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Complex Network Analysis of the NASDAQ Stock Market during the Initial Phase of COVID-19

Chin Jia Hou
Department of Mathematical and Actuarial Sciences, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, 43000 Kajang, Selangor, Malaysia
jhchin2013@gmail.com

Nor Aziyatul Izni
Centre of Foundation Studies, Universiti Teknologi MARA, Cawangan Selangor, Kampus Dengkil, 43800 Dengkil, Selangor, Malaysia
naizni@uitm.edu.my

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ABSTRACT
The United States (U.S.) plays an important role in the global economy, and the COVID-19 pandemic significantly affected the U.S. stock market. Over the past two decades, numerous studies have incorporated complex network analysis to analyze the stock market. However, there is a lack of study focused on identifying anomalies in the complex network structure of the U.S. stock market that could indicate impending financial crises. The main objective of this research is to implement complex network analysis in examining the changes in the network structures and centralities of the NASDAQ stock networks leading up to and during the initial phase of the COVID-19 pandemic. The opening prices of the stocks under the NASDAQ index in the last two quarters of 2019 and the first quarter of 2020 were collected from Yahoo Finance. The collected data was parsed into edges lists which were then used to construct multiple stock networks. The structures of the stock networks were analyzed using topological metrics such as network density, average clustering coefficient, average path length, network centralizations, and modularity of community structure. The centrality scores of the stocks in the networks were calculated and they were ranked according to the scores. The results show abnormal values in the number of edges, network density, betweenness centralization, and modularity of the community structure during the initial phase of the COVID-19 pandemic. However, no significant anomalies are observed in the average clustering coefficient, average path length, degree centralization, and closeness centralization. Meanwhile, degree centrality proves effective in identifying influential stocks, while closeness and betweenness centralities are found to be less suitable for this particular purpose in the networks used in this study. This paper provides insights into the changes within the stock market at both micro and macro levels around the financial crisis, where the anomalies serve as indicators of an impending financial crisis.

Corresponding Author:
Name: Chin Jia Hou
Affiliation: Department of Mathematical and Actuarial Sciences, Lee Kong Chian Faculty of Engineering and Science, Universiti Tunku Abdul Rahman, 43000 Kajang, Selangor, Malaysia
Email: chinjh2013@gmail.com

1. Introduction

Complex network analysis or network science is an emerging research field dedicated to exploring the properties and features inherent in complex networks. In general, complex networks consist of nodes denoting distinct entities, and edges describing the relationship amid these entities. The nature of the nodes and their respective relationships varies across individual networks. For instance, in a communication network, nodes are defined as Twitter users, and edges are used to link the users mentioned in a tweet [1]. In a container transportation network, nodes represent ports

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while edges denote the movements of vessels between ports [2]. Complex network analysis proved to be a feasible approach to providing insightful findings. For example, the optimization of electric power systems using complex network analysis can provide boosts in grid resilience in the event of a blackout [3]. On the other hand, the application of complex network analysis in managing water supply systems can reduce construction costs, while improving the service quality [4].

The United States (U.S.) holds an important position in the global economy. Thus, stock traders always need to closely analyze and respond to the U.S. stock market. The outbreak of COVID-19 had a profound effect on the U.S. stock market, sending momentous shock waves on indices such as the NASDAQ index, which is one of the primary stock indices in the U.S. Substantially, the interconnectedness of the U.S. stock market with the global financial system emphasizes the far-reaching effect of events such as the COVID-19 pandemic on stock markets.

The stock market comprises a lot of frequently interacting stocks. Hence, it can be considered as a complex system. Numerous research works were dedicated to understanding the stock market through complex network analysis. By examining patterns in network properties, the underlying structure of stock markets can be revealed. Furthermore, influential stocks can be identified using network centrality for further analysis. Despite the feasibility of complex network analysis in studying stock markets, there is a lack of studies utilizing this approach to investigate the evolution of stock behavior under the NASDAQ index during financial crises. Studies indicate that the stock market behaves differently during financial crises [5], [6]. By understanding the changes within the stock market at both micro and macro levels, anomalies could be identified which then serve as indicators of an impending crisis.

