

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

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This study examines the changes in the structure of major financial market sectors in Korea before and after the 1997 IMF financial crisis, the 2008 subprime mortgage crisis, and the 2020 COVID-19 pandemic. The study uses network analysis techniques such as Minimum Spanning Tree (MST) analysis, centrality measures, and community detection to reveal significant shifts in industry centrality and connectivity resulting from these crises. The findings suggest that market centrality generally increases, and the number of distinct communities decreases during economic downturns, indicating a unified market response to shocks. In addition, we create an efficient frontier based on the degree centrality scores of the companies. These insights can be valuable for investment strategies to improve stability and performance during economic disturbances, highlighting the importance of understanding financial market interdependencies.

ACM Reference Format:

Jaewoong Jeong, Hyeongmin Park, Juchan Lee, and Minkyung Choi. 2025. Analyzing the Network Structure and Dynamic Changes of Major Financial Market Sectors Before and After Economic Crises. 1, 1 (April 2025), 15 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 Introduction

1.1 Background

Economic downturns are[1] an inevitable cyclical occurrence throughout history. Even if the gains are small, a strategy is needed that allows one to gain, or at least not lose as much, when everyone else is losing. 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.

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ACM XXXX-XXXX/2025/4-ART

<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

During every economic downturn when everyone else is crumbling, there are those who seize opportunities from within and rise up.

To achieve this, we must consider that the financial market is not an independent structure, but rather has complex interdependencies between various economic factors. These interactions profoundly influence market trends and volatility. Consequently, understanding and analyzing the complexity of financial systems has emerged as an important research topic[1].

The Korean stock market, in particular, has undergone structural changes in the system due to various economic shocks. Events like the 1997 Asian financial crisis, the 2008 global financial crisis, and the 2020 COVID-19 pandemic have prompted a recalibration of the market's structure and relationships. These incidents were the result of a complex interplay of diverse factors, transcending mere economic shocks. The Korean financial crisis that erupted in late 1997 was triggered by a series of corporate bankruptcies initiated by the default of Hanbo Steel in January 1997, coupled with the rapid withdrawal of short-term foreign capital, radically restructuring industries and companies[2].

Economists have interpreted the causes and consequences of such shocks and crises from various perspectives. Policy aspects or macroeconomic analyses have predominated, with changes in the financial market structure between 1994-1996 identified as one of the key factors contributing to the 1997 foreign exchange crisis[3]. Short-term international capital flows and issues with the domestic economic structure have also been cited as major causes of the crisis[4]. These diverse interpretations have been presented through different analytical methodologies. However, they have fallen short in interpreting and utilizing the results.

Existing time series analysis and machine learning techniques have also been widely used in financial market research. However, these methods have limitations in fully capturing the interrelationships and structures between complex factors. Time series analysis is useful for tracking changes in data over time, but is limited in capturing the intricate interactions between various economic variables. Machine learning techniques excel at processing large-scale data and recognizing patterns, but struggle to fully model the dynamic and interconnected nature of financial markets[5].

To overcome these limitations, new approaches leveraging graph theory or graph neural networks (GNNs) have emerged. Utilizing the characteristics of GNNs, researchers are increasingly analyzing the complex interactions and structural relationships within financial markets, with many cases demonstrating their superior performance. For instance, Wang et al.[6] used GNN techniques to predict stock market volatility, outperforming state-of-the-art deep learning methods like SVMs, CNNs, and LSTMs. Such studies suggest that structural analysis of financial networks can provide essential insights for investment strategy formulation.

However, research on how these methodologies can be applied to investment strategies remains lacking. This study aims to develop an effective rebalancing strategy for the Korean stock market based on these new methodologies and evaluate it empirically.

By analyzing the periods before and after the major crises identified by the Bank of Korea's Composite Financial Pressure Index (CFPI), which reflects market instability

in banking, bonds, stocks, and foreign exchange, such as the 1997 foreign exchange crisis, the 2008 global financial crisis, and the 2020 COVID-19 pandemic, we analyze what investment strategies should be adopted for various situations. These events can be analyzed as representative cases of internal economic factors, external economic factors, and non-economic factors, respectively. For a practical application, we defined new sectors by categorizing companies as top third, middle third, and bottom third based on their degree centrality scores. Our goal is to create an efficient frontier by adjusting the weights of these sectors. This method helps us understand sector attributes based on theoretical knowledge and expert opinions. Utilizing these insights, we can build portfolios tailored for various market conditions, offering valuable guidance for investment strategies, especially during economic crises. Through this research, we aim to contribute to understanding the complexity of financial networks and developing more efficient and stable investment strategies.

