# Network Analysis of the Indian Stock Market

Ishaan Watts and Lakshika Rathi and Sayam Singla

*Indian Institute of Technology, Delhi*

**We constructed a network for the Indian stock market in this study using the correlation between various stock returns. The created network was then subjected to community detection techniques. Additionally, we utilised Gephi, an open-source network research and visualisation software, to create visualisations of the return correlations between several publicly traded equities. The visualisation results provide a very straightforward approach to examine the overall correlation structure of various public equities and to identify major market segments, which could be quite valuable in real-world applications such as market monitoring. One advantage of constructing a network that characterises several stocks within a market is that some critical global features of the stock within the network, such as degree centrality, average degree, and betweenness centrality, can be extracted. Additionally, we examined the stock market's behaviour during times of crisis.**

*Keywords: Financial Network, Stock market, Network Analysis, Time Series, Centrality, Community Detection, Correlation Matrix*

## 1. INTRODUCTION

The term "network analysis" is frequently used to describe the properties or behaviours of complex networks. Recent research has examined the use of networks to model the stock market. The stock market is influenced by a multitude of factors, one of which is the correlation between corporate sectors, industries, and the economy. By portraying each stock as a node and its interactions as edges, the stock market may be shown as a network. Time series data is used to construct these edges in order to explain the link, which is somewhat counter intuitive. Following that, community detection techniques are used and various statistical measures are produced to gain an understanding of the network's real-world features. As a result of recent financial crises in global markets, the demand for understanding the complicated relationship between financial markets has increased, drawing a varied set of scholars. This endeavour will enable us to visualise and comprehend these intricate connections. Additionally, we will examine the stock market's behaviour during times of crisis in this study. In practise, a well-developed model of crisis spreading behaviour could be extremely beneficial for forecasting market crises and mitigating investment risk.

## 2. LITERATURE SURVEY

There have been numerous techniques to analyze stock markets depending on the correlation between economy, industries and business sectors. Bonanno et al (1) looks at the co-movements of a group of capitalised equities over daily and intra-day time horizons using high-frequency data from the US equity markets. They begin by defining a distance matrix based on the correlation coefficient, which is defined as the difference in logarithms of stock prices over time. The MST connecting n stocks is then calculated using this matrix. The extent and type of correlations are dependent on the time horizon used to compute them, according to an analysis of the hierarchical structure in a set of stocks.

Dimitros et al (6) looked at the Greek stock market for two years, one prior to the economic crisis and the other during the crisis. He began by creating cross-correlation tables for a large number of stocks, which he subsequently filtered by increasing the threshold amount. To build a network, each table is used as adjacency metrics. About 70 distinct networks were investigated, as well as their impact on various threshold values. Using social network analysis methodologies, he employed different centrality metrics for varying degrees of stock correlation. Similar work is done in Sun et al (7)

George et al. (8) explored the most prominent sectors and stocks in the US market in this book, as well as the statistical aspects of the stock market. They built the US stock market network by collecting its patterns across a year in 2016, using various correlation coefficient thresholds for correlation larger than 0.7. They discovered that equities with a greater number of dependencies do not have as many dependencies as those with fewer dependencies. The Lobby Index was used to find key players who have connections to other players.

Kazemilari et al (5) used the RV correlation coefficient to define the complex network among the stocks in the form of vector correlation matrix, the concept of vector correlation was used to measure the similarity among multivariate time series in the stock market, namely opening, highest, lowest, and closing (OHLC) prices information. They used the network to examine the network in terms of topological structure of the stocks of all Minimum Spanning Trees (MSTs) based on weekly and intra-weekly price data for a period of seven years, utilising 30 Dow-jones stocks. In this method, they comprehend the similarity between stocks and topological aspects of the stock by treating it as a multi-dimensional entity. *RV coefficient. This measure generalizes the similarity among stocks represented by their closing prices only.

Namaki et al. (3) used biggest eigenvector of the correlation matrix to specify the market mode using Random Matrix Theory (RMT). A concept for removing common characteristics across all equities and then constructing a stock correlation network using the Tehran Stock Exchange (TSE). When applied to the Dow Jones Industrial Average, they clean the correlation matrix by removing the market mode from the data, which has a significant impact on the correlation coefficient distribution (DJIA). They illustrate that in certain intervals, the network follows a power-law model, as well as the behaviour of clustering coefficients and component numbers for certain thresholds.

Tse et al. (2) uses complex networks to study the closing prices of all US stocks across two time periods (2005-2009), with the nodes being the stocks and the edges being the cross correlations of variation in stock prices, price returns, and trading volumes. Its goal is to build networks that connect stock values with comparable variation patterns over a specific time period. The entire network that is produced retains all internal structure information, demonstrating the interconnectedness of stock prices. Their main finding is that a small number of stocks have a lot of effect over the bulk of equities, and the financial sector stocks have a lot of influence on the market.

Thitaweera et al. (9) used daily closing prices from the Thailand Stock Exchange (SET) from June 2018 to July 2020 in this study. The correlation coefficient is a linear measure of a relationship. As a result, they employ the DTW algorithm, a voice recognition tool, to evaluate similarity in a nonlinear way that can be measured when time series differ in length. They used a time series decomposition technique to deconstruct and remove irregular components from time series data, then used a dynamic time warping technique to unravel the correlation between each of the time series of different stocks. Then they used the DTW results to build a network of SET's top hundred stocks, interpreting the centrality values to show important and influential stocks as well as the stock community, using graph network analysis. By eliminating edges from the network, they used the Girvan-Newman algorithm to detect communities. *DTW is used for measuring similarity and finding an optimal alignment between two given time-dependencies.

Master's thesis by Peng (10) combines stock graphs with a neural network model to try to capture the effect of internal relations and the influence of other stocks on any individual stock. They use the Graph Convolutional Network (GCN) to develop a combination model to cope with multiple graph features because graphs produced by different methods include diverse information. The study creates sector graphs, which are used to aggregate stocks in the same sector, correlation graphs based on stock closing prices, and DTW graphs based on price sequence similarity between two stocks. The study is focused on comparing the current methodologies they define, mostly centred around the GCN, to try to predict the stock's closing price movement for the next day. They also use a transformer-based model to figure out how stocks are related. The study suggests that stock graphs can effectively boost prediction accuracy and that graphs based on correlation coefficients are superior to other graph kinds. Building an optimum stock graph network for the GCN and expanding the stock features can be added to the effort.

## 3. PROBLEM STATEMENT

Based on the background information and literature review, the problem to be investigated in this work is defined as follows:

**Network Visualization:** The datasets we are using do not include stock graphs, so we use the accessible information to construct the graphs utilizing techniques discussed in the literature review.

**Community Detection:** Following the construction of a stock graph, we investigate how different groups play distinct roles in the stock market. How powerful a stock is and how it affects the value of other stocks and communities. For each node, we compute multiple centrality measures. This network would be used for portfolio diversification and portfolio management.

**Crisis Analysis:** Using a smaller dataset, we also look at the stock market's behaviour before and during the COVID-19 pandemic. This enables us to visualise and examine the spread of market crisis behaviour.

## 4. DATA PREPARATION

For this study, we gathered two datasets. The NIFTY200 dataset is being used to analyse stock correlation, while the NIFTY top 30 dataset would be used to investigate the influence of Covid-19 on stock correlation. Both of these datasets contain stocks from several industries, as stated below, and were compiled using index constituents as of February 4, 2022. The website records five days of price per week because the stock market is closed on weekends. The daily open, high, low, close price, trading volume and market sector are all historical characteristics for each company. The open price is determined by the time of day when the markets open. The high price refers to the stock's highest price on that day, while the low price refers to the lowest price on that day. The close price is the stock's price on the day the market closes. The total number of securities or contracts exchanged on a given day is referred to as the trading volume.

