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Research article

Network, correlation, and community structure of the financial sector of Bursa Malaysia before, during, and after COVID-19

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Abstract: COVID-19 triggered a worldwide economic decline and raised concerns regarding its economic consequences on stock markets across the globe, notably on the Malaysian stock market. We examined how COVID-19 impacted Malaysia's financial market using correlation and network analysis. We found a rise in correlations between stocks during the pandemic, suggesting greater interdependence. To visualize this, we created networks for pre-pandemic, during-pandemic, and post-pandemic periods. Additionally, we built a network for the during-pandemic period with a specific threshold corresponding to pre- and post-pandemic network density. The networks during the pandemic showed increased connectivity and only contained positive correlations, reflecting synchronized stock movements. Last, we analyzed the networks' modularity, revealing highest modularity during the pandemic, which suggests stronger yet risk-prone communities.

Keywords: modularity; Louvain; community detection; Malaysia stock market; correlation network; COVID-19

JEL Codes: D53, D85, G01

Abbreviations: COVID-19: Coronavirus disease 2019; WHO: World Health Organization; KLFIN: Kuala Lumpur Financial Index; MST: Minimum spanning tree; PMFG: Planar maximal filtered graph

1. Introduction

The first case of the Coronavirus disease 2019 (COVID-19) emerged in late 2019, and its immediate global transmission led to the declaration of a pandemic by the World Health Organization (WHO) on March 11, 2020. The COVID-19 pandemic has undoubtedly ushered in an era of unprecedented challenges worldwide (Zhang et al., 2020). In addition to its significant impact on public health, the pandemic had far-reaching effects on various dimensions of the global economy, notably highlighting the heightened vulnerability of financial markets to its disruptive influences. It disturbed economic activities, led to market volatility (Bouhali et al., 2022), and caused significant uncertainty (Szczygielski et al., 2021; Zuhud et al., 2022). This was exacerbated by the interconnectedness of global financial markets, where volatility spillovers increased sharply during the pandemic, accelerating the transmission of volatility information and contributing to market volatility (Song et al., 2021). Therefore, this study expects that the correlation between financial sector stocks will strengthen due to significant market volatility as investors show a similar reaction among financial services during COVID-19. Thus, this tightening stock price correlation is expected to be reflected in its network structure, where network connectivity will be significantly higher during the pandemic, reflecting a stronger correlation between financial sector stocks due to increased market volatility and uncertainty, hence the use of network analysis. Additionally, a study on the network structure of the Malaysian consumer products and services sector found that the network showed interconnectedness among heterogeneous subsectors, highlighting common market dynamics across sectors (Dellow et al., 2024). The same behavior may also be shown in the Malaysian financial sector network.

The pandemic exerted a substantial influence on financial markets, specifically stock markets. Stock markets are often regarded as indicators of economic stability and investor sentiment (Cevik et al., 2022; Goodell, 2020). Furthermore, Asian markets displayed a particularly pronounced (Topcu & Gulal, 2020) and rapid response to the news of the COVID-19 outbreak (Sun & Hou, 2019). This heightened sensitivity can be partially attributed to the extensive financial integration of countries in Southeast Asia, including Malaysia, Vietnam, and Thailand, with China (Liu et al., 2020).

There are several research focusing on the impact of COVID-19 on global stock indices (Ashraf, 2020; Aslam et al., 2020; Huang et al., 2024; Hui & Chan, 2022; Zhang et al., 2020) and the emerging stock market (Bahaludin et al., 2022; Baker et al., 2020; Bouhali et al., 2022; Chakrabarti et al., 2021; Hassan et al., 2023; Hong et al., 2021; Mazur et al., 2021; Memon, 2022; Qian et al., 2023; Rehman et al., 2022; Song et al., 2021; Topcu & Gulal, 2020; Yaya et al., 2024; Zuhud et al., 2022). The Malaysian stock market experienced a significant decline during the initial Movement Control Order (MCO) due to fear of the anticipated economic consequences of the virus (Song et al., 2021). Song et. al (2021) demonstrated that the number of new death cases had a negative impact on Malaysia's stock returns. Moreover, both domestic and global case increases were linked to decreased trading activity, leading to a significant negative impact on the Malaysian stock market (Mohammed et al., 2021). This decline possibly stemmed from the pandemic's adverse effects on demand for goods and services, leading to poor overall performance (Ming & Jais, 2021). Certain sectors, particularly aviation and tourism, were especially hit by the pandemic within the Malaysian market (Mohd Rosli et al., 2023).

COVID-19 significantly impacted the Malaysian stock market, with the Kuala Lumpur Financial Index (KLFIN) declining by 1.3% between January 1, 2020, and July 31, 2020, mainly due to concerns about the virus and its impact on the finance sector (Hassan et al., 2023). Some significant challenges experienced by the financial sector are slow loan growth, reduced earnings, increased provisions, and liquidity issues (Deloitte, 2020).

A study by Zuhud et al. (2022) focused on the KLFIN with the aim of identifying and analyzing the individual constituent's causal intensity from early 2018 to the end of 2021. The findings revealed changes in causal intensity among the constituents, with the insurance subsector showing a rapid increase in causality. This suggests that the pandemic had a significant impact on the financial services sector in Malaysia. Thus, this study focuses on the dynamics of the financial sector and its three subsectors, which are banking, insurance, and other financial services, in Bursa Malaysia, with an emphasis on analyzing network properties and modularity to find communities in the network. A few studies have utilized network and community detection to examine the effects of previous financial crises on various local markets, such as the 2008 global crisis (Li & Pi, 2018; Nobi et al., 2014; Wu et al., 2015). Thus, we intend to analyze the effects of the COVID-19 pandemic on the Malaysian market. We consider three periods: before (2019), during (2020), and after (2021) COVID-19.