2 Data Overview and Preprocessing

2.1 KOSPI Data Description

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. This comprehensive dataset provides a robust foundation for constructing and analyzing the stock market network.

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. The pre-crisis and post-crisis periods for each event are selected to capture the market conditions before and after these crises, ensuring a thorough analysis of the stock market's response and recovery.

Crisis Period	Pre-Crisis Period	Post-Crisis Period
IMF	1996-11-01 to 1996-12-31	1997-01-01 to 2001-08-23
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

2.2 Preprocessing for Graph Structure of KOSPI Data

To analyze the KOSPI stock market using a Graph, we followed several preprocessing steps to convert the raw stock data into a suitable graph structure.

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:

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

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:

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

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:

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

2.2.3 Graph Construction. Using the distance matrix, we constructed the adjacency matrix for the graph. To simplify the network and focus on the most significant relationships, we retained only the edges with distances below the 10th percentile, effectively filtering out weaker connections. This threshold was chosen to ensure the graph's sparsity and manageability.

3 Method

In this study, we implemented two different graph analysis methods to analyze the stock market: one for Minimum Spanning Tree (MST) analysis and the other for centrality and community detection. Each track utilized different methods for constructing the graph structures based on stock correlations.

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:

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

where d_{ij} is the distance and ρ_{ij} is the correlation coefficient between stocks i and j .

- (6) **Filtering Significant Connections:** We retained only the top 10% of edges with the smallest distances, ensuring the graph focused on the most significant relationships.
- (7) **Adding Nodes and Edges to the Graph:** Nodes represented stocks, and edges represented the significant correlations between them, with distances as edge weights.
- (8) **Removing Isolated Nodes:** We removed any nodes not connected to others, maintaining a meaningful network structure.

The MST was constructed using Kruskal's algorithm, ensuring the minimum total edge weight while avoiding cycles. The formulation for the MST is:

$$\text{MST} = \arg \min_{\substack{T \subseteq G \\ T \text{ is a spanning tree}}} \sum_{(u,v) \in T} w(u,v), \quad (5)$$

where G is the graph, T is the spanning tree, and $w(u,v)$ is the edge weight.

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:

- **Degree Centrality:**

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

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

- **Closeness Centrality:**

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

where $d(v, t)$ is the shortest path distance between nodes v and t , and $n-1$ is the number of nodes reachable from u .

- **Betweenness Centrality:**

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

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:**

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

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

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:

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

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.

4 Result and Discussion

4.1 1997 IMF financial crisis

4.1.1 Minimum Spanning Tree. The minimum spanning trees before and after the IMF financial crisis are shown in figure 1.

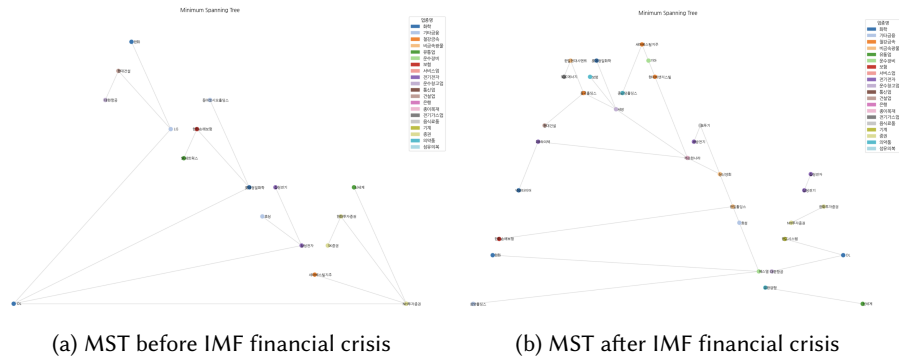


Fig. 1. Comparison of MST before and after the IMF financial crisis

The two MSTs display networks of companies, showing how different industries cluster together and highlighting central companies with numerous connections. Before the IMF crisis, the connection between securities companies was strong. In particular, the distance between Hanwha Investment Securities, NH Investment Securities, and SK Securities is very close, and a cluster has been formed between them. However, the 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.

4.1.2 Node Centrality. The degree centrality measures the number of edges connected to each node. In this network, it represents the number of high correlations with other stocks connected to each stock. The top-5 degree centrality and the corresponding item names before and after the IMF crisis are shown in tables 2 and 3.