### 4.1. NIFTY200 dataset

This dataset was collected from National Stock Exchange (NSE), India website. The NIFTY 200 Index is designed to reflect the behaviour and performance of large and mid market capitalization companies. All firms in the NIFTY 100 and NIFTY Full Midcap 100 indexes are included in the NIFTY 200. Information for each stock was collected from 1st Feb 2021 until 31st Jan 2022. We have grouped sectors with less than 2% contribution as Others and will be subsequently removed from the dataset. Thus, we have chosen 11 sectors for the purpose of our study. The sector-wise stats are as follows:

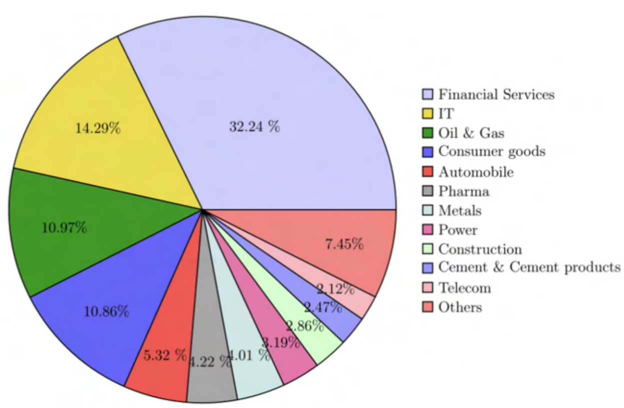



Figure 1: Sector-wise distribution of NIFTY200 Dataset

| Company's name | Weight (%) |
|---|---|
| Reliance Industries Ltd. | 8.06 |
| HDFC Bank Ltd. | 6.37 |
| Infosys Ltd. | 6.30 |
| ICICI Bank Ltd. | 5.36 |
| Housing Development Finance Corporation | 4.46 |

**Table 1.** Top Constituents by Weightage for the NIFTY 200 Dataset

### 4.2. NIFTY Top 30 dataset

This dataset was collected from Yahoo Finance website. It comprises the top 30 performing NIFTY50 firms as of February 4, 2022, according to Yahoo Finance. Information for each stock was collected over a period of 4 years from 31st Jan 2018 until 28th Jan 2022. The data will be divided into 2 timelines i.e., Pre-COVID (Jan 2018 - Jan 2020) and during COVID (Jan 2020 - Jan 2022). The sector-wise stats are as follows:

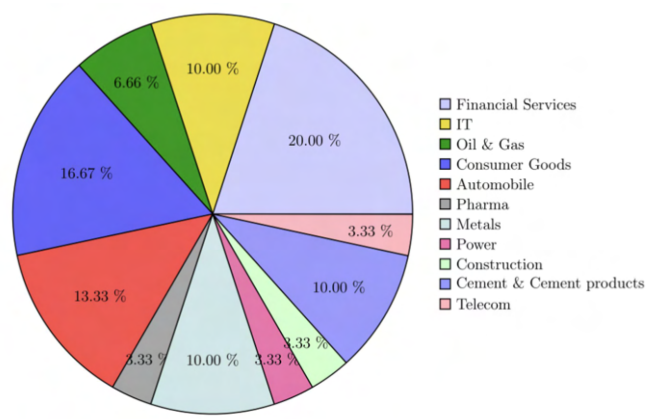



Figure 2: Sector-wise distribution of NIFTY30 Dataset

## 5. METHODOLOGY

### 5.1. Defining Nodes and Edges

The nodes represent stock firms, and the edges between them are constructed using cross-correlations of stock price changes.

### 5.2. Detrending data and computing log returns

Among the strategies discussed in literature, we chose **Time-lag correlations of price movements** (14) over a specified time period. Stock prices are highly moving time series data with intrinsic trends.

A time series of prices can be defined as $[P_0, P_1, P_2, ...., P_N]$ which can in turn be written as

$[P_0, P_0+C_1, P_0+C_1+C_2, ...., P_0+C_1+...+C_N]$ where $C_t = P_t - P_{t-1}$. As we can see, the early returns in the correlation of prices are given a greater weight than they should, which might result in analysis errors. Thus, we compute correlations using returns defined as the difference between daily values. To further simplify, we use log returns, which are additive in nature.

Assume $P_i(t)$ is the closing price of a stock i on day t. The function of the log return price is defined as:

$$R_i(t) = \log \frac{P_i(t)}{P_i(t-1)}$$

Plotting the log return price as a function of time for all the companies, we deduce some interesting results:

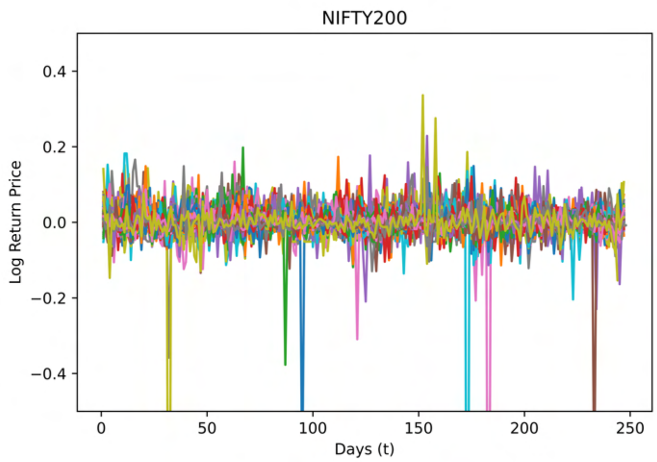



Figure 3: NIFTY200 : Log Return Price v/s Days

The sudden peaks in the plot for NIFTY200 companies denotes that a stock split has happened in that equity. A stock split is a business move taken by firms to increase the number of outstanding shares while decreasing the value of individual shares. In other words, if the value of a company's stock increases, investors benefit from higher returns. This has been also verified by the equity data. For example:

- The company AARTIIND had a closing price of Rs. 1778.62.10 per stock on 21st June 2021 while a closing price of Rs. 885.5 per stock on 22nd June 2021.
- IRCTC splits it's stock 5 times, on 28th Oct 2021 IRCTC had closing prices of Rs. 4130 per stock to Rs. 913.5 per stock on 29th Oct 2021.
- Similarly, for DIXON stock split of 5 times took place on 19th March 2021 from previous closing price of Rs. 20,074.95 to Rs. 4240.30 per stock.

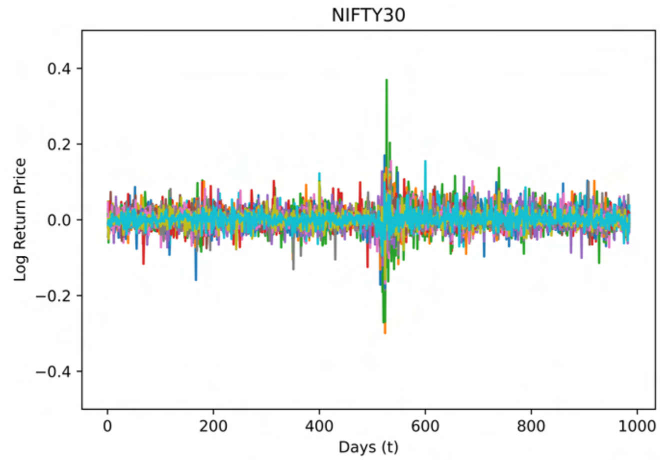



Figure 4: NIFTY30 : Log Return Price v/s Days

In the plot for the 4 year dataset, we observe a large deviation in the middle which was the period during the onset of Covid-19 and the subsequent lockdown. This deviation, which is smaller than stock split, helps us to visualise the sudden impact Covid had on the whole stock market.

### 5.3. Computing Correlation Matrix

The Pearson correlation coefficient (12) was then calculated between the defined log returns. The data is partitioned into windows of width (T) in order to reveal the networks' dynamic features. From a market standpoint, T = 62 days corresponds to these companies' quarterly reporting period, and hence we felt it was an appropriate pick.

Let $x_i$(t) and $x_j$(t) be the return price of stock i and stock j respectively on day t, where $1 \leq t \leq T$ and T is the number of days we used for evaluation (i.e the size of the sequence). The method is comparing two time series without any relative time shift. The correlation $c_{ij}$ between sequence $x_i$ and $x_j$ is defined as:

$$c_{ij} = \frac{\sum_t (x_i(t)-\bar{x_i})(x_j(t)-\bar{x_j})}{\sqrt{\sum_t (x_i(t)-\bar{x_i})^2 \sum_t (x_j(t)-\bar{x_j})^2}}$$

Where $\bar{x_i}$ and $\bar{x_j}$ are the means of the return price sequence $x_i$ and $x_j$ respectively, over the period t = 0 to t = T.

### 5.4. Winner Takes All Method

The Winner Take All method (2)(17) revolves around building a network from the correlation matrix if the value of the correlation coefficient is greater than a certain defined threshold. The threshold is set to a positive fractional number of $\rho < 1$. If $c_{ij} > \rho$, the stocks i and j are related with a value higher than or equal to our defined limit.