A network is defined as a graph, which is a collection of nodes that are connected by edges. In a correlation-based network, the edges (connections) between nodes (stocks) are defined by their correlation coefficients. The correlation coefficient is a measure of the strength of the relationship between two variables. It is used to quantify the similarities between the two stocks. Popular methods used to obtain a correlation network include choosing a threshold to determine edges (Dellow et al., 2024; Musa & Razak, 2021; Nobi et al., 2014; Tse et al., 2010; Wu et al., 2015; Xia et al., 2018; Zuhud et al., 2022), minimum spanning tree (MST) (Bahaludin et al., 2019; Mahamood et al., 2019; Mantegna, 1999; Memon, 2022; Memon et al., 2020; Memon & Yao, 2021; Roy & Sarkar, 2011), and planar maximal filtered graph (PMFG) (Millington & Niranjan, 2021; Tumminello et al., 2005, 2007). These methods are popular because they provide noise-free information that can be used to analyze interactions among financial assets (Marti et al., 2021). However, in some cases, both MST and PMFG suffer from information loss, since edges with high correlation are sometimes deleted, while edges with low correlation are kept because their topological conditions meet the topological reduction criterion (Tse et al., 2010).

Thus, we construct a correlation network of the stocks by choosing a threshold to define edges. Selecting an appropriate threshold is crucial to ensure the validity and reliability of the results and, most importantly, to avoid loss of information. In this study, the threshold is chosen based on the mean plus the standard deviation of the correlation coefficients (Preis et al., 2012) for each period. Therefore, similar to past works (Nobi et al., 2014; Xia et al., 2018), we consider different thresholds for the three periods since the distribution of correlations is different for each period.

Moreover, we use the Louvain algorithm to identify communities of related stocks and measure the community structure using modularity. Community structure is an important characteristic of a network (Fortunato, 2010; Lancichinetti et al., 2010; Newman, 2006; Porter et al., 2009). A network with high modularity has many densely connected communities that are sparsely connected to each other, while a network with low modularity has few or no densely connected communities. By identifying communities within the network, it is possible to assess the risk associated with different groups of stocks during a crisis. By studying the communities, investors, policymakers, and market participants, one can gain insights into the vulnerabilities and potential sources of contagion within the network. This study may help investors diversify their portfolios. Investors can ensure that they are not overexposed to any one particular asset. This can help to reduce the risk and increase the overall return on investment, especially during a financial crisis.

This study makes several contributions to the financial network literature. We present a new pipeline to analyze herding behavior and structural changes in interconnectedness during crises and their implications for the Malaysian stock market (Bursa Malaysia) by using complex network analysis, especially modularity. To the best of our knowledge, no previous studies have used modularity to analyze and compare network structural changes during the COVID-19 financial crisis. In addition, we suggest the threshold method to consider the network density, as it is suggested to have a comparable density, to make comparisons between networks. With the purpose of understanding the impact of COVID-19 on the Malaysian stock market, we compare and investigate the network structure and the quality of communities in the network before, during, and after COVID-19. This study on the financial sector correlation network provides us with a general overview of the Malaysian financial stock market around the crisis of COVID-19.

This paper is presented as follows. We explain the data, definition, and methodology in Section 2. Section 3 discusses the correlogram of stock correlation, Section 4 discusses the network properties, Section 5 analyzes the community structure of the networks, and Section 6 summarizes the conclusion of this paper.

2. Data and methods

Table 1. Name of companies and subsectors of 30 stocks under the financial services sector in Bursa Malaysia.

Stock symbol	Company	Subsector
AFIN	Affin Bank	Banking
AINM	Allianz Malaysia	Insurance
ALLI	Alliance Bank Malaysia	Banking
AMMB	AMMB Holdings	Banking
ANCR	Aeon Credit Service	Other financial services
APES	APEX Equity Holdings	Other Financial services
BIMB	Bank Islam Malaysia	Banking
BMYS	Bursa Malaysia	Other financial services
CIMB	CIMB Group Holdings	Banking
ECMI	ECM Libra Group	Other financial services
ELKD	Elk-Desa Resources	Other financial services
HLBB	Hong Leong Bank	Banking
HLCB	Hong Leong Financial Group	Banking
INSS	Insas	Other financial services
JHHS	Johan Holdings	Other financial services
KCDS	Kuchai Development	Other financial services
KNNK	Kenanga Investment Bank	Other financial services
LOND	LPI Capital	Insurance
MAAS	MAA Group	Insurance
MBBM	Malayan Banking	Banking
MBSS	Malaysia Building Society	Other financial services
MNLF	Manulife Holdings	Insurance
MNRB	MNRB Holdings	Insurance
MPHB	MPHB Capital	Insurance
PACO	Pacific and Orient	Insurance
PUBM	Public Bank	Banking
REDI	RCE Capital	Other financial services
RHBC	RHB Bank Berhad	Banking
TAKA	Syarikat Takaful Malaysia Keluarga	Insurance
TUNE	Tune Protect Group	Insurance

Note: 1 Stock symbol or ticker symbol is a unique letter assigned to a stock.
1. The subsector of a stock is categorized based on the definition of a company business provided by Bursa Malaysia.

The dataset utilized in our research comprises the daily closing prices of companies within the financial services sector listed in Bursa Malaysia. Companies were chosen based on their consistent listing under the Financial Services Index from 2019 to 2021, as recorded in the DataStream database. Then, the daily closing prices were retrieved from the Eikon Datastream, covering the timeframe from January 1, 2019, to December 31, 2021, resulting in 23,520 records. Among the $n = 30$ companies, there are 10 banks, 9 insurance companies, and 11 other financial services, as categorized by Bursa Malaysia's subsector classification (Bursa Malaysia, 2023). Three time periods were identified based on the year, labeled as before COVID-19 (2019), during COVID-19 (2020), and after COVID-19 (2021). Additional information about the stocks can be found in Table 1.

There are four common practices that we use for data cleaning. First, we handle missing values by identifying them through methods like checking for null values (NaNs) and removing rows or columns with excessive missing data. Second, we check for consistency and data alignment, such as time alignment, to ensure all stock price data is aligned on the same dates. This may involve managing different time zones and trading days. Next, we filter non-trading days by removing weekends and holidays when markets are closed to avoid gaps in the time series data. Last, we handle duplicates by identifying and removing any duplicate records to ensure each date has a unique entry.