In this study, we propose the implementation of complex network analysis to examine the structure of the NASDAQ stock market leading up to and during the initial phase of the COVID-19 pandemic. This involves the analysis of the changes in network structure via the network metrics, including network density, average clustering coefficient, average path length, network centralization, and modularity of community structure. Furthermore, we investigated the variation in the influence of individual stocks by assessing their centralities in the networks.

2. Literature Review

The crucial component of complex network analysis lies in the construction of the network of interest by defining the relationship between entities in a complex system. In stock networks, the entities are stocks and their correlation in terms of their prices or volumes will define the connections between them. One of the most used models to capture the correlations among stocks is Pearson's correlation with threshold [7], [8].

Node centralities in stock networks can highlight the influential stocks in the networks. Wang et. al. [9] utilized PageRank to identify influential energy stocks under 30 China financial institutions. In a study on the Shanghai and Shenzhen stock markets, it was found that stocks with smaller market capitalization have more central positions in networks [10]. Similar phenomena can be observed in the Iranian stock market, where stocks with higher centralities have higher market capitalization and price fluctuation, as well as larger transaction volume [11]. Furthermore, Wang et. al. [12] investigated the correlation between centralities and financial indicators to find out the centralities that contribute the most to identifying influential stocks.

Aside from centralities, by observing the changes in the network topology and structure, the behavior of the stock market could be unveiled [13], [14]. Huang et. al. [15] proposed a new indicator to detect subprime crisis, which has better performance than classical indicators such as degree and clustering coefficient. For financial network analysis, the changes in the distribution and average of the centralities in dynamic networks (i.e. networks that evolve through time) reveal the evolution of behaviors of the stock market during the financial crisis and normal periods [16]. Community structure within a network provides insights into the presence of stock clusters which can be focused on to avert potential damages to the entire stock market [17]. By using a modularity-based community detection method, Chen et. al. [10] categorized A-Share stocks by industries and measured the intra- and inter-industry connectivity of the stocks. Numerous research works suggested that stock complex networks exhibit scale-free properties, where the degree distribution follows a power law distribution [18] - [20]. Scale-free networks are complex networks that show a preferential attachment process. The main characteristic of this kind of network is the existence of "hub" nodes with exceptionally high degrees than the other nodes.

Complex network analysis has been applied to the study of the U.S. stock market. Aslam et. al. [21] investigated the centralities of global stock market indices in the pre- and post-COVID-19 periods, and the results suggested that the U.S. index (DOW 30) did not lead global stock markets before or during the COVID-19 period. In a study of global stock market co-movement during the COVID-19, Huang et. al. [22] showed that the centrality rankings of the U.S. stock price index, based on degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality, changed only marginally from 2020 to 2022. Furthermore, the U.S. maintained a stable position in the global stock market network throughout this period.

Korkusuz et al. [23] analyzed volatility spillovers during financial crises using network centralities, showing that the U.S. was a major source of financial volatility during the Global Financial Crisis. Furthermore, this volatility remained significant during the COVID-19 Crisis, increasing the overall transitivity of the volatility network. Li and Pi [24] investigated the clustering coefficients and community structure within the complex networks of global stock indices. They found that the U.S. stock market exhibited regional clustering, particularly during financial crises. The correlation among global stock indices, including U.S. indices, increased during such periods.

3. Methodology

3.1 Data Collection and Network Construction

Stock data of the stocks under the NASDAQ index were retrieved from the Yahoo Finance website using the “quantmod” package in R. Aside from the symbols and security names of the stocks, their daily opening prices from 1 July 2019 to 31 March 2020 were retrieved. In total, data for 3063 stocks were collected. The cross-correlations between the stocks were calculated. Let $x_i(t)$ and $x_j(t)$ be the daily opening prices of stock i and j, respectively, over the period $t = 0$ to $t = n - 1$. The cross-correlation between the stocks with no time shift is defined as [25] depicted in Equation (1).

$$c_{ij} = \frac{\Sigma_t[(x_i(t) - \overline{x_i})(x_j(t) - \overline{x_j})]}{\sqrt{\Sigma_t(x_i(t) - \overline{x_i})^2}\sqrt{\Sigma_t(x_j(t) - \overline{x_j})^2}} \tag{1}$$

where $\overline{x_i}$ and $\overline{x_j}$ are the means of the time series, and c_{ij} ranges from 0 to 1.