Given that one of the study's primary aims is to determine if stocks behave in groups, we sought to establish a threshold that maximised modularity. As a second step, we constructed the network using several thresholds ranging from 0.40 to 0.90 for the discovered windows and chose the value of the threshold that maximised modularity. The optimal modularity was discovered at a threshold of approximately 0.65. Certain windows had a threshold for optimal modularity greater than 0.65; nevertheless, the number of edges was extremely low at that threshold. As a result, in these instances, we manually determined the threshold and constructed the network.

We treated both positive and negative correlations the same and looked at the absolute value. Here we have modified this method by using weighted edges (not binary) for edges whose absolute value is greater than threshold to show the strength of the stock connections through edge width while visualising using the Gephi software.

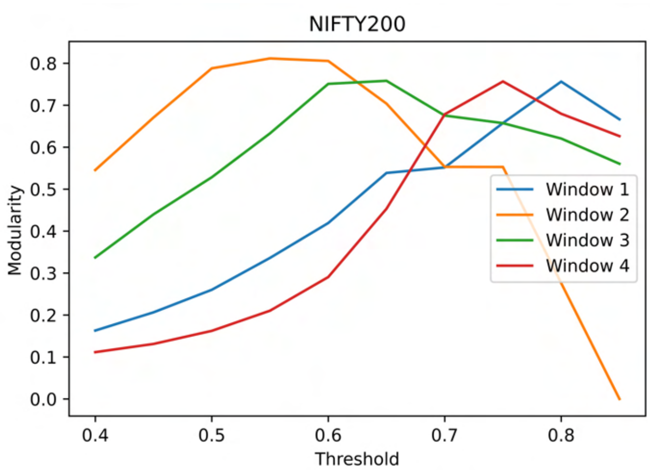



Figure 5: Modularity v/s Threshold

The Diameter and Avg Shortest Path Length for this method are calculated to be undefined since all nodes are not connected.

| Window | No. of nodes | No. of edges | Avg Clustering | Slope |
|---|---|---|---|---|
| 1 | 199.0 | 252.0 | 0.230 | -1.083 |
| 2 | 199.0 | 180.0 | 0.206 | -1.289 |
| 3 | 199.0 | 225.0 | 0.215 | -1.227 |
| 4 | 199.0 | 158.0 | 0.189 | -1.234 |

**Table 2.** Network Properties for each Window in Winner Takes All method

### 5.5. Minimum Spanning Tree Method

The Minimum Spanning Tree method (13) used the distance matrix calculated as -

$$d_{ij} = \sqrt{2(1 - c_{ij})} \tag{1}$$

where $c_{ij}$ is the correlation coefficient and $d_{ij}$ is the edge distance between stocks i and j. The distance matrix D is then used to determine the MST connecting the n stocks.

| Window | No. of nodes | No. of edges | Avg Shortest Path Length | Diameter | Slope |
|---|---|---|---|---|---|
| 1 | 199.000 | 198.000 | 8.906 | 22.000 | -2.150 |
| 2 | 199.000 | 198.000 | 11.659 | 34.000 | -1.900 |
| 3 | 199.000 | 198.000 | 11.831 | 31.000 | -2.355 |
| 4 | 199.000 | 198.000 | 8.764 | 19.000 | -1.980 |

**Table 3.** Network Properties for each Window in MST method

The MST is the shortest spanning tree, which is a theoretical notion in graph theory. A spanning tree is a graph that connects all of the n nodes with n–1 links and has no loops. Distance $d_{ij}$ decreases with increasing $c_{ij}$. As a result, the MST chooses the n-1 strongest (i.e. shortest) linkages that span all nodes.

### 5.6. Cumulative return of a stock

A cumulative return on an investment is the aggregate amount that the investment has gained or lost over time, independent of the amount of time involved (7). We have calculated this metric taking the relative difference of average adjusted closing price of each year instead of a particular day of that year $P_{avg}$ (year) and the price on first day of analysis $P_0$. The cumulative return is expressed as a percentage, and it is represented as:

$$CP(year) = \frac{P_{avg}(year) - P_0}{P_0} * 100 \tag{2}$$

## 6. RESULTS AND DISCUSSION

### 6.1. Average Degree of the network

We looked at the average degree varying over time for four quarters in the case of NIFTY200. We can see that the networks from the Winner Takes All technique fluctuates, demonstrating the stock market's dynamic nature. The Average degree is constant for networks based on the MST approach, which is one of the biggest shortcomings of the MST method, as major market changes are not properly represented in the network.

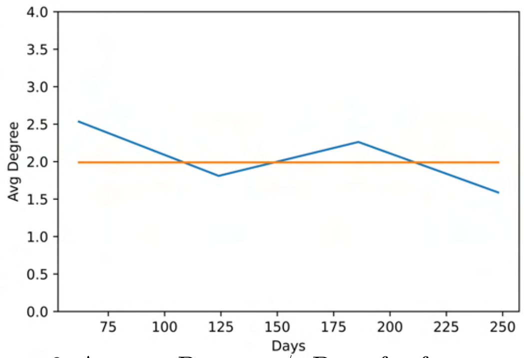



Figure 6: Average Degree v/s Days for four quarters

## 6.2. Degree distribution and Scale Free Properties

We plotted the degree distribution for NIFTY200 on a histogram as well as on a log scale complemented with a regression fitted line whose slope gives the power law exponent. The plots show that network shows scale free properties in most of the windows. The scale free nature is more evident in the Networks generated based on the Minimum Spanning Tree Method where the power law exponent is between 2 and 3.

- **Winner Take All Method**

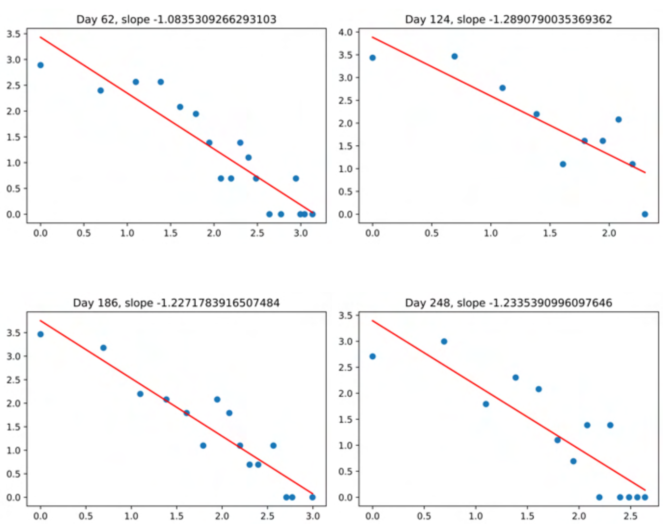
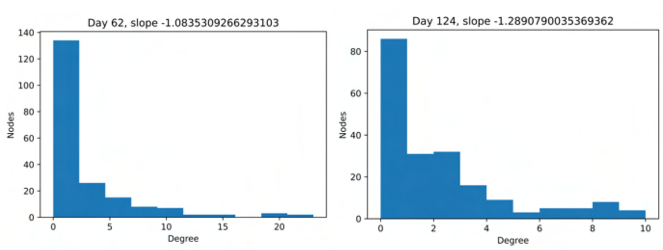