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
Hanwha InvestmentSecurities	Securities	0.297

Table 3. Degree Centrality after IMF

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

Before the IMF crisis, security firms such as NH Investment Securities, SK Securities, and Hanwha Investment 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, leading these major firms to vanish from the list and allowing companies from other industries to emerge.

The betweenness centrality measures how many times a particular stock traverses the shortest path between pairs of other stocks. The top-5 betweenness centrality and the corresponding item names before and after the IMF crisis are shown in tables 4 and 5.

Table 4. Betweenness Centrality before IMF

Item	Industry	Betweenness Centrality
Harwha 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

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. Regarding both the degree centrality and the betweenness centrality, the industry was dominated by securities firms before the crisis. However, their ranking has been replaced by companies in secondary industries such as steel and metals, chemicals, and paper and wood, with the centrality of raw material companies that can earn immediate revenue increasing significantly.

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	1	0	1	0	3	0	1	1	0	4	2
Community 2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Community 3	0	0	2	1	1	0	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

The number of communities has increased by almost twice, from 3 to 7. Internally, the structure of companies has become more unstable, yet we can observe an increase in soundness due to the rise in previously unnecessary connections with other companies.

4.2 Subprime Mortgage Crisis

4.2.1 Minimum Spanning Tree. The minimum spanning trees before and after the Subprime Mortgage crisis are shown in figure 2.

Before the subprime mortgage crisis emerged, securities tended to be clustered close together, and most heavy industrial companies were located on the outskirts. However, clusters of heavy industry and high-tech companies have emerged after

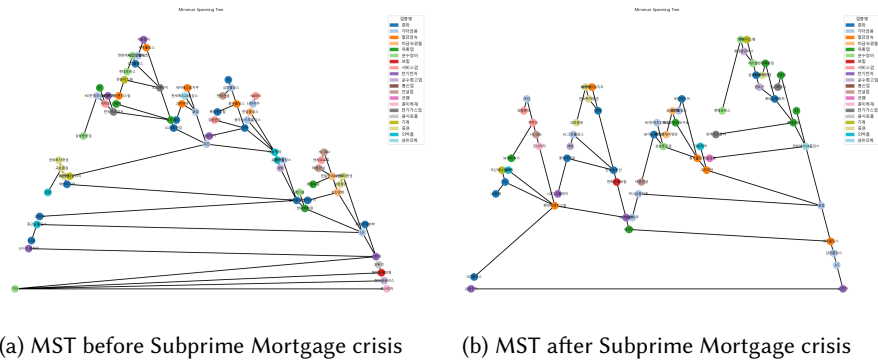


Fig. 2. Comparison of MST before and after the Subprime Mortgage crisis

the crisis, such as LG Chemical, DL, and Hyundai BNG Steel, or LG Display, Lotte Chemical, and Hanhwa Solution. This indicates that network connections and the central roles within the industry have changed after the crisis.

4.2.2 Node Centrality. The top-5 degree centrality and the corresponding item names before and after the subprime mortgage crisis are shown in tables 8 and 9.

Table 8. Degree Centrality before the Subprime Mortgage Crisis

Item	Industry	Degree Centrality
KOGAS	Electricity and Gas	0.275
Nexen Tire	Chemical	0.275
LG	Finance	0.260
Doosan	Finance	0.260
Hyosung	Finance	0.260

Table 9. Degree Centrality after the Subprime Mortgage Crisis

Item	Industry	Degree Centrality
DL	Chemical	0.492
Hanhwa Solution	Chemical	0.459
Hyundai BNG Steel	Steel metal	0.426
Hanhwa General Insurance	Insurance	0.409
Pan Ocean	Transportation warehousing	0.393

Overall, the degree centrality increased from 1.5 to 2 times. This indicates that the industry is sharing a similar response to the economic crisis. In addition, the centrality of finance companies has decreased, potentially due to the foreign exchange reserves issues.

The top-5 betweenness centrality and the corresponding item names before and after the subprime mortgage crisis are shown in tables 10 and 11.

Table 10. Betweenness Centrality before the Subprime Mortgage Crisis

Item	Industry	Betweenness Centrality
Donguk Holdings	Steel metal	0.194
Hanhwa Investment and Securities	Securities	0.143
Hyosung	Finance	0.134
Doosan	Finance	0.128
LG	Finance	0.124

Table 11. Betweenness Centrality after the Subprime Mortgage Crisis

Item	Industry	Betweenness Centrality
SL	Transportation equipment	0.1120
Hanhwa General Insurance	Insurance	0.0919
Hyundai BNG Steel	Steel metal	0.0701
DL	Chemical	0.0695
Lotte Shopping	Distribution	0.0647

Similar to the degree centrality, the betweenness centrality of finance companies has decreased, showing that the finance companies no longer play a central role in the network. In addition, most stocks with high degree centrality also show high betweenness centrality. Finally, the centrality of the transportation and distribution industries has increased. This indicates that internal connectivity has increased within the domestic market, rather than relying on exports or imports due to foreign exchange issues from the economic crisis.