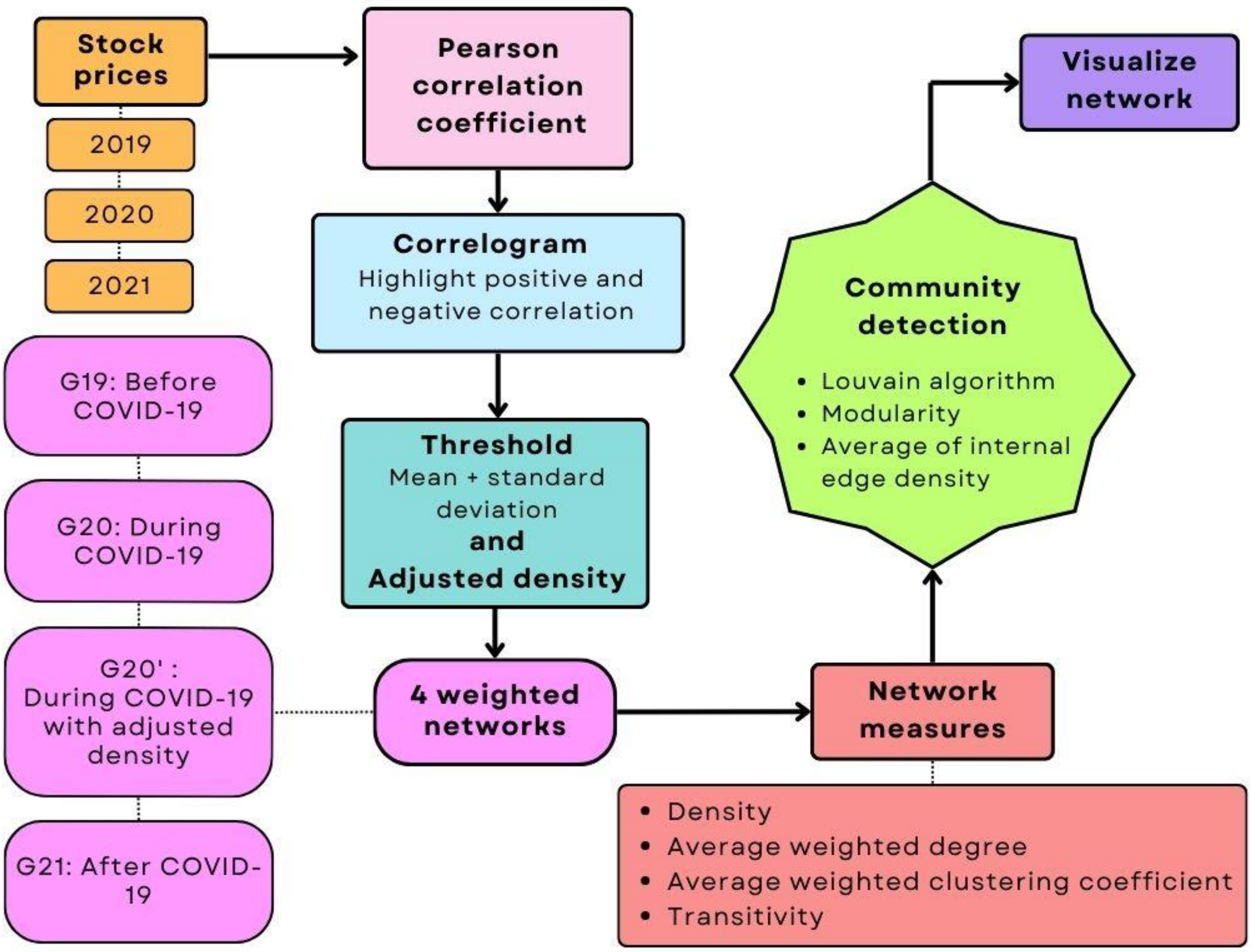


Figure 1. The flowchart highlights the methodology in this article. The sequence of important steps is shown in the diagram.

Figure 1 highlights the outline of our analysis. First, from the stock prices, we calculated Pearson's correlation coefficient and built the correlogram of the stock correlation. Then, we calculated the threshold and built three weighted networks. We also chose one threshold that estimates the network density, which we refer to as the threshold with adjusted density, and built one more weighted network. So, we will analyze four weighted networks for Section 4 and Section 5. We applied the network measures to analyze the networks' structure and used community detection on the networks to visualize and analyze the community structure of the networks.

2.1. Correlation network and threshold

A graph or a network can be represented by $G = (V, E)$, consisting of a set of nodes, V, and a set of edges, E. For a network with n nodes and m edges, the node set can be expressed as $V = \{v_1, v_2, v_3, \dots, v_n\} = |V|$ and the set of edges can be represented as $E = \{(v_i, v_j) | v_i, v_j \in V \text{ and } (v_i, v_j) \in E\} = |E|$ (Abdul Razak et al., 2019; Abdul Razak & Expert, 2021; Zhu et al., 2023). First, we calculate the Pearson correlation coefficient, ρ_{ij}, between stocks i and j to define the relationship between the stocks. Then, we build networks where each stock is represented by a node, and the correlation values between these stocks satisfying the threshold value are taken as edges. We build three weighted networks based on the correlation coefficients before (G19), during (G20), and after (G21) COVID-19. So, these networks would have the same set of nodes but different sets of edges, which are written as $G19 = (V, E_{19}), G20 = (V, E_{20})$, and $G21 = (V, E_{21})$. A weighted network is a type of graph in which each edge is assigned a numerical weight or value (correlation), representing the strength of the relationship between those nodes.