Subsequently, stock networks were constructed by using cross-correlations, where the nodes represent stocks that are connected by edges if c_{ij}, which serves as the edge weight, is a positive value. Due to the excessively high number of edges in the networks constructed without restriction in c_{ij}, a winner-take-all approach is employed to reduce the networks. Specifically, three threshold values (T1 = 0.7; T2 = 0.8; T3 = 0.9) were chosen. Edges with weights (c_{ij}) less than the threshold values were removed from the networks. Furthermore, the stock dataset is divided into three periods, namely 2019_Q3 (2851 out of 3063 stocks) for 1 Jul 2019 to 30 Sept 2019 (quarter 3 of year 2019), 2019_Q4 (2889 out of 3063 stocks) for 1 Oct 2019 to 31 Dec 2019 (quarter 4 of year 2019), and 2020_Q1 (2923 out of 3063 stocks) for 1 Jan 2020 to 31 Mar 2020 (quarter 1 of year 2020). Hence, nine stock networks that depict the cross-correlations of the stocks at various periods and cross-correlations threshold values were constructed: 2019_Q3_T1, 2019_Q3_T2, 2019_Q3_T3, 2019_Q4_T1, 2019_Q4_T2, 2019_Q4_T3, 2020_Q1_T1, 2020_Q1_T2, 2020_Q1_T3. Since there is no direction when defining the cross-correlations of the stocks, the stock networks are undirected and weighted. Gephi was used to visualize the stock networks.

3.2 Network Theory

The density of a network quantifies the proportion of the actual number of edges relative to the total possible number of edges in a network. For an undirected network, network density is defined as Equation (2).

$$ND = \frac{2|E|}{N(N-1)} \tag{2}$$

where $|E|$ is the number of edges while N is the number of nodes in the network. The density of a network ranges between 0 and 1, with higher values indicating stronger interconnectedness between the nodes in the network.

The clustering coefficient measures the probability of connection between the neighboring nodes of a node. The local clustering coefficient of node i in an undirected and weighted network is defined as [26] depicted in Equation (3).

$$CC_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{w_{ij} + w_{ih}}{2} a_{ij} a_{ih} a_{jh} \tag{3}$$

where s_i is the strength of node i, a_{ij} is an element of the adjacency matrix (row i column j), k_i is the degree of node i, and w_{ij} is the weight of the edge connecting node i and j. The average clustering coefficient of a network is the mean of the local clustering coefficients. It ranges from 0 to 1, with higher values indicating higher tendency of nodes in the network to cluster together.

The average path length denotes the average number of steps that are required to move from one node to another in a network. It is calculated by averaging the lengths of the shortest paths between all pairs of nodes in the network [27]. The shortest path lengths in weighted networks can be calculated using Dijkstra's algorithm. The average path length offers a glimpse of the connectivity of the network.

In general, the centralities of nodes quantify the importance of the nodes within a network. The degree centrality, closeness centrality, and betweenness centrality [28] are the most used centrality measures in complex network analysis. The centralities of node i in an undirected and weighted network are defined as:

$$\text{Degree centrality: } C_D(i) = \sum_j a_{ij} = k_i \tag{4}$$

$$\text{Closeness centrality: } C_C(i) = \frac{N-1}{\sum_{j=1}^{N} d(i,j)} \tag{5}$$

$$\text{Betweenness centrality: } C_B(i) = \sum_{i \neq j \neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{6}$$

where $d(i,j)$ is the shortest path length between nodes i and j, σ_{jk} is the total number of shortest paths between nodes j and k, and $\sigma_{jk}(i)$ is the number of shortest paths between nodes j and k that go through node i. Closeness centrality and betweenness centrality can be normalized to range between 0 and 1. Each centrality is interpreted differently. A node with a high degree centrality is important as it has a lot of connections. On the other hand, a node with high closeness centrality can swiftly interact with all other nodes in a network. Meanwhile, a node with high betweenness centrality plays a crucial role as a bridge that connects various components within the network.