4.2.3 Community Detection. The results of community detection before and after the subprime mortgage crisis are shown in tables 12 and 13.

Table 12. Community Detection before the Subprime Mortgage Crisis

	Construction	Machinery	Plastics	Automotive	Non-Metallic minerals	Service	Textile Clothing	Transportation Equipment	Transportation Warehouse	Distribution	Food and Beverage	Medicine	Electricity and Gas	Electronics	Paper Wood	Securities	Steel Metal	Chemical
Community 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Community 2	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
Community 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Community 4	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Community 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 13. Community Detection after the Subprime Mortgage Crisis

	Construction	Machinery	Plastics	Automotive	Non-Metallic Minerals	Service	Textile Clothing	Transportation Equipment	Transportation Warehouse	Distribution	Food and Beverage	Medicine	Electricity and Gas	Electronics	Paper Wood	Securities	Steel Metal	Chemical
Community 1	0	2	0	0	0	2	0	1	0	2	0	0	0	0	0	0	0	0
Community 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Community 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Community 4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The number of communities has decreased, indicating that the industry shares a similar response to the economic 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.

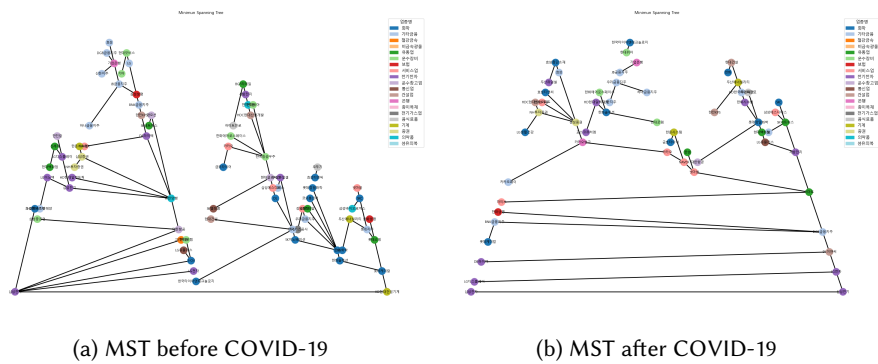


Fig. 3. Comparison of MST before and after COVID-19

Transportation and aviation industries located in the central area of the MST have moved to the peripheral. In particular, Korean Air moved from being in the center to

the leaf node. The main reason is that overseas travel has been banned and non-face-to-face business has increased after the pandemic. In addition, companies focusing on portal and Internet businesses, such as Naver, Kakao, and Netmarble, have moved to the center. This suggests that the importance of technology and non-face-to-face industries has increased after the pandemic. For similar reasons, previously only connections were made between securities firms, but after the pandemic, connections with Internet banking services were also strengthened. In particular, this can be seen in the connections between Samsung Securities, Kakao Bank, Kakao Pay, and NH Investment Securities.

4.3.2 Node Centrality. The top-5 degree centrality and the corresponding item names before and after the pandemic are shown in tables 14 and 15.

Table 14. Degree Centrality before COVID-19

Item	Industry	Degree Centrality
Samsung	Electronics	0.395
Pan Ocean	Transportation Warehousing	0.382
Korean Air	Transportation Warehousing	0.368
JB Financial Group	Finance	0.368
Samsung Life Insurance	Insurance	0.340

Table 15. Degree Centrality after COVID-19

Item	Industry	Degree Centrality
Sebang Global Battery	Electronics	0.554
Hansem	Distribution	0.554
Naver	Service	0.536
Emart	Distribution	0.536
Netmarble	Service	0.517

Overall degree centrality increased significantly after the pandemic, indicating that the industry shares a similar response to the crisis. Before the pandemic, the centrality of transportation and warehouse companies related to overseas markets such as Pan Ocean and Korean Air, was high. However, the centrality of domestic market distribution companies such as Hanssem and Emart has increased after the pandemic. In addition, the centrality of Internet companies such as Netmarble and Naver has increased.

The top-5 betweenness centrality and the corresponding item names before and after the pandemic are shown in tables 16 and 17.