The threshold value, θ, for $G19$, $G20$, and $G21$ is set based on standardized values that approximate the sum of the mean and their standard deviation of the correlation coefficient, which is $\theta(G) = \bar{\rho}_{ij} + \sigma$. This is to maintain the level of consistency and standardize the correlation for each period. The mean and standard deviation for all pairs of stock correlation coefficients for each network is calculated using (1) and (2), respectively (Preis et al., 2012; Xia et al., 2018). We also build one weighted network based on a chosen threshold that estimates the density of the network for the period of crisis (2020); we named it $G20'$, which is written as $G20' = (V, E_{20'})$. Further discussions pertaining to why $G20'$ is needed are in later sections.

$$\bar{\rho}_{ij} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} \tag{1}$$

$$\sigma = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| \rho_{ij} - \bar{\rho}_{ij} \right|^2} \tag{2}$$

The adjacency matrix $A = (a_{ij})_{n \times n}$ of G is frequently used to represent a network (Bahari et al., 2023; Kostylenko et al., 2019). The element of the matrix a_{ij} is the correlation coefficient from using Pearson correlation coefficient, both positive and negative, that satisfies the threshold value θ and represents the edge weight between nodes i and j, as illustrated in Equation (3).

$$a_{ij} = \begin{cases} \rho_{ij}, & if\ \rho_{ij} \geq \theta \ \wedge\ \rho_{ij} \leq -\theta \\ 0, & otherwise \end{cases} \tag{3}$$

Components are portions of the network that are disconnected from each other. A giant component has the most nodes out of all the components. An isolated node has no connections to any other node in the network and represents a node that is completely separated from the rest of the network. For each network, we assessed the number of components, network density, average weighted degree, average weighted clustering coefficient, and network transitivity. Except for the components, all these metrics range from 0 to 1. Network metrics such as density and transitivity focus primarily on the presence or absence of connections in the network. These measures are useful for understanding the network's overall structure and connectedness. Thus, we use the unweighted version to measure these metrics. In contrast, weighted network measures, like average weighted degree and average weighted clustering coefficients, consider not only the presence of connections but also their strength (the weight of the edges between the nodes) when analyzing relationships between stocks in the network.

Density, d, quantifies the relationship between existing connections and the total potential connections within a network, offering a quick indicator of its connectivity. Density can be calculated using (4), where m is the number of edges and n is the number of nodes in the network. A higher density usually suggests a denser or more interconnected network, while a lower density indicates a sparser network.

$$d = \frac{2m}{n(n-1)} \tag{4}$$

Meanwhile, the average weighted degree $\langle s \rangle$ of the network represents the average of the sum of the weighted edges that each node has in the network, calculated using equation (5) where n is the number of nodes and s_i is the weighted degree or strength of a node i ($s_i = \sum_{j \in V} a_{ij}$). It provides a measure of the network's overall connectivity strength, indicating how many connections there are and their respective strengths, on average.

$$\langle s \rangle = \frac{1}{n} \sum\nolimits_{i \in V}^{n} s_i \tag{5}$$

Clustering measures the tendency for edges to form between neighboring nodes and reflects the clustering of nodes into tightly connected neighborhoods. The weighted clustering considers how much weight or intensity is present in the neighborhood of the node (Onnela et al., 2005). Thus, the average weighted clustering coefficient $\langle C \rangle$ of a network is calculated for each node by assessing the fraction of the intensity of its neighbors that are connected to each other (Saramäki et al., 2007). The network's overall average weighted clustering coefficient is an average of these local values; higher values signify a stronger tendency for nodes to form tightly knit clusters. The formula shown in (6) is from (Onnela et al., 2005; Saramäki et al., 2007) where n is the number of nodes, k_i is the degree of node i (the number of edges connected to a node), and the weight of edges is normalized by the maximum weight in the network, $\tilde{a}_{ij} = a_{ij}/\max(a)$.

$$\langle C \rangle = \frac{1}{n} \sum\nolimits_{i=1}^{n} \left(\frac{2}{k_i(k_i - 1)} \sum\nolimits_{j,h} \left(\tilde{a}_{ij} \tilde{a}_{jh} \tilde{a}_{hi} \right)^{1/3} \right) \tag{6}$$

Network transitivity, T, is also known as the global clustering coefficient. It is the ratio of the actual triangles in the network to all the potential triangles that could exist in the network. These potential triangles are identified based on the count of "triads", which consist of two edges sharing a common node. In simpler terms, it determines the likelihood that if node i is connected to node j and node j is connected to node h, then node i is directly connected to node h, which is also known as the triadic closure effect. Network transitivity offers insights into the presence of transitive relationships or "triangular" connectivity within the network; a higher transitivity value indicates a greater tendency for nodes to form these transitive relationships or triangles in the network. It is measured as in (7), where α is the number of triangles in the network, and β is the number of triads in the network.

$$T = 3\frac{\alpha}{\beta} \tag{7}$$

2.2. Modularity and Louvain algorithm

Modularity, Q, is a measure of the clustering or partitioning of a network into densely connected subgroups or modules. It measures the strength or quality of community grouping in the network. The higher the modularity (close to one), the stronger the connectivity of a community. A modularity value of more than 0.3 is a good benchmark for indicating significant community structure in a network (Clauset et al., 2004). Modularity is calculated using (8), where m is the number of edges, A_{ij} is the adjacency matrix of the network, k_i is the degree of i, and $\delta(i,j)$ is one if i and j are in the same community, otherwise is zero (Blondel et al., 2008; Girvan & Newman, 2002).

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(i,j) \tag{8}$$

We used the Louvain algorithm in the Network X package in Python to find communities in G19, G20, G20', and G21. The Louvain algorithm is based on a modulation optimization value (Blondel et al., 2008), and it is divided into two phases that are repeated. In the first step, every node within the network begins as its own distinct community. The first phase will then begin by removing a node i from its community and placing it in the community of its neighbor. The algorithm evaluates which community would be the best fit for each node i by assessing the modularity gain, ΔQ_i, when node i is relocated to different communities. If a node i relocation leads to an increase in ΔQ_i, it is reassigned to the community that maximizes this value; otherwise, its assignment remains unchanged. This step is performed for each node in turn. It will continue doing this for each node until no further improvements are possible, which is known as the local maximum of modularity. The equation in (9) gives ΔQ_i.

$$\Delta Q_i = \left[\frac{\sum_{in} + 2s_{i,in}}{2s} - \left(\frac{\sum_{tot} + s_i}{2s}\right)^2\right] - \left[\frac{\sum_{in}}{2s} - \left(\frac{\sum_{tot}}{2s}\right)^2 - \left(\frac{s_i}{2s}\right)^2\right] \tag{9}$$

Where $\sum_{in}$ is the sum of the weights of the edges inside the community of i, $\sum_{tot}$ is the sum of the weights of the edges incident to nodes in the community i, s_i is the sum of the weights of the edges incident to node i, $s_{i,in}$ is the sum of the weights of the edges from i to nodes in the community of i, and s is the sum of the weights of all edges in the network (Blondel et al., 2008).