Centralization of a network is a network-level metric derived from the centrality scores of individual nodes, enabling the comparison of different networks. Essentially, when network centralization is high, there is a greater likelihood that a single node holds a central position within the network. Let X_i be the degree, closeness, or betweenness centrality, the centralization is then defined as Equation (7).

$$X_g = \frac{\sum_{i=1}^{N}(X^* - X_i)}{\max \sum_{i=1}^{N}(X^* - X_i)} \tag{7}$$

where $X^* = \max(X_i)$. D_g, C_g and B_g are used to denote degree, closeness, and betweenness centralities, respectively.

The Leiden algorithm was implemented in the detection of communities in the networks [29]. Modularity (Q) was utilized to gauge the quality of the detected communities [30]. The value of Q ranges from 0 to 1, with high Q values signifying a strong community structure within a network.

4. Results and Discussion

4.1 Network Topological Metrics of the NASDAQ Stock Networks

Table 1 depicts the changes in network metrics across different cross-correlation threshold values over consecutive periods, while the visualization of the 2019_Q3_T3, 2019_Q4_T3, and 2020_Q1_T3 stock networks are depicted in Figures 1 to 3.

Given that the threshold values determine the presence of edges between stocks in the networks, it is natural that the number of nodes and edges diminishes with an increase in the threshold value. Notably, changes in the number of nodes across the threshold values are marginal, except for a 26% reduction in the number of nodes during 2019 Q3 at the threshold value of 0.9. An interesting observation is the sudden surge in the number of edges during 2020 Q1, marking the initial phase of the COVID-19 pandemic. This increase is consistent across all threshold values. Specifically, the number of edges during 2020 Q1 surpasses that of 2019 Q4 by 2.8 times, 4.3 times, and 8.9 times at the corresponding threshold values. The onset of the COVID-19 pandemic brought about widespread market shock, inducing analogous responses among investors dealing with economic uncertainty. This collective reaction is reflected in the intensified connectivity among stocks during this period.

The network densities observed in 2019 Q3 and 2019 Q4 are below 0.3, indicating a low level of interconnectivity among stocks during those periods. This suggests a lack of noticeable overall co-movement among the stocks. However, the advent of the COVID-19 pandemic significantly raises the network density in 2020 Q1, particularly at the threshold value of 0.9. The notable increase aligns with the substantial rise in the number of edges during this period. It can be observed from Figures 1 to 3 that the networks are getting denser with the increase in the number of edges connecting the nodes in the networks.

Table 1. The statistics and network metrics of the stock networks at various periods and cross-correlation threshold values.

Networks	N	$\|E\|$	ND	ACC	APL	D_g	C_g	B_g	Q
Threshold Value = 0.7									
2019_Q3_T1	2745	476353	0.126	0.687	1.801	0.338	0.349	0.163	0.367
2019_Q4_T1	2856	868357	0.213	0.768	1.656	0.648	0.664	0.083	0.073
2020_Q1_T1	2894	3336955	0.797	0.938	1.043	0.137	0.177	0.032	0.004
Threshold Value = 0.8									
2019_Q3_T2	2549	224516	0.069	0.649	2.353	0.306	0.345	0.298	0.355
2019_Q4_T2	2848	533450	0.132	0.766	1.886	0.731	0.699	0.099	0.043
2020_Q1_T2	2863	2821094	0.689	0.896	1.194	0.215	0.263	0.034	0.007
Threshold Value = 0.9									
2019_Q3_T3	1883	41482	0.023	0.572	3.367	0.241	0.319	0.528	0.310
2019_Q4_T3	2834	166507	0.041	0.803	2.157	0.826	0.707	0.125	0.006
2020_Q1_T3	2756	1653329	0.436	0.810	1.562	0.331	0.340	0.051	0.010

Notes: N and $|E|$ are the numbers of nodes and edges in the network, while ND, ACC, APL, D_g, C_g and B_g denote the density, average clustering coefficient, average path length, degree, closeness, and betweenness centralizations of the networks, respectively. Q is the modularity of the detected communities.

