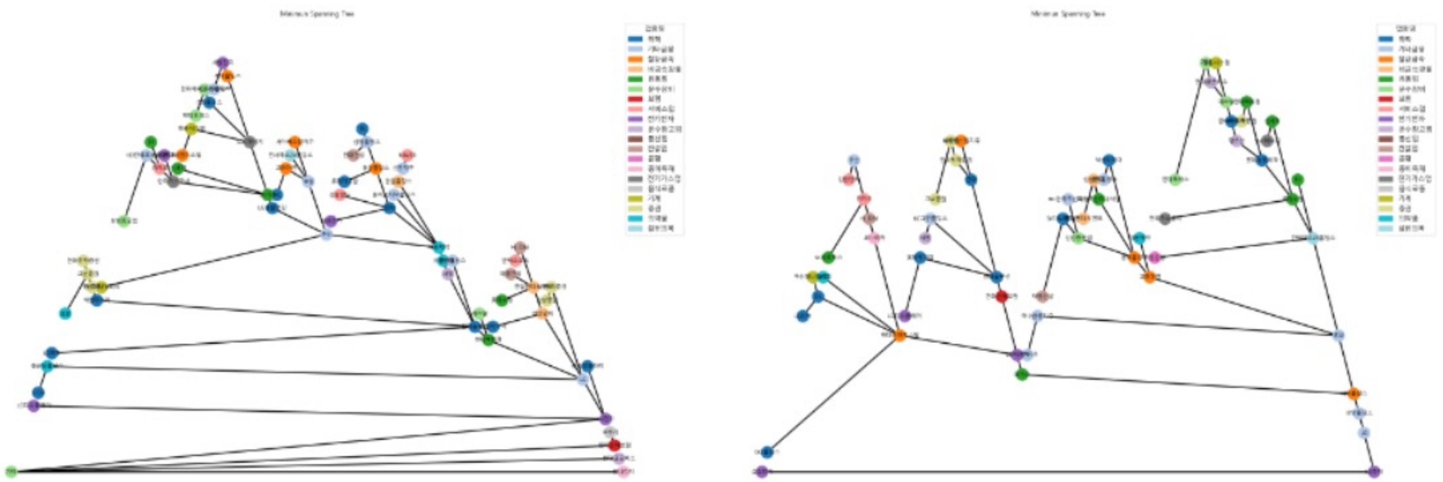
	Construction	Finance	Insurance	Transportation	Distribution	Electronics	Securities	Steel	Chemistry
Community 1	1	1	0	0	0	0	2	1	1
Community 2	0	1	1	0	1	0	0	0	2
Community 3	0	1	0	1	1	2	1	0	2

Table 7. Community Detection after IMF

	Construction	Machinery	Other Finance	Insurance	Non-metallic Minerals	Transportation Equipment	Transportation Warehousing	Distribution	Food	Medicine	Electricity Gas	Electronics	Paper Wood	Securities	Steel	Chemistry
Community 1	0	0	0	0	0	0	1	1	0	3	0	1	1	0	4	2
Community 2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Community 3	0	0	2	1	1	1	0	0	0	0	0	0	0	0	0	3
Community 4	1	0	0	0	2	0	0	0	1	0	1	0	0	0	0	0
Community 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Community 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
Community 7	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0

- **(Increase in the number of communities)** The number of communities has clearly increased from 3 to 7, almost twice.
- **(Decrease in the soundness of corporate structure)** Internally, it can be interpreted that the corporate structures have become more robust, with unnecessary connections reduced and only the valuable ones remaining.