In the second phase, the algorithm builds a new network with the communities found in the first phase as "super nodes". This super node forms a closed loop pointing to itself, representing the cumulative weight of the edges within the community. The weights of the edges connecting any two new nodes are determined by the sum of the weights of all edges linking the two original communities. The first steps were repeated until there were no more changes or maximum modularity was achieved. At the end, the optimal division of this network into communities will be formed.

We iterated the algorithm 100 times to ensure a robust result due to the randomness of node choice to calculate modulation gain in phase 1. For each node, we consider the mode of community that they have formed in each iteration, and then we calculate the Q of the resulting community of the network. We reported the standard deviation and the mean of Q from the $N = 100$ iterations. The mean of Q can be calculated as $\bar{Q} = \frac{1}{N}\sum_i^N Q_i$ for $i = 1,2,3, \dots, N$.

Finally, average internal edge density, $f(CS)$, is a scoring function for communities within the network that evaluates the quality of a community by providing a score that reflects its connectivity structure. Scoring functions are designed based on the concept that communities are sets of nodes that exhibit strong internal connections while maintaining fewer connections with nodes outside the community (Yang & Leskovec, 2015).We assessed the average internal edge density to measure the internal density of the community in the network (Rossetti et al., 2020). Consider a function $f(CS)$ that characterizes the community quality in the network. Let $CS \in V$ be the community obtained from the steps above, where n_{CS} is the number of nodes in CS, $n_{CS} = |CS|$, and m_{CS} is the number of edges in CS and $m_{CS} = |\{(u, v) \in E: u \in CS, v \in CS\}|$ (Yang & Leskovec, 2015). A score close to 1 indicates that the communities in the network have a high interrelationship level. The formula (10) calculates this score.

$$f(CS) = \frac{m_{CS}}{n_{CS}(n_{CS} - 1)/2} \tag{10}$$

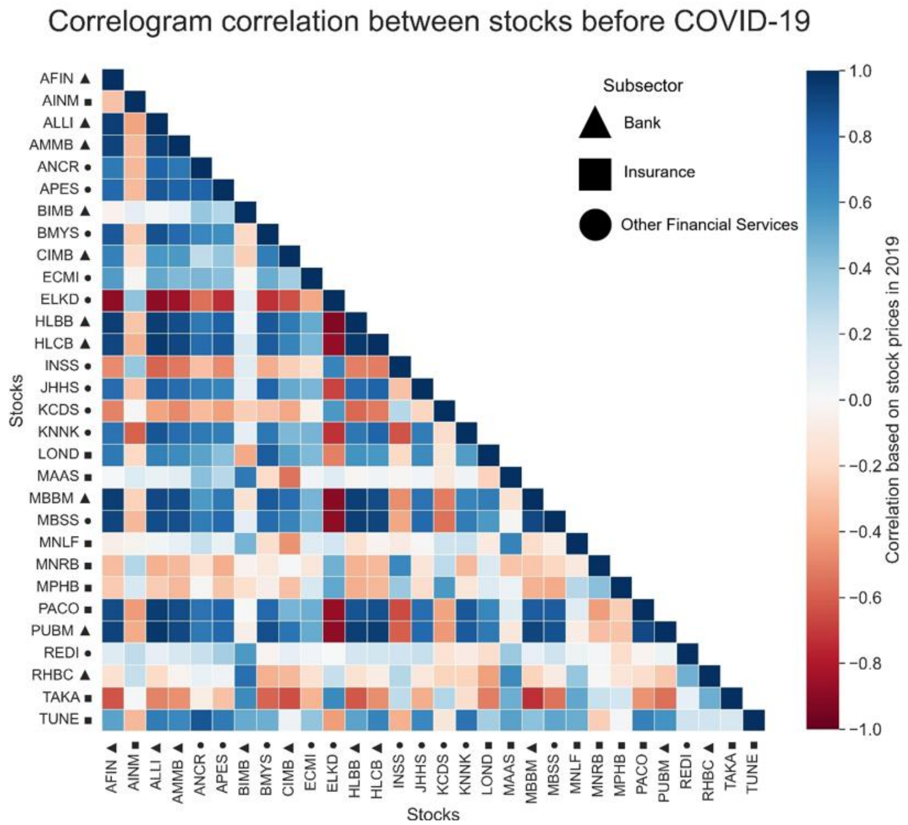
3. Correlogram of stock correlations

The Pearson correlation coefficient is used to delve into the dynamics of the stock market by examining the closing prices of stocks. This step is important to see how individual stocks move in relation to one another. It quantifies the strength (magnitude of the correlation) and direction (positive or negative correlation) of these relationships, aiding in the identification of underlying market trends and patterns. We depict the correlation in a correlogram as shown in Figure 2.

The data shows a significant increase in positive correlation during COVID-19, as shown in Figure 2(b), in stark contrast to the periods before COVID-19, as shown in Figure 2(a), and after COVID-19, as shown in Figure 2(c). The proportion of positive correlations out of all pairs before COVID-19 is 59.08%, during COVID-19 is 86.90%, and after COVID-19 is 59.54%, which clearly shows the sharp increase during a crisis or turbulent period, revealing a shift in how stocks move in relation to each other. Moreover, the strength of the positive correlation pairs also increases during COVID-19, which is depicted with a dark shade of blue. This is in line with several studies that have found a high number of positive correlations between the stocks during the COVID-19 period (Aslam et al., 2020; Bahari et al., n.d.; Dellow et al., n.d.; Memon, 2022). In addition, the high positive correlation among stocks during COVID-19 can lead to increased risk and volatility in the market (J. Wu et al., 2022). This can make it difficult for investors to diversify their portfolios and protect against market downturns. This trend is even more concerning when we consider the banking sector, where a high degree of interdependence suggests that the sector may be vulnerable to shocks and fluctuations in the financial markets.

