# 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.

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## 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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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:

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

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 $\rho_{ij}$ between stocks $i$ and $j$ is calculated as:

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

where $\mathrm{Cov}(r_i, r_j)$ is the covariance between the returns of stocks $i$ and $j$, and $\sigma_i$ and $\sigma_j$ 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:

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

*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:

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

where $d_{ij}$ is the distance and $\rho_{ij}$ 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:

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

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**:
$$C_D(v) = \frac{\deg(v)}{n-1}, \tag{6}$$
where $\deg(v)$ is the degree of node $v$, and n is the number of nodes in Graph.
- **Closeness Centrality**:
$$C_C(v) = \frac{n-1}{\sum_{t \neq v} d(v,t)}, \tag{7}$$
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**:
$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{8}$$
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 $\lambda$ is the eigenvalue.

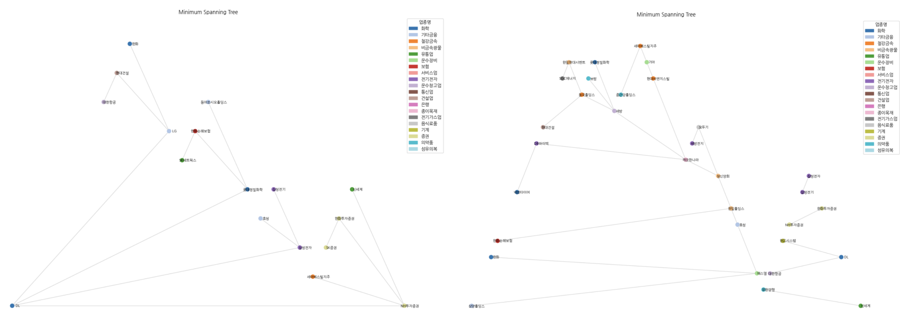
*3.2.3 Community Detection.* Community detection identifies groups of stocks that are more densely connected to each other than to the rest of the network. We used the Louvain method to maximize modularity:
$$Q = \frac{1}{2m} \sum_{i,j} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j), \tag{10}$$
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.

## 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.




(a) MST before IMF financial crisis

(b) MST after IMF financial crisis

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 |
| 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 |

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 |
|---|---|---|
| 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 |

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

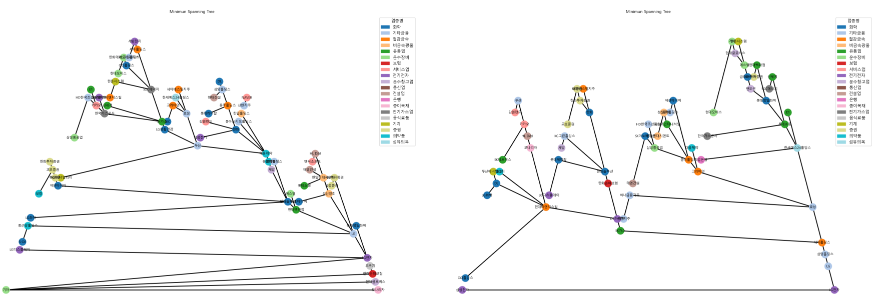
| | Construction | Machinery | Other Finance | Insurance | Non-metallic Minerals | Transportation Equipment | Transportation Warehousing | Distribution | Food | Medicine | Electricity Gas | Electronics | Paper Wood | Securities | Steel | Chemistry |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Community 1 | 0 | 0 | 0 | 0 | 0 | 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 |

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



(a) MST before Subprime Mortgage crisis (b) MST after Subprime Mortgage crisis

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 |
| Hanwha Solution | Chemical | 0.459 |
| Hyundai BNG Steel | Steel metal | 0.426 |
| Hanwha 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 |
| Hanwha 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 |
| Hanwha 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 | Finance | Insurance | Non-Metallic minerals | Service | Textile Clothing | Transportation Equipment | Transportation Warehousing | Distribution | Food and Beverage | Medicine | Electricity and Gas | Electronics | Paper Wood | Securities | Steel metal | Chemical |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Community 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 2 | 1 | 2 | 0 | 3 |
| Community 2 | 0 | 0 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Community 3 | 2 | 0 | 3 | 0 | 2 | 1 | 0 | 1 | 1 | 2 | 0 | 3 | 0 | 0 | 0 | 3 | 0 | 4 |
| Community 4 | 0 | 2 | 2 | 0 | 0 | 1 | 0 | 3 | 0 | 3 | 0 | 0 | 2 | 2 | 0 | 0 | 3 | 4 |
| Community 5 | 1 | 0 | 4 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 0 | 0 | 3 | 4 |