Table 16. Betweenness Centrality before COVID-19

Item	Industry	Betweenness Centrality
Hanwha	Chemical	0.385
DL	Chemical	0.297
Samsung SDS	Service	0.261
Hyundai Glovis	Transportation Warehousing	0.246
Lotte Chemical	Chemical	0.229

Table 17. Betweenness Centrality after COVID-19

Item	Industry	Betweenness Centrality
Hanon Systems	Machinery	0.0792
Sebang Global Battery	Electronics	0.0720
HD	Finance	0.0630
Doosan Fuel Cell	Electronics	0.0488
Doosan Enerbility	Machinery	0.0319

Overall betweenness centrality decreased after the pandemic. As different industries adopt different business models or form new partnerships, the role of certain companies as exclusive mediators is likely to have diminished. As a result, each node has more direct connections than before, suggesting that the mediating role of specific nodes has been weakened. In particular, as digital transformation and remote work rapidly spread during the pandemic, technology companies and online service companies have

become important. As the technology-based network strengthened, the betweenness centrality of specific nodes decreased, and more nodes assumed the central role, reducing the overall betweenness centrality value.

4.3.3 Community Detection. The results of community detection before and after the pandemic are shown in tables 18 and 19.

Table 18. Community Detection before COVID-19

	Construction	Machinery	Finance	Insurance	Service	Transportation Equipment	Transportation Warehousing	Distribution	Bank	Food and Beverage	Medicine	Electricity and Gas	Electronics	Securities	Steel metal	Telecommunication	Chemical
Community 1	0	2	0	0	0	2	0	2	1	0	0	0	2	1	1	1	1
Community 2	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1
Community 3	1	1	0	0	1	1	0	2	0	0	2	0	0	1	0	0	0
Community 4	1	0	1	0	1	2	0	1	1	0	0	1	1	0	0	2	0
Community 5	1	0	0	0	2	1	2	1	0	1	0	1	0	0	0	1	1

Table 19. Community Detection after COVID-19

	Construction	Machinery	Finance	Insurance	Service	Transportation Equipment	Transportation Warehousing	Distribution	Bank	Food and Beverage	Electronics	Securities	Telecommunication	Chemical
Community 1	0	0	4	1	3	0	0	0	1	0	5	2	0	3
Community 2	0	0	0	0	0	3	0	0	0	0	2	0	0	1
Community 3	0	0	3	0	0	0	0	0	0	0	0	0	0	0
Community 4	1	1	2	0	4	0	0	3	0	0	1	0	0	4
Community 5	0	0	1	0	0	0	0	0	1	0	0	0	0	0
Community 6	2	1	1	0	0	0	1	1	0	1	2	0	1	4
Community 7	0	0	0	0	0	1	0	0	0	0	0	0	0	1

The number of communities has increased during the pandemic. It is assumed that there are two factors for this phenomenon. First, many companies altered their current business models and began new ventures, leading to the emergence of new communities. Second, as global supply chain management has changed significantly, domestic connectivity has been strengthened, which has led to new connections and cooperation across industries. This resulted in existing communities being divided or new communities being created.

4.4 Application

4.4.1 Sector Definition. We found that **degree centrality** among other methodologies has the highest explanatory power in crisis situations. Based on this, we defined new sectors by dividing companies into the 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.

- Define new sectors based on communities discovered through network analysis
- Understand sector characteristics by reflecting theoretical backgrounds and expert opinions

As a result, Figure 4 shows the newly defined sectors based on degree centrality. These sectors are categorized and named them into Hub & Spoke, Chain Link, and Fringe Player.

4.4.2 Portfolio Optimization. Portfolio optimization is a mathematical framework used to allocate assets to maximize the expected return for a given level of risk or, equivalently, minimize the risk for a given level of expected return. This is often achieved using techniques such as mean-variance optimization or risk parity methods.