Therefore, some investors seek negatively correlated stocks to diversify their portfolios and reduce risk (Bahaludin et al. 2022). By strategically incorporating negatively correlated stocks, investors can offset potential losses in one stock with gains in another, leading to a more resilient portfolio. Based on the correlogram in Figure 2, we can identify stocks with a negative correlation pair. Particularly during COVID-19, there are four stocks (APES, BMYS, JHHS, and KNNK; all stocks are in the "other financial services" subsector) that have the most negative correlation pairs compared to the others. Although generally, the strength of the negative correlation between stocks during COVID-19 is weaker compared to before and after COVID-19; investors may pick the stocks with a negative correlation to build a relatively balanced portfolio that is less vulnerable to market fluctuations.

(a)



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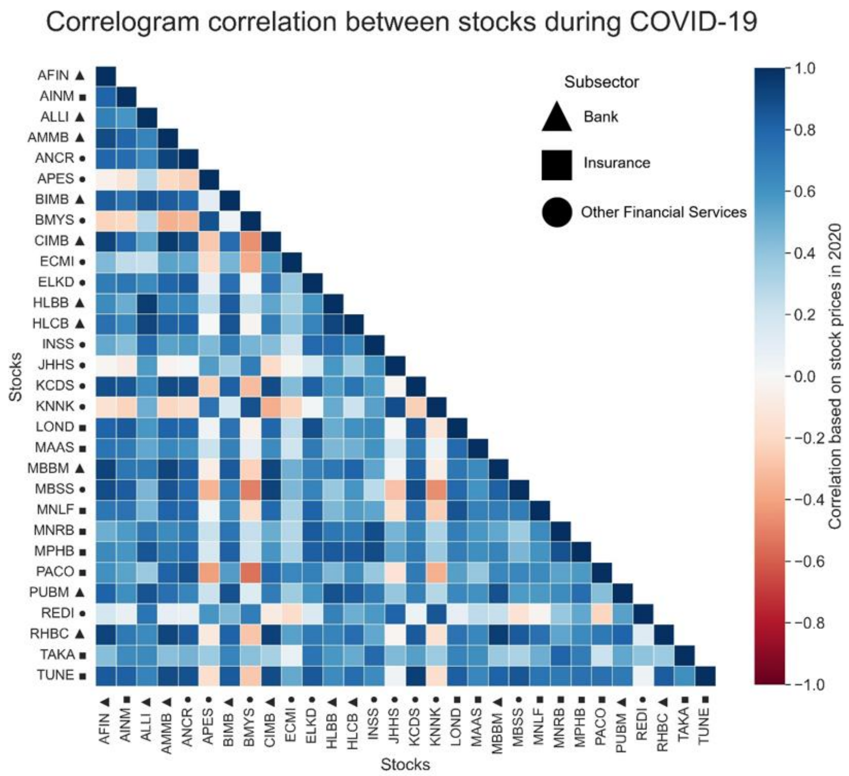
(b)



(c)

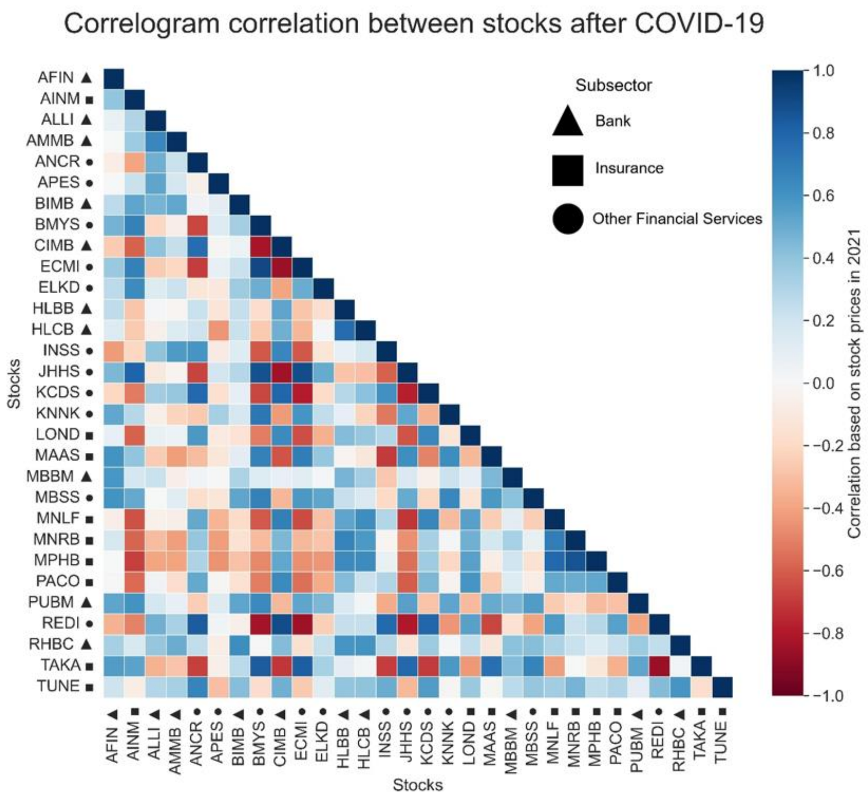


Figure 2. Correlogram of stock correlation (a) before, (b) during, and (c) after COVID-19. The x-axis and y-axis represent 30 stock indexes in the financial sector. Blue indicates a positive correlation and red indicates a negative correlation between stocks. The shape represents the subsector of the stock: a triangle is a bank, a square is an insurance company, and a circle is "other financial services" companies.