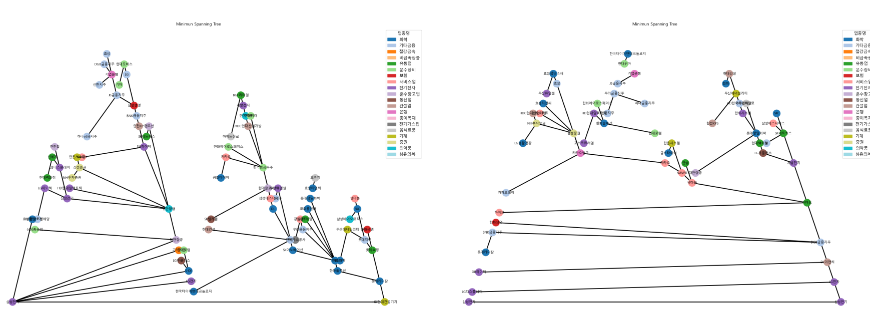
Table 13. Community Detection after the Subprime Mortgage Crisis

| | Construction | Machinery | Finance | Insurance | Non-metallic Minerals | Service | Textile Clothing | Transportation Equipment | Transportation Warehousing | Distribution | Food and Beverage | Medicine | Electricity and Gas | Electronics | Paper Wood | Securities | Steel Metal | Chemical |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Community 1 | 2 | 2 | 4 | 0 | 1 | 2 | 0 | 1 | 0 | 2 | 0 | 1 | 0 | 0 | 1 | 0 | 4 | 3 |
| Community 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Community 3 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 3 | 1 | 6 |
| Community 4 | 0 | 1 | 4 | 0 | 1 | 0 | 1 | 1 | 2 | 5 | 1 | 1 | 2 | 1 | 0 | 1 | 1 | 3 |

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.



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

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 | 5 | 2 | 0 | 2 | 0 | 2 | 1 | 0 | 0 | 0 | 2 | 1 | 1 | 1 | 3 |
| Community 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Community 3 | 1 | 1 | 4 | 0 | 3 | 1 | 3 | 2 | 0 | 0 | 2 | 0 | 6 | 1 | 0 | 0 | 3 |
| Community 4 | 1 | 0 | 3 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 9 |
| Community 5 | 1 | 0 | 0 | 0 | 2 | 3 | 2 | 1 | 0 | 1 | 1 | 0 | 1 | 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 | 1 | 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 |
|---|---|---|---|---|
| 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 |

(a) Hub & Spoke

| | 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 |

(b) Chain Link

| | 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 |

(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**.

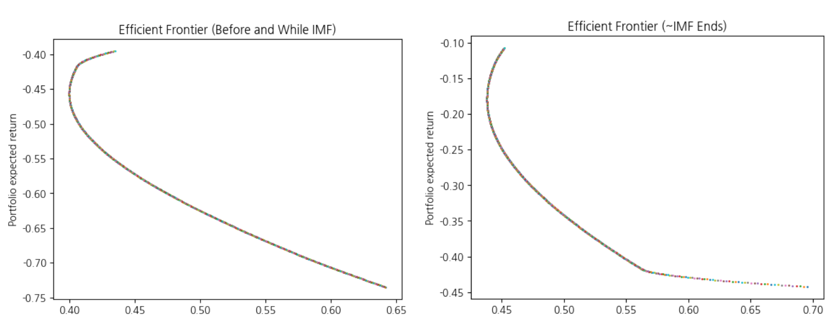



Fig. 5. Efficient Frontier Before and During IMF (Left) and Efficient Frontier Until the End of IMF (Right)

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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