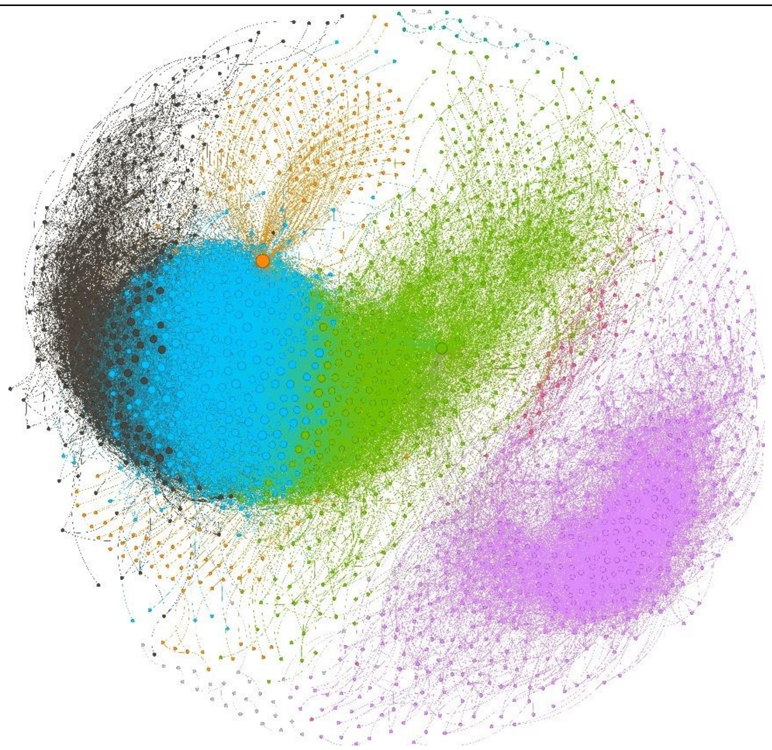

Figure 1. Visualization of the NASDAQ stock network during 2019 quarter 3 at the threshold value of 0.9 (2019_Q3_T3). The size of the nodes denotes the degree centrality score of the nodes. The nodes are colored by communities.

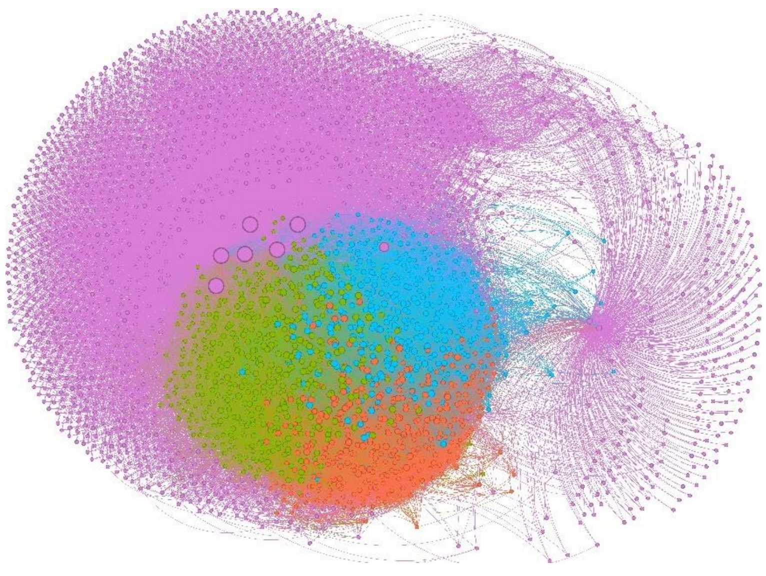

Figure 2. Visualization of the NASDAQ stock network during 2019 quarter 4 at the threshold value of 0.9 (2019_Q4_T3). The size of the nodes denotes the degree centrality score of the nodes. The nodes are colored by communities.