Results (2): 2008 Subprime Mortgage



(a) MST before Subprime Mortgage crisis

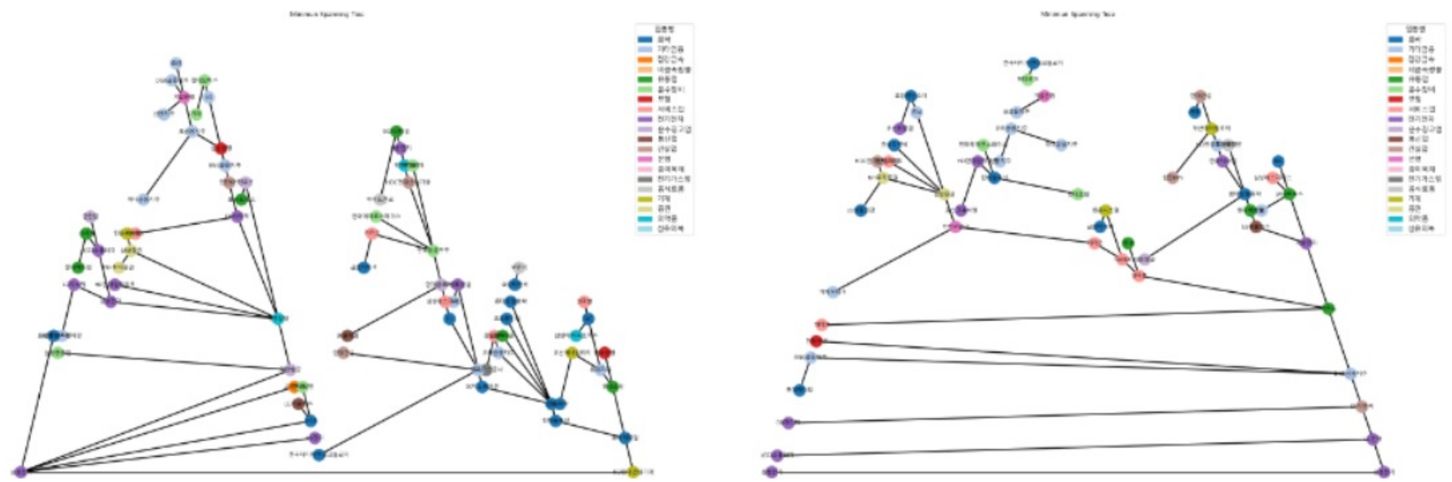
(b) MST after Subprime Mortgage crisis

Fig. 2. Comparison of MST before and after the Subprime Mortgage crisis

Results (3): 2020 Covid-19 Crisis

4.3 COVID-19 Pandemic

4.3.1 Minimum Spanning Tree. The minimum spanning trees before and after the pandemic are shown in figure 3.



(a) MST before COVID-19 (b) MST after COVID-19

Fig. 3. Comparison of MST before and after COVID-19

Discussion & Conclusion (1): Graph Analysis

- Analysis used graph methodologies such as Minimum Spanning Tree (MST) analysis, centrality measures, and community detection.
- Findings revealed significant shifts in industry centrality and connectivity.
  - Before the IMF crisis, securities firms had high centrality but were later replaced by raw materials and cement industries due to the crisis.
  - During the subprime mortgage crisis, the centrality of financial firms decreased, with heavy industries and technology firms becoming more central.
  - The COVID-19 pandemic highlighted the growing importance of technology and domestic market-oriented companies, with increased centrality for internet service companies and domestic distribution firms.
- **<u>During economic crises, overall centrality measures generally increase, and the number of distinct communities decreases, indicating a more unified market response to external shocks.</u>**
- These structural changes offer valuable insights for creating investment strategies resilient to economic disturbances.
- -Advanced network analysis techniques can enhance our ability to predict market changes and develop strategies for improved stability and performance during economic crises.

Application (1)

- We found that **<u>degree centrality</u>** among other mythologies has the highest explanatory power in crisis situations. Based on this, we defined new sectors by dividing companies into top 33%, middle 33%, and bottom 33% according to their degree centrality scores.
- We aim to plot the efficient frontier by adjusting the weights of these newly defined sectors.