Figure 7: Degree Distribution : Log Curves



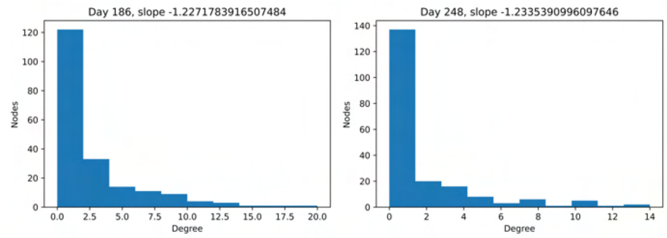




Figure 8: Degree Distribution : Histograms

- **Minimum Spanning Tree Method**

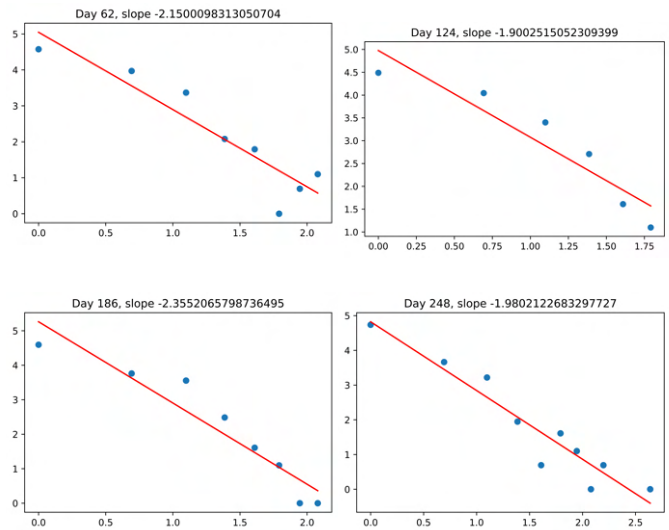



Figure 9: Degree Distribution : Log Curves

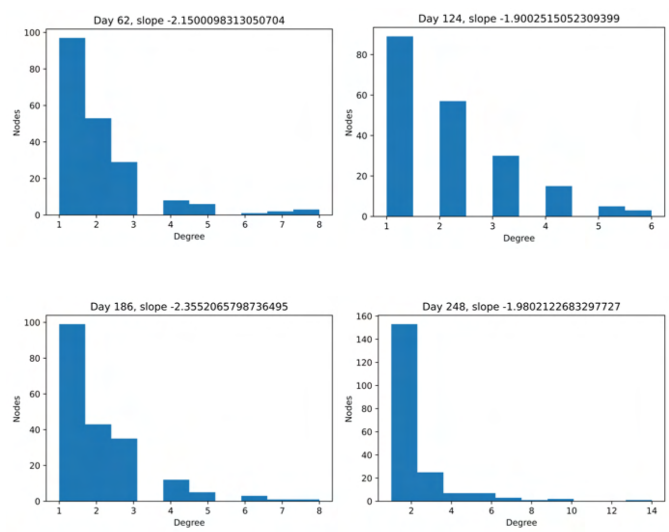



Figure 10: Degree Distribution : Histograms

### 6.3. High Degree Stock in the network

We examined the NIFTY200 network's high degree stocks at various points in time to identify important stocks with a lot of influence or that serve as a solid indicator of how the stock market is performing as a whole. Financial sector stocks have the highest degree in a number of windows, as illustrated in Appendix.

We plotted the count of high-degree stocks in the windows, and it's evident that finance stocks are at the heart of the market network. Because finance stocks are intrinsically dependent on what happens in other sectors, we can anticipate them to be the market's most significant equities.

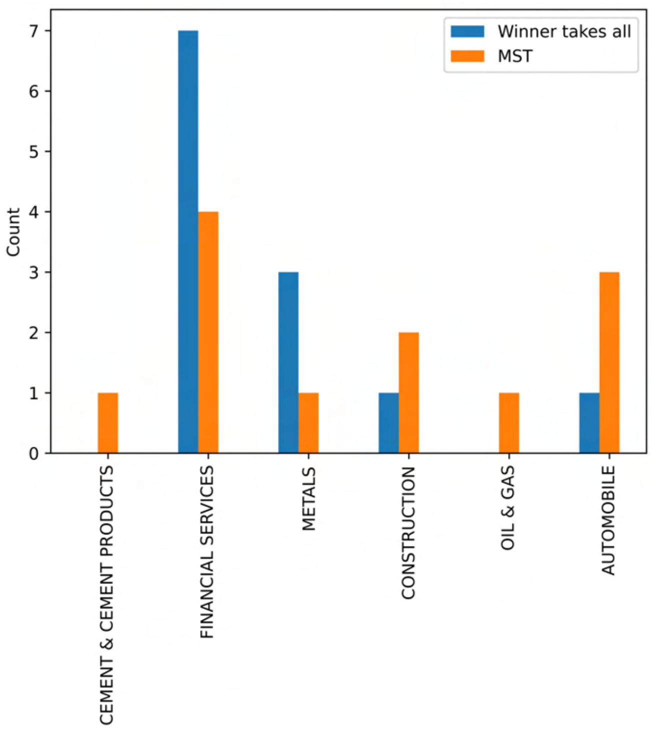



Figure 11: Bar plot for High Degree Stocks in Winner Takes All and MST

### 6.4. Stocks With High Betweenness Centrality

We looked at companies in NIFTY200 with high Betweenness Centrality in the network at different windows to identify important stocks that, due to their network position, will be good indicators of stock price volatility. As can be seen, financial equities continue to outperform in most periods.

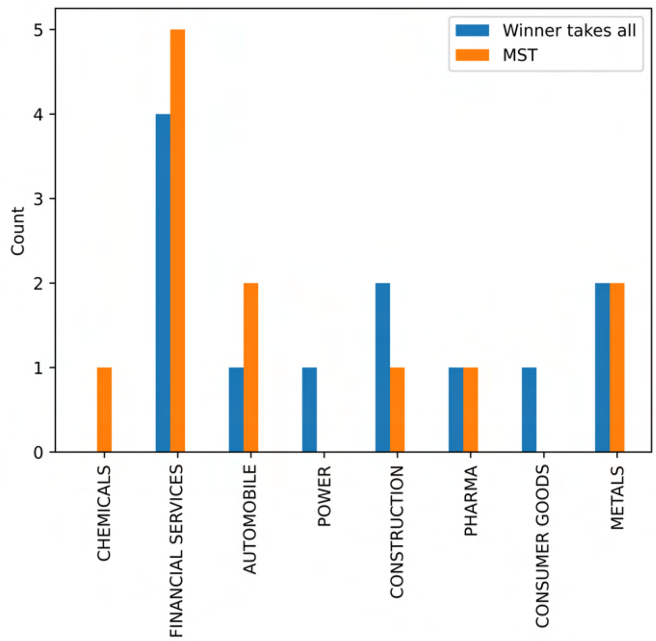



Figure 12: Bar plot for High Betweenness Centrality Stocks in Winner Takes All and MST

### 6.5. Communities Detected

We looked at the number of communities discovered throughout time in NIFTY200. The fluctuation in the number of communities reflects the market's dynamic nature. We used Louvain algorithm which checks modularity score in order to identify the relevant communities.

| Window | Winner Takes All Communities | MST Communities |
|---|---|---|
| 1 | 118 | 15 |
| 2 | 105 | 16 |
| 3 | 110 | 14 |
| 4 | 131 | 15 |

**Table 4.** Communities detected in Winner Takes All and MST in each window

We can observe a large number of communities in the Winner Takes All method due to the many singleton nodes present in the graph, whereas MST gives a better representation of the change in communities. We visualised these communities through Gephi Software as shown in the Appendix.

### 6.6. Crisis Analysis

We constructed a dynamic network (Figure A1) to illustrate the spread of bearish stock performance across the market during the Covid crisis. The price return from January 2018 to January 2022 was utilised to create the network and colour each stock node. Stocks with a cumulative return greater than 0% are coloured green, those with a cumulative return less than 0% are coloured light blue, and those with a cumulative return less than -20% are coloured red. We can observe how the negative return began in 2019 and persisted through 2020, before reversing course in 2021 as normalcy was restored.

GRASIM began to exhibit bearish behaviour in 2018 with a share price of around Rs. 1160 per share, eventually falling to as low as Rs 460 per share. By the end of 2020, it had recovered with a stock price of Rs. 900 and bullish behaviour, eventually increasing to Rs. 1660 per share with high market returns. Our visualisations reflected this behaviour as well.

We have further calculated an average bias score for each stock during Covid from 2018-2022, -1 for red, 0 for white and 1 for green nodes. Next we averaged the scores to calculate for each industry.

| | Industry | Score |
|---|---|---|
| 0 | AUTOMOBILE | -0.75 |
| 1 | CEMENT & CEMENT PRODUCTS | 1.0 |
| 2 | CONSTRUCTION | 0.0 |
| 3 | CONSUMER GOODS | 3.0 |
| 4 | FINANCIAL SERVICES | 3.0 |
| 5 | IT | 3.67 |
| 6 | METALS | -1.33 |
| 7 | OIL & GAS | 0.5 |
| 8 | PHARMA | 2.0 |
| 9 | POWER | 0.0 |
| 10 | TELECOM | 2.0 |

Figure 13: Score for each sector during Covid

From the results we can see that the Consumer Goods, Financial Services and IT sectors were least affected. Metals and Automobile sectors suffered a dip. This was also verified by real world data.

## 7. CONCLUSION

In this study, we have extensively analysed the NIFTY200 dataset and tried to decode the nature of the Indian Stock Market. We have also looked at the behavior of stock market during crisis in the NIFTY30 dataset.