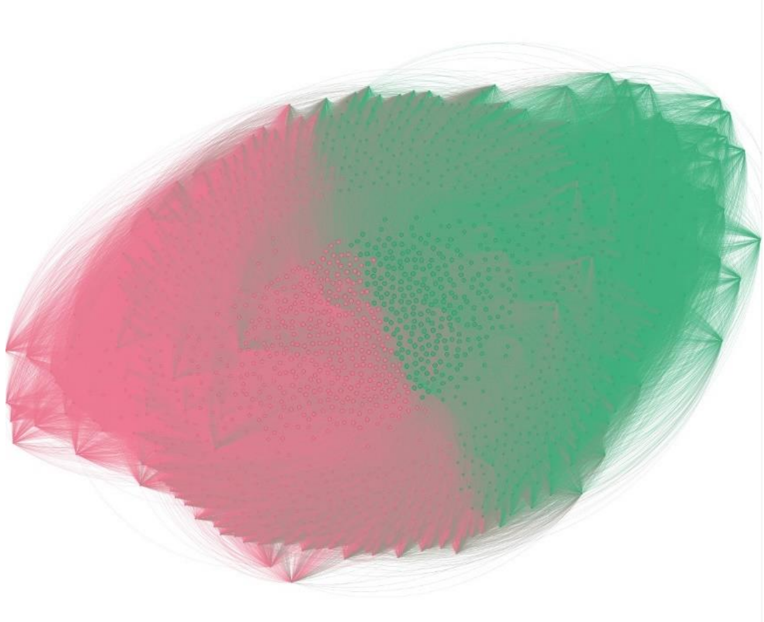

Figure 3. Visualization of the NASDAQ stock network during 2020 quarter 1 at the threshold value of 0.9 (2020_Q1_T3). The size of the nodes denotes the degree centrality score of the nodes. The nodes are colored by communities.

Although the average clustering coefficient is the highest in 2020 Q1, the increment is gradual over the periods. Specifically, at the threshold value of 0.9, the average clustering coefficient increases merely by 0.8% from 2019 Q3 to 2020 Q4. Given the diverse sectors encompassed by NASDAQ, including energy, financials, healthcare, technology, and telecommunications, it is foreseeable that stocks within the same sector form tightly knit clusters, showing strong interconnectedness within sectors. However, despite the tendency of stocks to cluster together due to the high average clustering coefficient, the low modularity scores (Q) of the identified community structure in 2020 Q1 indicate a diminished community structure during the economic turbulence caused by COVID-19. As displayed in Figure 1, the communities in the 2019_Q3_T3 network are distinguishable, with one cluster of stocks (purple) separated from the other clusters. On the other hand, all the stocks are tightly clustered together in the 2020_Q1_T3 network, with no clear boundary between the two detected communities (pink and green). Hence, in 2020 Q1, the co-movement of stocks is observed on an overall scale, rather than within sectors. Nonetheless, it is interesting to note that the community structure in 2019 Q4 is as weak as in 2020 Q1. Further investigation into the network structure of the stocks during this period is needed to gain insights into this observation.

Examining the average path lengths of stock markets provides insights into the speed at which shocks spread across networks. In general, NASDAQ stock networks exhibit very small average path lengths, with the largest value reported at 3.367 for the threshold value of 0.9 in 2019 Q3. Coupled with the relatively large average clustering coefficients in the corresponding networks, it indicates that the NASDAQ stock networks demonstrate a small-world property [31]. Stock networks with such property are more sensitive to systemic risk and demonstrate distinct co-movements during financial crises.