- 1. Sector Definition
  - Define new sectors based on communities discovered through network analysis
  - Understand sector characteristics by reflecting theoretical backgrounds and expert opinions
- 2. Portfolio Optimization
  - Set the newly defined sectors as asset classes
  - Perform portfolio optimization using mean-variance or risk parity methods

Application (2)

	종목코드	종목명	업종명	Degree Centrality
18	004170	신세계	유통업	0.413793
1	000210	DL	화학	0.344828
6	000880	한화	화학	0.344828
7	000990	DB하이텍	전기전자	0.344828
3	000370	한화손해보험	보험	0.310345
0	000070	삼양홀딩스	기타금융	0.275862
9	001430	세아베스틸지주	철강금속	0.275862
17	004000	롯데정밀화학	화학	0.241379
23	004980	성신양회	비금속광물	0.206897
22	004800	효성	기타금융	0.206897

1) Hub & Spoke

	종목코드	종목명	업종명	Degree Centrality
4	000640	동아쏘시오홀딩스	기타금융	0.068966
28	007310	오뚜기	음식료품	0.068966
16	003850	보령	의약품	0.034483
14	003490	대한항공	운수창고업	0.034483
11	001630	종근당홀딩스	의약품	0.034483
20	004490	세방전지	전기전자	0.034483
24	004990	롯데지주	기타금융	0.034483
26	005930	삼성전자	전기전자	0.034483
27	006390	한일현대시멘트	비금속광물	0.034483
29	018880	한온시스템	기계	0.034483

2) Chain Link

	종목코드	종목명	업종명	Degree Centrality
19	004360	세방	운수창고업	0.206897
2	000270	기아	운수장비	0.172414
25	005850	에스엘	운수장비	0.172414
5	000720	현대건설	건설업	0.172414
12	002350	넥센타이어	화학	0.172414
15	003530	한화투자증권	증권	0.137931
13	003300	한일홀딩스	비금속광물	0.137931
8	001230	동국홀딩스	철강금속	0.137931
21	004540	깨끗한나라	종이목재	0.068966
10	001510	SK증권	증권	0.068966

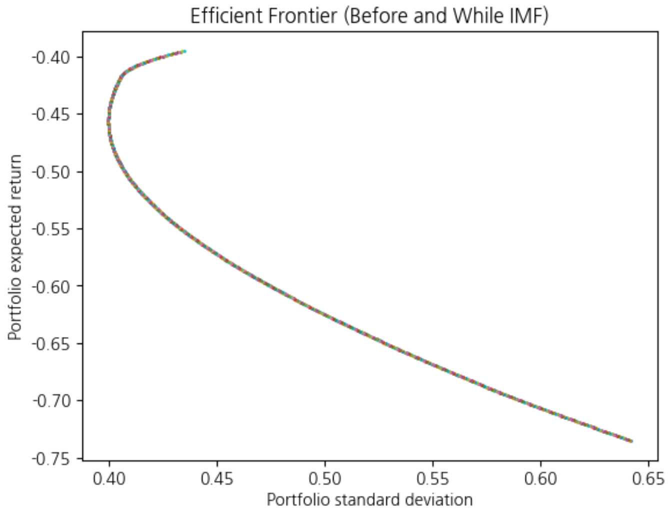
3) Fringe Player

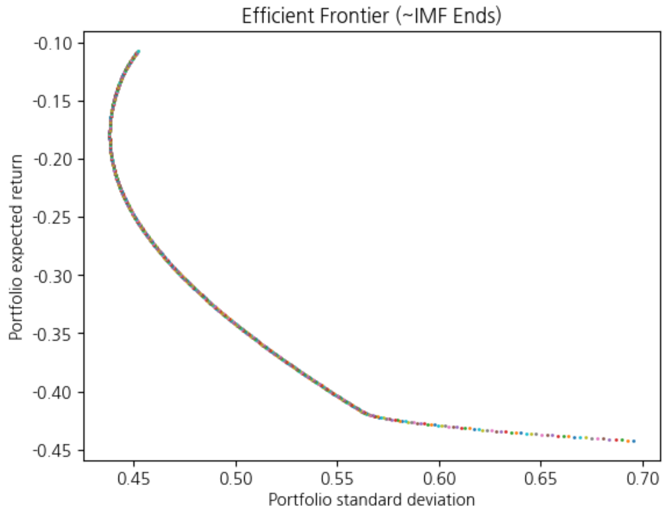
Newly Defined Sectors

- 1) Hub & Spoke Sector (High Degree Centrality)
  - Companies playing a central hub role in the network
- 2) Chain Link Sector (Degree Centrality)
  - Companies forming connecting links with the central firms
- 3) Fringe Player Sector (Low Centrality)
  - Peripheral companies located at the fringe of the network