- Using the time series data we discovered several interesting features of both the datasets. We visualised stock splits and examined the influence of Covid on the stock market.
- Following that, we constructed the networks using the Winner Takes All and Minimum Spanning Tree approaches and comprehensively compared them. We divided the timeline into four windows to demonstrate the stock network's dynamic character.
- We observed that the networks created by both the methods indeed exhibited the scale-free property with the MST method giving a better evidence. The average clustering coefficient calculated for Winner Takes All method and the small world property depicted by average shortest path length for MST method also agree with the real world graphs.
- By observing the degree of the nodes in the networks, we found that the Financial sector stocks have a major game-play in the stock market. We identified the main stocks to predict the movement of prices in the network using the betweenness centrality as a measure and yet again the Financial sector acted as a major pathway.
- We identified communities in networks using the Louvain technique for community detection, which is based on the modularity score. To visualise the discovered communities, we showed the stock networks for both approaches in appendix.
- From the Winner Takes All network as shown in Figure A1, we observe that few sectors like IT (pale green) and Metals (dark blue) have a dense cluster within their own sector.
- Finally we visualised the results of the stock market during crisis using the NIFTY30 dataset.

By studying the evolution of these communities over time, we can conclude that some sectors essentially trade together as a group while others don't.

## REFERENCES

Giovanni Bonanno, High-frequency Cross-correlation in a Set of Stocks, 2000

Chi K. Tse, Jing Liu, A network perspective of the stock market, 2010

A. Namaki, A.H. Shirazi, Network analysis of a financial market based on genuine correlation and threshold method, 2011

D. Ashok Kumar, S. Murugan, Performance Analysis of Indian Stock Market Index using Neural Network Time Series Model, 2013

Kazemilari, Mansooreh, Correlation network analysis for multi-dimensional data in stocks market, 2015

Kydros Dimitrios, Oumbailis Vasileios, A Network Analysis of the Greek Stock Market, 2015

Wenyue Sun, Chuan Tian, Guang Yang, Network Analysis of the Stock Market

Susan George, Manoj Changat, Network approach for stock market data mining and portfolio analysis, 2017

Nuttapol Thitaweera, Sukree Sinthupinyo, Correlation Network Analysis in the Stock Exchange of Thailand (SET), 2021

Shuyi Peng, Stock Forecasting using Neural Network with Graphs, 2021

Karthick Venkatesan, Network Analysis of Financial Markets, 2017

Vladimir Boginski, Sergiy Butenko, Panos Pardalos Statistical analysis of financial networks, 2005

G. Bonanno, G. Caldarelli, F. Lillo, S. Miccich‘e, N. Vandewalle and R. N. Mantegna Networks of equities in financial markets, 2004

Boris Podobnik, Duan Wang, Davor Horvatic, Ivo Grosse, Halle-Wittenberg Time-lag cross-correlations in collective phenomena, 2010

Hierarchical Structure in Financial Markets, 1998

K. V. Mardia, J. T. Kent, and J. M. Bibby Multivariate Analysis, 1979

R. N. Mantegna and H. E. Stanley An Introduction to Econophysics: Correlations and Complexity in Finance, 2000

# APPENDIX

## A.1. HIGH DEGREE STOCKS

| Window | Symbol | Company Name | Degree | Industry |
|---|---|---|---|---|
| 1 | CANBK | Canara Bank | 23.0 | Financial Services |
| 1 | RBLBANK | RBL Bank Ltd. | 21.0 | Financial Services |
| 1 | FEDERALBNK | Federal Bank Ltd. | 20.0 | Financial Services |
| 2 | RBLBANK | RBL Bank Ltd. | 10.0 | Financial Services |
| 2 | BANKBARODA | Bank of Baroda | 9.0 | Financial Services |
| 2 | CANBK | Canara Bank | 9.0 | Financial Services |
| 3 | NMDC | NMDC Ltd. | 20.0 | Metals |
| 3 | SAIL | Steel Authority of India Ltd. | 16.0 | Metals |
| 3 | TATASTEEL | Tata Steel Ltd. | 15.0 | Metals |
| 4 | DLF | DLF Ltd. | 14.0 | Construction |
| 4 | TATAMOTORS | Tata Motors Ltd. | 13.0 | Automobile |
| 4 | CANBK | Canara Bank | 12.0 | Financial Services |

**Table A1.** Winner Takes All method

| Window | Symbol | Company Name | Degree | Industry |
|---|---|---|---|---|
| 1 | TATAMOTORS | Tata Motors Ltd. | 8.0 | Automobile |
| 1 | CANBK | Canara Bank | 8.0 | Financial Services |
| 1 | DLF | DLF Ltd. | 8.0 | Construction |
| 2 | IOC | Indian Oil Corporation Ltd. | 6.0 | Oil & Gas |
| 2 | L&TFH | L&T Finance Holdings Ltd. | 6.0 | Financial Services |
| 2 | BANKBARODA | Bank of Baroda | 6.0 | Financial Services |
| 3 | BANKBARODA | Bank of Baroda | 8.0 | Financial Services |
| 3 | NMDC | NMDC Ltd. | 7.0 | Metals |
| 3 | APOLLOTYRE | Apollo Tyres Ltd. | 6.0 | Automobile |
| 4 | TATAMOTORS | Tata Motors Ltd. | 14.0 | Automobile |
| 4 | AMBUJACEM | Ambuja Cements Ltd. | 9.0 | Cement & Cement Products |
| 4 | DLF | DLF Ltd. | 9.0 | Construction |

**Table A2.** MST method

### A.2. HIGH BETWEENNESS CENTRALITY STOCKS

| Window | Symbol | Company Name | Betweenness Centrality | Industry |
|---|---|---|---|---|
| 1 | TATAPOWER | Tata Power Co. Ltd. | 0.036 | Power |
| 1 | CANBK | Canara Bank | 0.019 | Financial Services |
| 1 | DLF | DLF Ltd. | 0.019 | Construction |
| 2 | CADILAHC | Cadila Healthcare Ltd. | 0.092 | Pharma |
| 2 | BANKBARODA | Bank of Baroda | 0.070 | Financial Services |
| 2 | NMDC | NMDC Ltd. | 0.044 | Metals |
| 3 | NMDC | NMDC Ltd. | 0.041 | Metals |
| 3 | BANKBARODA | Bank of Baroda | 0.016 | Financial Services |
| 3 | PNB | Punjab National Bank | 0.013 | Financial Services |
| 4 | DLF | DLF Ltd. | 0.046 | Construction |
| 4 | TATAMOTORS | Tata Motors Ltd. | 0.029 | Automobile |
| 4 | UBL | United Breweries Ltd. | 0.023 | Consumer Goods |

**Table A1.** Winner Takes All method

| Window | Symbol | Company Name | Betweenness Centrality | Industry |
|---|---|---|---|---|
| 1 | TATAMOTORS | Tata Motors Ltd. | 0.5887 | Automobile |
| 1 | LICHSGFIN | LIC Housing Finance Ltd. | 0.5764 | Financial Services |
| 1 | L&TFH | L&T Finance Holdings Ltd. | 0.5638 | Financial Services |
| 2 | CADILAHC | Cadila Healthcare Ltd. | 0.7043 | Pharma |
| 2 | BANKBARODA | Bank of Baroda | 0.5597 | Financial Services |
| 2 | CANBK | Canara Bank | 0.4718 | Financial Services |
| 3 | NMDC | NMDC Ltd. | 0.6759 | Metals |
| 3 | BANKBARODA | Bank of Baroda | 0.5497 | Financial Services |
| 3 | JSWSTEEL | JSW Steel Ltd. | 0.5024 | Metals |
| 4 | DLF | DLF Ltd. | 0.6661 | Construction |
| 4 | TATAMOTORS | Tata Motors Ltd. | 0.6506 | Automobile |
| 4 | TATACHEM | Tata Chemicals Ltd. | 0.4650 | Chemiclas |

**Table A2.** MST method

### A.3. NIFTY200 : NETWORK GRAPHS

Network Graphs using the Winner Takes All and Minimum Spanning Tree methods are shown in this section-