The exceptionally low betweenness centralization values across all threshold values in the stock networks emphasize the influence of COVID-19 on the stock market structure. In 2020 Q1, the market was decentralized in terms of betweenness centrality, with most stocks possessing similar betweenness centrality scores. This suggests that all sectors under NASDAQ were affected simultaneously during the initial phase of COVID-19, instead of spreading from sector to sector. In contrast, the changes in degree and closeness centralizations during 2020 Q1 are not as pronounced as those observed in betweenness centralization. The relatively low network centralization values across various threshold values and periods indicate that NASDAQ has a decentralized market structure. However, in 2019 Q4, degree, and closeness centralizations are relatively high, indicating the existence of a few stocks with a high number of connections that could rapidly influence a large portion of NASDAQ stocks. This can be observed in Figure 2, where there are 5 purple nodes which are significantly larger than the other nodes in the network.

4.2 Identification of Influential Stocks in the NASDAQ Stock Networks

The degree centrality of stocks within the stock networks serves as a measure of their influence regarding the co-movement of stocks in the stock market. Table 2 shows the top 5 NASDAQ stocks ranked by degree centrality.

Table 2. The top 5 NASDAQ stocks ranked by degree centrality at various periods and cross-correlation threshold values. The stocks are represented by their symbols.

Rank	**2019_Q3_T1**	**2019_Q3_T2**	**2019_Q3_T3**
1	TFII (1275) (Logistic)	TFII (956) (Logistic)	DTP (498) (Utilities)
2	DTP (971) (Utilities)	DTP (835) (Utilities)	TFII (381) (Logistic)
3	LNC (862) (Finance)	CIT (617) (Finance)	PUK (278) (Finance)
4	FLS (854) (Industrials)	MET (606) (Finance)	NGVT (275) (Industrials)
5	MET (849) (Finance)	NGVT (603) (Industrials)	CIT (269) (Finance)
Rank	**2019_Q4_T1**	**2019_Q4_T2**	**2019_Q4_T3**
1	BFYT (2457) (Finance)	BFYT (2457) (Finance)	BFYT (2457) (Finance)
2	BPYU (2457) (Real Estate)	BPYU (2457) (Real Estate)	BPYU (2457) (Real Estate)
3	BPYUP (2457) (Real Estate)	BPYUP (2457) (Real Estate)	BPYUP (2457) (Real Estate)
4	PIPR (2457) (Finance)	PIPR (2457) (Finance)	PIPR (2457) (Finance)
5	TFII (2457) (Logistic)	TFII (2457) (Logistic)	TFII (2457) (Logistic)
Rank	**2020_Q1_T1**	**2020_Q1_T2**	**2020_Q1_T3**
1	WTRG (2703) (Utilities)	TFII (2585) (Logistic)	TFII (2113) (Logistic)
2	TFII (2697) (Logistic)	QQQX (2536) (Finance)	DIAX (2055) (Finance)
3	MGU (2666) (Finance)	CAPE (2532) (Finance)	GDV (2053) (Finance)
4	IPG (2664) (Consumer Discretionary)	GAM (2532) (Finance)	AIR (2034) (Industrials)
5	MORN (2664) (Finance)	PIPR (2530) (Finance)	DOV (2034) (Industrials)

Notes: The first bracket in each cell denotes the degree centrality scores, while the second bracket denotes the sector.

As shown in Table 2, TFI International Inc. (TFII), a logistics company, emerges as an influential stock across all threshold values and periods. This observation is reasonable considering the important role logistics plays in the supply chain, affecting various sectors and industries. Furthermore, a general trend is observed where stocks within the finance sector are influential during the periods investigated in this study, especially during the early phase of the COVID-19 pandemic (2020 Q1).

Upon closer examination of the degree centrality scores for all stocks in 2019 Q4, it can be noticed that the top 5 influential stocks, namely Benefytt Technologies, Inc. (BFYT), Brookfield Property REIT Inc. - Class A (BPYU), Brookfield Property REIT Inc. - 6.375% Series A (BPYUP), Piper Sandler Companies (PIPR), and TFI International Inc. (TFII), possess higher degree centrality scores than the remaining stocks in the networks. This difference contributes to the relatively high degree centralization during 2019 Q4, as discussed in the previous subsection. Notably, the top 5 influential stocks during 2019 Q4 remained the same across all threshold values.