Application (3)

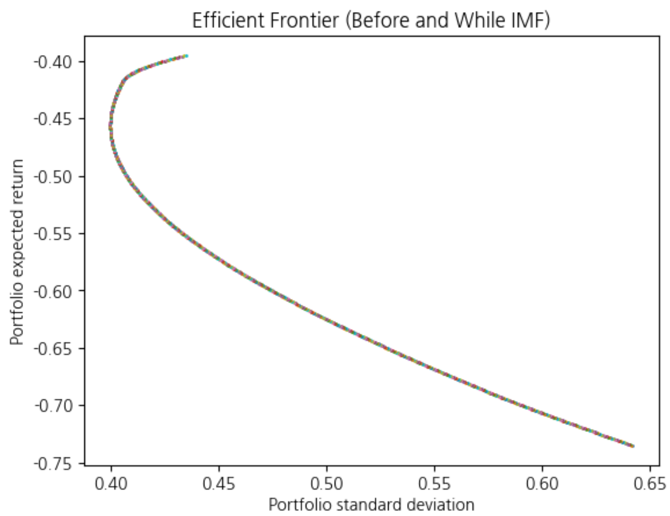
- We focused on the **IMF crisis** to determine what strategies should be adopted before and during the crisis based on the results.
- Using data from **before and during the IMF crisis, we defined sectors**. We will maintain the initially defined sectors.
- We 1) Plot the efficient frontier **before and during the IMF crisis**, and 2) Plot the efficient frontier **until the end of the IMF crisis**.

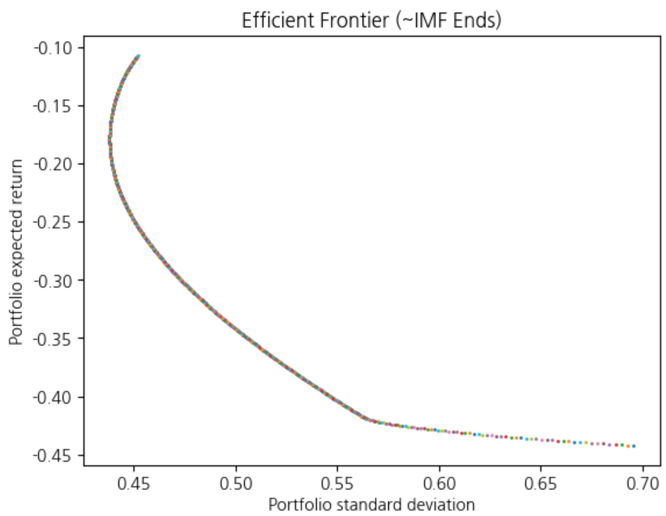




Application (3)

- We calculated the required weightings for each sector to achieve our target return. This provides insights into how we should construct our portfolio when investing. **The target return is the average return across all stocks during the period.** We can obtain information on **how to construct our portfolio** to at least achieve the average return.
- Before .6601 -> .6602
- Return: -0.6602, Weights: [0.73268891 0.21628933 0.05102176]
- After .3949 -> .3950
- Return: -0.3950, Weights: [0.45998449 0.46699919 0.07301632]





Discussion & Conclusion (2): Significance and Limitations

- Significance
  - The significance of our work lies in defining a new sector, rather than using existing industry classifications.
  - While it may be challenging to achieve substantial effects using this approach, defining sectors through network analysis and applying this to strategy is a novel attempt.

- Limitations
  - graph composition.
    - There were too many edges, which, if reflected, would greatly reduce interpretability.
    - To prevent this, only edges with lower distances were selected, which could introduce bias.
    - This issue arises because companies that disappeared after the IMF crisis do not have current data available.
  - lack of a solid foundation for adequate explanations based on the graph analysis.
    - Although there were sufficiently explanatory points, they were still lacking.
    - An economic interpretation was needed.
    - number of companies included in the defined sector was very small.
  - strategy was not attempted for periods other than the IMF crisis.