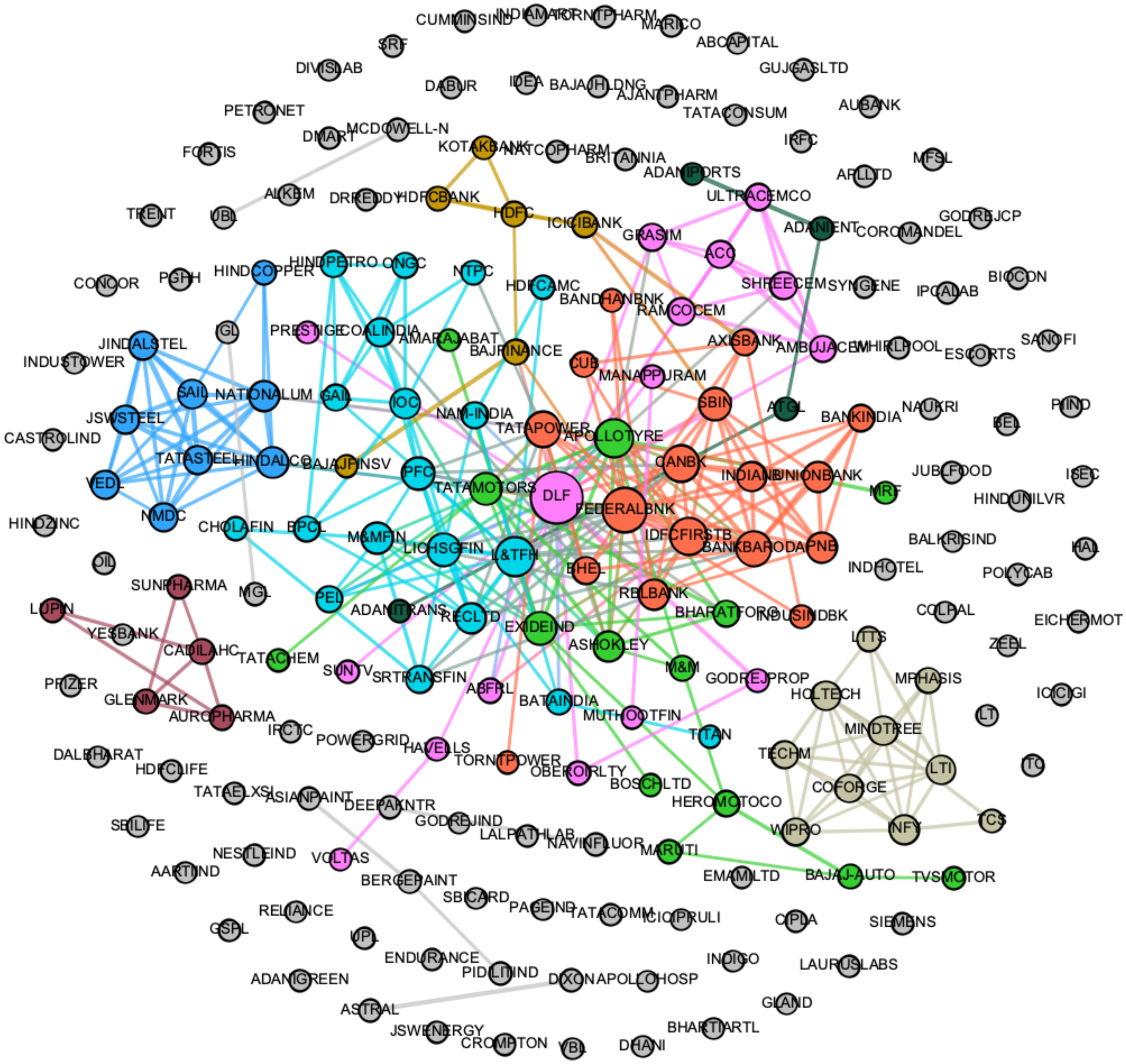



Figure A1: Stock Network of NIFTY200 from Jan 2021 to Jan 2022 : Winner Takes All Method