Table 2. Descriptive statistics of Pearson correlation coefficients of stock prices before, during, and after COVID-19.

Statistics of correlation	Before COVID-19	During COVID-19	After COVID-19
Mean, $\bar{\rho}_{ij}$	0.2052	0.5158	0.1284
Standard deviation, σ	0.5090	0.3557	0.4418
Maximum correlation value in P, $\max(\rho_{ij})$	0.9651	0.9545	0.9051
Minimum correlation value in P, $\min(\rho_{ij})$	−0.9147	−0.5399	−0.8661

Note:

1. Mean of correlation, $\bar{\rho}_{ij}$ and standard deviation, σ of correlation based on stock prices before, during, and after COVID-19.
2. Maximum, $\max(\rho_{ij})$ and minimum, $\min(\rho_{ij})$ correlation values mean the highest and lowest Pearson correlations between stocks i and j in a correlation matrix P.

Table 2 contains descriptive statistics of Pearson correlation before, during, and after COVID-19. The mean correlation before COVID-19 was 0.2052, indicating a moderate level of interdependence among stocks. During COVID-19, the mean correlation is 0.5158, suggesting a higher degree of association among these stocks; the mean correlation after COVID-19 is 0.1284. There are also several studies that show a tighter correlation between the stocks and a high mean of correlation during the crisis period (Lee & Nobi, 2018; Memon & Yao, 2019; Nobi et al., 2014; Xia et al., 2018; Yao & Memon, 2019).

Before the outbreak of COVID-19, the maximum correlation of 0.9651 was observed, indicating an exceptionally strong positive relationship during that period. In contrast, the minimum correlation during this period was −0.9147, signifying a strong negative relationship. During the COVID-19 pandemic there was a strong positive relationship with the highest correlation of 0.9545. The minimum correlation of −0.5399 has a weak relationship compared to the other periods. The financial industry kept developing as the global economy gradually recovered from the COVID-19 epidemic. The highest correlation recorded after COVID-19 was 0.9051, indicating a highly significant positive association. The minimum correlation after COVID-19, on the other hand, was −0.8611, indicating a very adverse association.

The performance of the stock market is closely intertwined with various economic, social, and geopolitical factors. The pandemic necessitated government actions like lockdowns, travel restrictions, and fiscal support to mitigate its effects (Azah et al., 2020; Keh & Tan, 2021; Shah et al., 2020). While these measures were imperative for public health and the economy, they injected considerable ambiguity into financial markets, leading to unparalleled levels of volatility and uncertainty (Haroon & Rizvi, 2020). Our results show that the stocks have high dependencies and little variation. This results in significant fluctuations in stock prices (Mamaysky, 2023), because the stock prices incorporate available information about a market at that particular time (Aldhamari et al., 2023), which reflects the prevailing market circumstances.

4. Network characteristics of G19 (before COVID-19), G20 and G20' (during COVID-19), and G21 (after COVID-19)

To investigate the network structure and connectivity of our data we use networks. The definitions of the metrics we use are explained in Section 2. Table 3 contains the network properties for the four networks representing the three periods, namely G19 (before COVID-19), G20 (during COVID-19), G20' (during COVID-19 with adjusted density), and G21 (after COVID-19), which were built based on different thresholds—except for G20', which we will explain later. Note that the threshold values themselves vary among the periods, aligning with the distinctive market conditions and dynamics of each period explained in the methods.

The highest threshold is 0.8715 for the G20, corresponding to the period during COVID-19. This high threshold is a result of the strong connectivity and increased association that have been seen throughout this turbulent period. Meanwhile, G21 has the lowest threshold, 0.5702, which may indicate a shift in market dynamics and less interconnectedness among the stocks. The threshold for G19 is 0.7142. This intermediate threshold illustrates the period before COVID-19 stock correlation patterns.

Thus, the number of edges within each of the three networks varies. These networks distinguish between edges with positive correlations, referred to as positive edges, and those with negative correlations, referred to as negative edges. Once we use the threshold, G19 has the highest number of edges, with 100 edges composed of 87 positives and 13 negative edges. G19 exhibits a high proportion, with 87% of its edges being positive. The number of edges in the G20 is 33, comprising 100% positive edges. This indicates an overwhelming synchronized movement and a strong tendency for stocks to move in tandem during uncertainties and market volatility brought about by the pandemic (Aslam et al., 2020; Memon, 2022; Xia et al., 2018). Lastly, G21 has 94 edges; 60 are positive and 34 are negative edges, displaying a proportion of 63% positive edges. The presence of both positive and negative edges in G21 reflects a more balanced and diverse correlation structure compared to the other periods, which may be reflective of a shift away from the pronounced market uncertainty experienced during the pandemic.

Table 3. The network properties for G19 (before COVID-19), G20 and G20' (during COVID-19), and G21 (after COVID-19).

Network properties	G19	G20	G20'	G21
Threshold, θ	0.7142	0.8715	0.8	0.5702
Number of edges, m	100	33	88	94
Number of positive edges, $\rho_{ij} \geq \theta$	87	33	88	60
Number of negative edges, $\rho_{ij} \leq -\theta$	13	0	0	34
Density, d	0.2299	0.0758	0.2023	0.2161
Average weighted degree, $\langle s \rangle$	5.5879	1.9903	5.0461	4.3219
Average weighted clustering coefficient, $\langle C \rangle$	0.4510	0.3863	0.5177	0.4010
Transitivity, T	0.8301	0.6429	0.6229	0.6564

Note: Network properties consist of a variety of metrics that depict the characteristics, structure, and behavior of a network.

1. The threshold value, θ, for $G19$, $G20$, and $G21$ is the sum of the mean and their standard deviation of the correlation coefficient from Table 2, which is $\theta(G) = \bar{\rho}_{ij} + \sigma$ based on the respective year. Meanwhile, $G20'$ was selected based on the resulting density that was comparable to $G19$ and $G21$.