On the other hand, it can be observed from Table 3 that the highest closeness and betweenness centrality scores in all the stock networks are remarkably low (falling below 0.1), except the betweenness centrality of TFI International Inc. (TFII) in the 2019_Q3_T2 and 2019_Q3_T3 networks, Immunovant, Inc. (IMVTU) in the 2019_Q4_T2 network, and Benefytt Technologies, Inc. (BFYT) in the 2019_Q4_T3 network. This observation implies that even though stocks can be ranked based on closeness and betweenness centralities, they are not considered influential, given the low centrality scores during the periods examined in this study.

Table 3. The stocks with the highest closeness and betweenness centralities at various periods and cross-correlation threshold values.

Networks	Highest Closeness Centrality	Highest Betweenness Centrality
2019_Q3_T1	TFII (0.00029)	TFII (0.08998)
2019_Q3_T2	TFII (0.00025)	TFII (0.21752)
2019_Q3_T3	TFII (0.00026)	TFII (0.49398)
2019_Q4_T1	BFYT (0.00031)	IMVTU (0.07384)
2019_Q4_T2	BFYT (0.00031)	IMVTU (0.10027)
2019_Q4_T3	BFYT (0.00029)	BFYT (0.10977)
2020_Q1_T1	IPHI (0.00038)	RFM (0.02560)
2020_Q1_T2	BSTZ (0.00034)	RFM (0.02590)
2020_Q1_T3	TFII (0.00030)	RFM (0.04658)

Notes: The stocks are represented by their symbols and the values in the brackets represent the corresponding degree centrality scores

5. Conclusion

In this paper, the structure of the NASDAQ stock market and the co-movement behaviors of NASDAQ stocks around COVID-19 were analyzed through the lens of complex network analysis. The findings reveal abnormal values in the number of edges, network density, betweenness centralization, and modularity of the community structure during the early phase of COVID-19. While the average clustering coefficient, average path length, degree centralization, and closeness centralization do not exhibit distinctive anomalies during this period, they offer valuable insights into the intrinsic structure of the NASDAQ stock market. The application of various centralities on the NASDAQ stock networks indicates that degree centrality can effectively identify influential stocks, whereas closeness and betweenness centralities are less suitable for this purpose.

For future research, it would be interesting to observe the structural changes in the NASDAQ stock market across different phases of COVID-19. Furthermore, extending this study to other stock markets such as S&P500 and Dow Jones could provide a more comprehensive understanding of the U.S. stock market during financial crises.

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Conflict of Interest

The authors declare no conflict of interest in the subject matter or materials discussed in this manuscript.

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Biography of all authors

Picture	Biography	Authorship contribution
	Chin Jia Hou is an assistant professor in Universiti Tunku Abdul Rahman, Sungai Long Campus. He graduated in B.Sc. in the Computational and Industrial Mathematics from the Department of Mathematical Sciences, University of Malaya, Kuala Lumpur in 2008. He also obtained his M.Sc. in atomic collision theory and Ph.D. in complex network analysis from the same university in 2012 and 2018. His research interest is network science, particularly social networks and community structure of complex networks.	Design the research work, data analysis and interpretation, drafting article.
	Nor Aziyatul Izni is a senior lecturer at the Centre of Foundation Studies, Universiti Teknologi MARA, Selangor Branch, Dengkil Campus. She is awarded a Professional Technologist by the Malaysia Board of Technologists since November 2021. She graduated in Bachelor of Applied Science (Honours) in Mathematical Modelling in 2012, and a Master of Science (Mathematics) in 2013 from Universiti Sains Malaysia, Malaysia. She then completed her Ph.D. in 2019 from Universiti Teknologi Malaysia, Kuala Lumpur. Her research interests are data analytics, applied mathematics and statistics, signal processing, fusion algorithm, artificial intelligence as well as prediction and forecasting methods.	Data processing, data analysis and interpretation, drafting article.