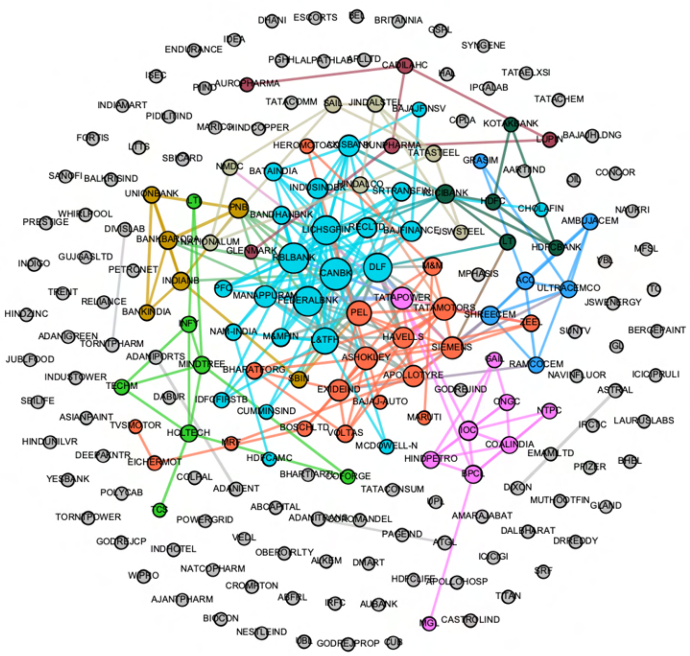


Figure A2: Window 1

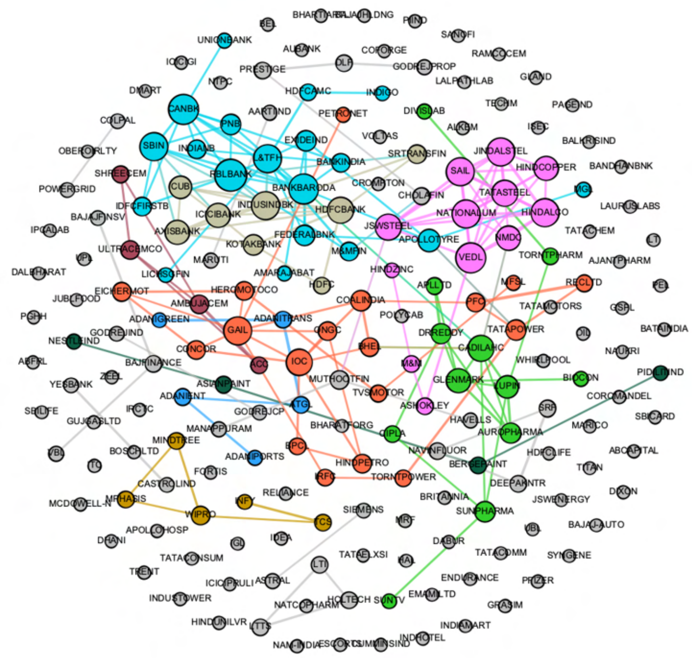


Figure A3: Window 2

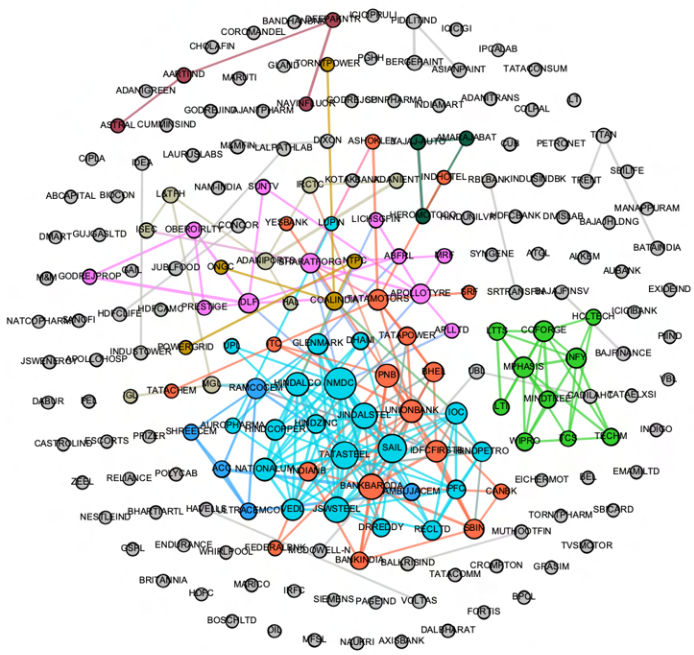


Figure A4: Window 3

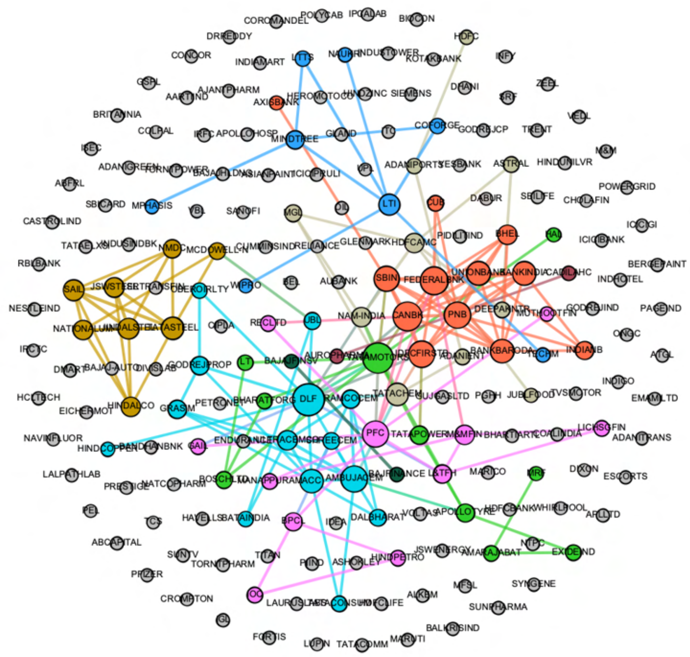


Figure A5: Window 4

**NIFTY200 Dataset : Window size = 62 days : Winner Takes All Method**

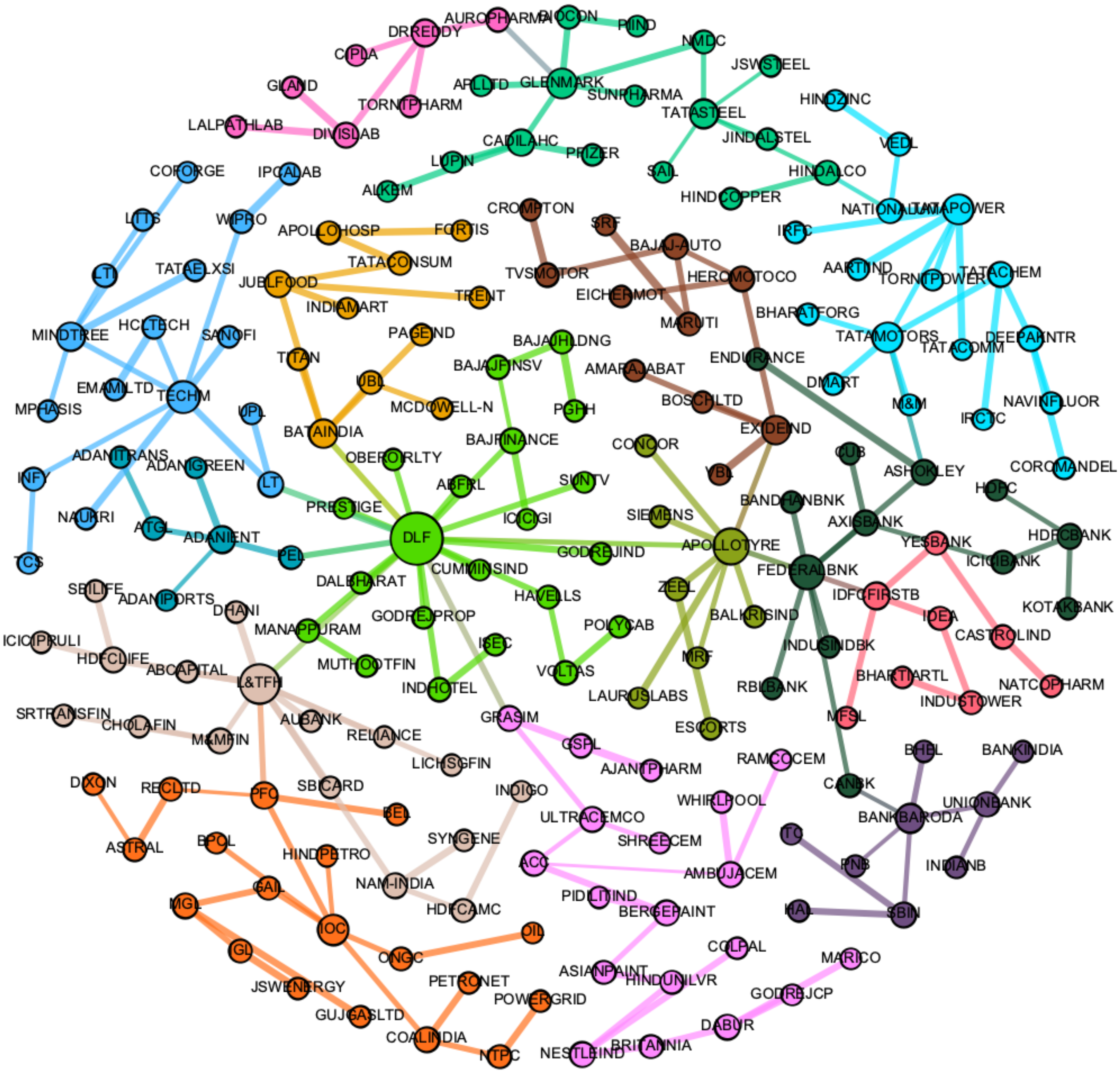



Figure A6: Stock Network of NIFTY200 from Jan 2021 to Jan 2022 : MST Method

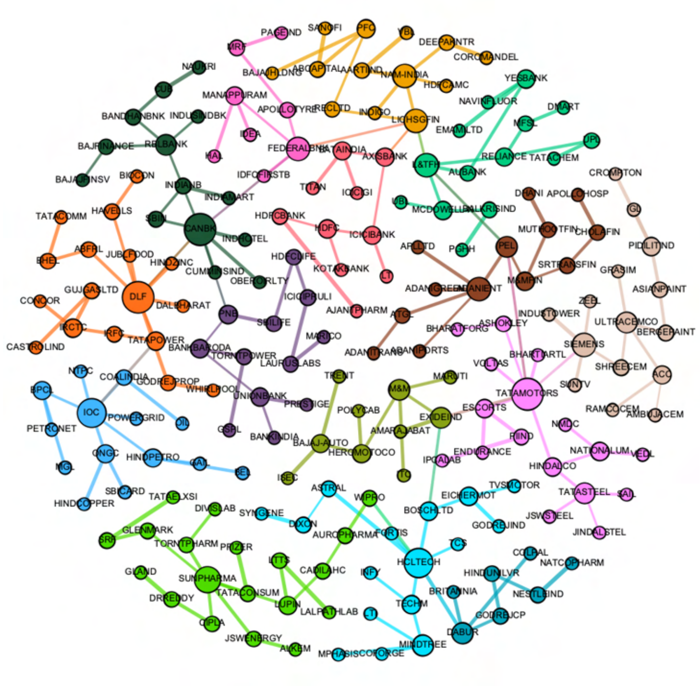


Figure A7: Window 1