종목코드	종목명	업종명	Degree Centrality	종목코드	종목명	업종명	Degree Centrality	종목코드	종목명	업종명	Degree Centrality			
18	004170	신세계	유통업	0.413793	19	004360	세방	운수창고업	0.206897	4	000640	동아쏘시오홀딩스	기타금융	0.068966
1	000210	DL	화학	0.344828	2	000270	기아	운수장비	0.172414	28	007310	오뚜기	음식료품	0.068966
6	000880	한화	화학	0.344828	25	005850	एसЭЛ	운수장비	0.172414	16	003850	보령	의약품	0.034483
7	000990	DB하이텍	전기전자	0.344828	5	000720	현대건설	건설업	0.172414	14	003490	대한항공	운수창고업	0.034483
3	000370	한화손해보험	보험	0.310345	12	002350	넥센타이어	화학	0.172414	11	001630	종근당홀딩스	의약품	0.034483
0	000070	삼양홀딩스	기타금융	0.275862	15	003530	한화투자증권	증권	0.137931	20	004490	세방전자	전기전자	0.034483
9	001430	세아서비스투자	월간금융	0.275862	13	003300	한일홀딩스	비금융광물	0.137931	24	004990	롯데자이	기타금융	0.034483
17	004000	롯데정밀화학	화학	0.241379	8	001230	동국홀딩스	월간금융	0.137931	26	005930	삼성전자	전기전자	0.034483
23	004980	삼성안회	비금융광물	0.206897	21	004540	계국한나라	종이목재	0.068966	27	006390	한일현대증권	비금융광물	0.034483
22	004800	효성	기타금융	0.206897	10	001510	SK증권	증권	0.068966	29	018880	한온시스템	기계	0.034483

(a) Hub & Spoke (b) Chain Link (c) Fringe Player

Fig. 4. Degree Centrality Sectors

In our study, 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 maintained these initially defined sectors throughout our analysis.

We aimed to plot the efficient frontier by adjusting the weights of these newly defined sectors. The steps involved were:

- (1) Plotting the efficient frontier **before and during the IMF crisis**, and
- (2) Plotting the efficient frontier **until the end of the IMF crisis**.

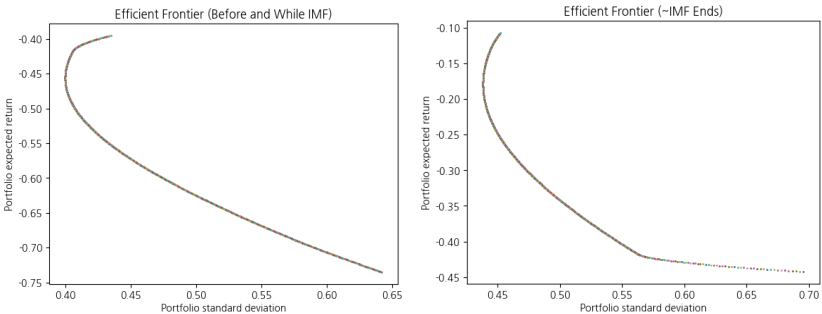


Fig. 5. Efficient Frontier Before and During IMF (Left) and Efficient Frontier Until the End of IMF (Right)

The efficient frontier graphs in 5 show the performance of the portfolios before and during the IMF crisis, and until the end of the IMF crisis. The results indicate how the sector weights were adjusted to meet the target returns during these periods.

We then 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. By achieving this, we obtain information on how to construct our portfolio to at least achieve the average return.

Table 20 summarizes the portfolio optimization results before and after the IMF crisis, showing the target returns and the corresponding portfolio weights.

Period	Target Return	Portfolio Weights
Before IMF	-0.6602	[0.73268891, 0.21628933, 0.05102176]
After IMF	-0.3950	[0.45998449, 0.46699919, 0.07301632]

Table 20. Portfolio Optimization Results

This analysis allows us to understand the impact of different sectors during a financial crisis and helps in making informed investment decisions to minimize losses. The results from our portfolio optimization indicate the adjustments needed in sector weights to meet target returns during the IMF crisis period.

5 Conclusion

This study examined the network structure and dynamic changes in major financial market sectors in Korea, before and after significant economic crises: the 1997 IMF financial crisis, the 2008 subprime mortgage crisis, and the 2020 COVID-19 pandemic. We used a graph of the stocks and methodologies like Minimum Spanning Tree (MST) analysis, centrality measures, and community detection to analyze how the stock market responded to these crises. Our findings revealed significant shifts in industry centrality and connectivity. Before the IMF crisis, securities firms held high centrality but were later replaced by raw materials and cement industries, indicating structural changes due to the crisis. Similarly, 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, as internet service companies and domestic distribution firms saw an increase in centrality.

The analysis showed that during economic crises, overall centrality measures generally increase and the number of distinct communities decreases. This suggests that the market tends to have a more unified response to external shocks. These structural changes provide valuable insights for creating investment strategies that can withstand economic disturbances. This study highlights the importance of understanding the intricate interconnections within financial markets and how they change during crises. Using advanced network analysis techniques, we can improve our ability to predict market changes and develop strategies that improve stability and performance during economic crises.

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