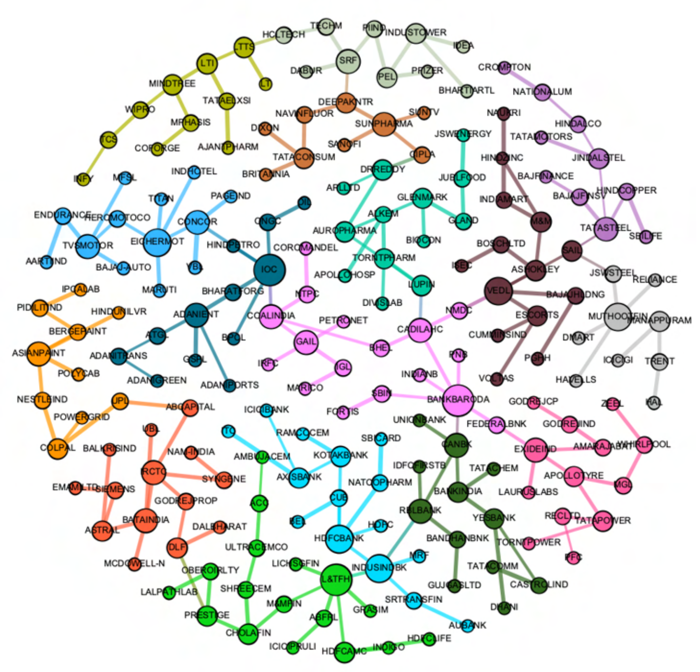


Figure A8: Window 2

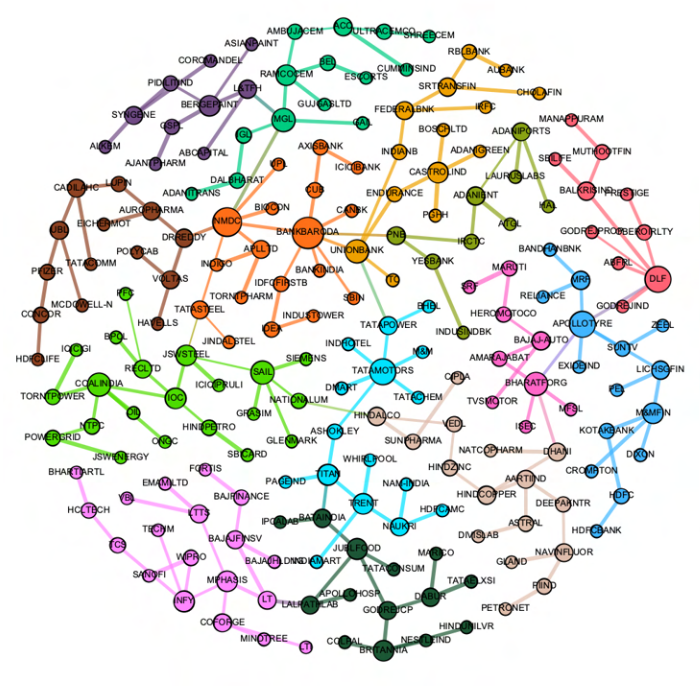


Figure A9: Window 3

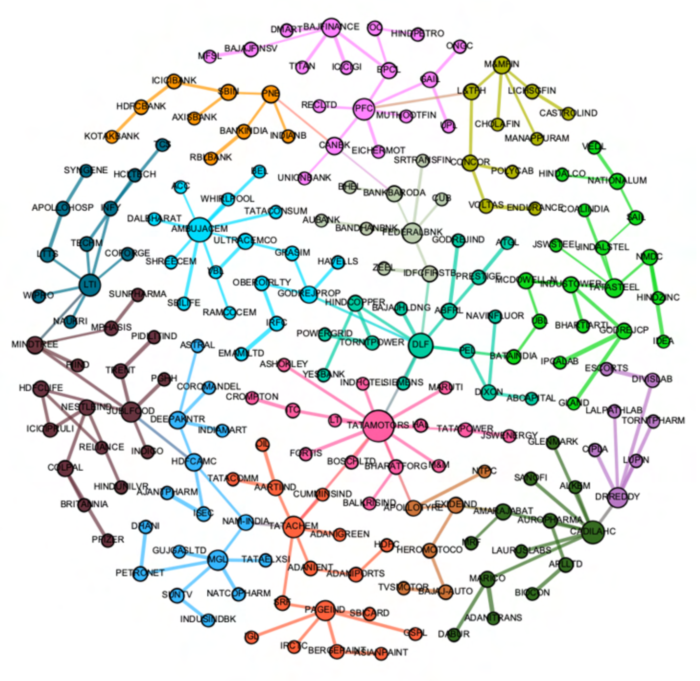


Figure A10: Window 4

**NIFTY200 Dataset : Window size = 62 days : MST Method**

## A.4. CRISIS ANALYSIS

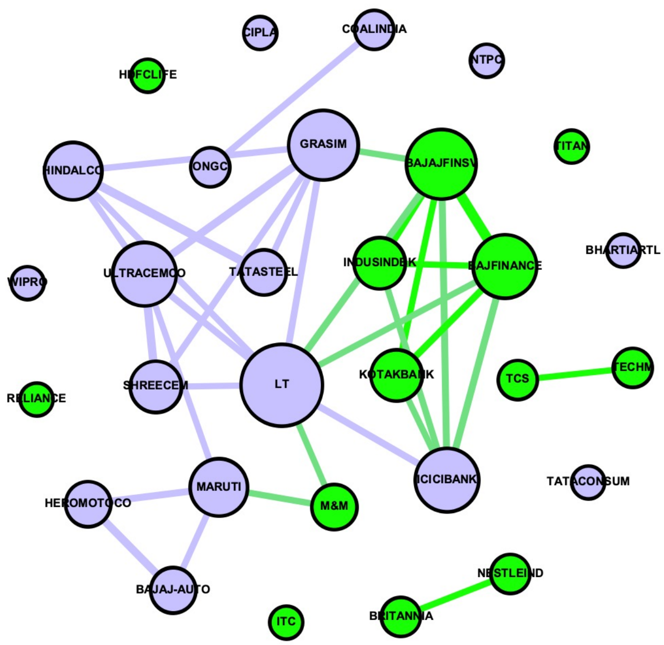



Figure A1: Year 2018

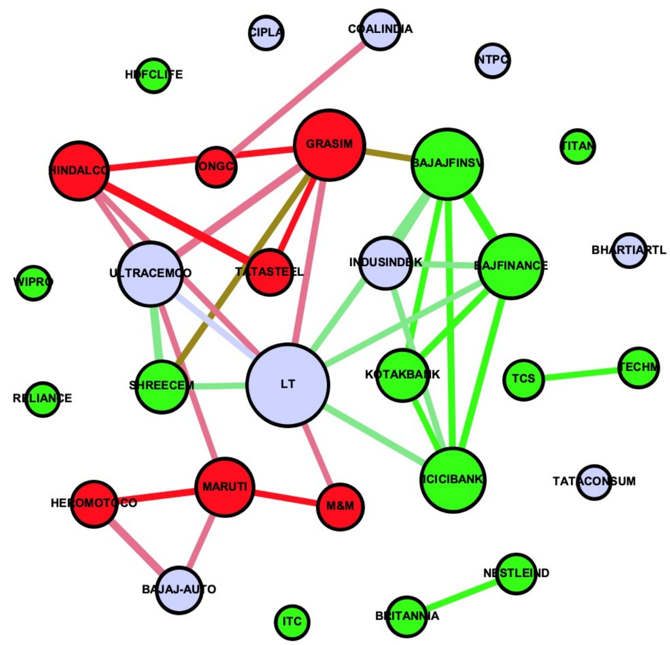



Figure A2: Year 2019

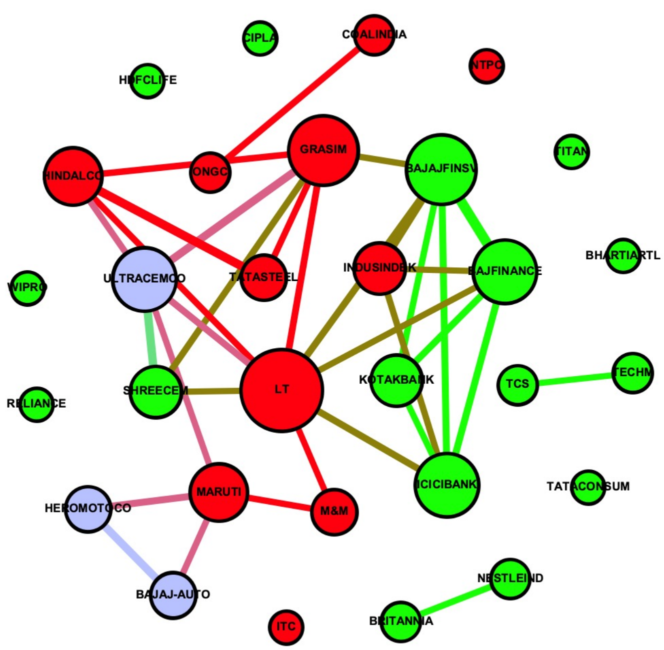



Figure A3: Year 2020

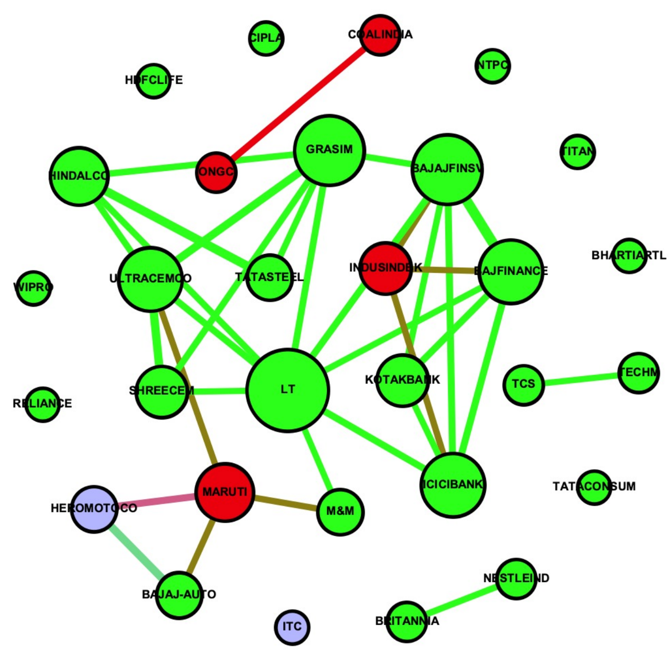



Figure A4: Year 2021