2. The number of edges m is the count of the connections between stocks in the network.
3. The number of positive edges $\rho_{ij} \geq \theta$ is the count of connections with positive correlation.
4. The number of negative edges $\rho_{ij} \leq -\theta$ is the count of connections with negative correlation.
5. Density d is the ratio of the number of edges in a network to the maximum potential number of edges. High d shows a dense network.
6. The average weighted degree $\langle s \rangle$ is the average of the sum of the weighted edges (correlation between two stocks) that each node (stock) has in the network. A high $\langle s \rangle$ shows a high connection and strong correlations between the stock.
7. The average weighted clustering coefficient $\langle C \rangle$ is the fraction of the intensity of neighbors of nodes that are connected to each other indicating the tendency of nodes to form tightly knit clusters. A high $\langle C \rangle$ shows a high tendency for stocks to form a group.
8. Transitivity T is the ratio of the actual triangles (three nodes are connected to each other) in the network to all the potential triangles that could exist in the network. A high T suggests that the stocks are well connected in forming triangular connections in the network.

The density values provide quantitative measures of how densely connected the networks are during each period. G19 has a relatively significant portion of connections among nodes with a density of 0.2299, whereas G21 has a density of 0.2161 that is clearly higher than G20 (0.0758) but slightly lower than G19, with a comparable level of interconnectedness among nodes. G20 has a density that is different in magnitude from G19 and G21, thus leading to a sparser network compared to the other periods. Some have suggested that during the turbulent times of the pandemic, the low density could potentially reflect increased market volatility and unpredictability (Memon, 2022). However, this low density of G20 makes it less comparable with G19 and G21 since it captures less of the interaction due to the high threshold value (mean).

Therefore, utilizing just mean and standard deviations to obtain a threshold for building networks may not accurately capture the underlying patterns during crises, particularly when comparing networks with substantial density disparities. To mitigate this effect, we have chosen a threshold designed to yield a network density within a comparable range to those of G19 and G21. We shall refer to this approach as the threshold method with adjusted density and we named the network G20'. A threshold of 0.8 was selected to produce a network with a density comparable to that of the other networks, yielding a density of 0.2023. G20' has 88 more edges than G20. Notably, after thresholding, both networks only contain positive edges, implying that the negative correlations for 2020 during COVID-19 times are negligible.

In addition, the average weighted degree for G20 further highlighted this sparse characteristic, since G20 ($\langle s \rangle = 1.9903$) has a lower value than G19 ($\langle s \rangle = 5.5879$) and G21 ($\langle s \rangle = 4.3219$). This finding highlights the small number of nodes that have high correlation connected in the G20 network. G20' yields a high average weighted degree ($\langle s \rangle = 5.0461$), indicating that on average, its nodes experience strong connections, which is in line with the herding behavior expected during a crisis.

To further investigate the network's structure and connectivity, we look at the network's average weighted clustering coefficient and transitivity. The average weighted clustering coefficient explores the presence of cohesive groups (groups that contain nodes that are tightly connected to each other) within the network and shows that nodes in the network tend to have neighbors that are themselves connected to each other (Moody & Coleman, 2015).

G19 has a high average weighted clustering coefficient of 0.4510. This suggests that, before COVID-19, the network had a robust presence of small-scale substructures within the network and exhibited clustering coefficient behavior, indicating the nodes were tightly connected. G21 has a weighted average clustering coefficient of 0.4010, which is relatively comparable to G19. G20, on the other hand, has the lowest average weighted clustering coefficient of 0.3863, showing a decrease in the tendency for nodes to form such tight local clusters. It may indicate that G20 is more rigid to random node failures because of the low local weighted clustering coefficient structures that are less likely to maintain connectivity compared to other networks with higher average weighted clustering coefficients. However, this is probably the result of it being much less dense than the G19 as well as G20. In contrast, G20' exhibits the highest average weighted clustering coefficient with 0.5177; this reflects the presence of significant structural clusters within the network, indicating that its nodes tend to be densely connected and thus mirroring the expected herding behavior.

Transitivity measures the likelihood of nodes in a network being connected in triangles. G19 has the highest transitivity of 0.8301, implying that it is composed of well-connected nodes and has many stocks that are connected in triangles. G20 has a low transitivity of 0.6429 and G21 has a transitivity of 0.6564, slightly higher than G20, which may suggest a partial recovery in clustering behavior. Conversely, G20' exhibits the lowest transitivity, at 0.6229. This suggests that its low transitivity is not driven by the sparseness of G20 but rather reflects the weaker triadic closure and implies that the direct connection between nodes is more prominent in the network during COVID-19.

The network properties and connectivity patterns evolved significantly across the different periods, reflecting the impact of the COVID-19 pandemic. Before COVID-19 (G19), there was high connectivity and robust substructures. During the pandemic (G20), there was a notable increase in threshold and synchronization among stocks, resulting in sparse networks with fewer clusters. Adjusting the threshold (G20') created a denser network, emphasizing strong connections and structural clustering. After COVID-19 (G21), there was a shift toward reduced interconnectedness and more balanced correlation structures, indicating a move away from the pronounced market uncertainty experienced during the pandemic. In summary, these results portray the evolving dynamics of network properties and connectivity within correlation networks across different periods, emphasizing the impact of the COVID-19 pandemic on these structural patterns.

5. Community structure of G19 (before COVID-19), G20 and G20' (during COVID-19), and G21 (after COVID-19)

In the previous sections, we looked at the connectivity of the network and found that networks during COVID-19 reflected a period of increased market volatility and potential disconnections among the stocks, as shown by the average weighted degree, average weighted clustering coefficient, and transitivity in G20 and G20'. Therefore, in this subsection, we analyze the community structure for these four networks using the Louvain algorithm, to investigate the community's connectivity in the network.

The modularity value indicates the strength of community structures in the network, with values exceeding 0.3 serving as a benchmark for a good quality community structure in the network. Meanwhile, the average edge density provides further insights into the connectivity within the detected communities; a higher value represents a higher interrelationship.

Table 4 shows the community properties for G19, G20, G20', and G21. It shows that G19 has the lowest modularity of 0.0695 and the lowest average internal edge density of 0.1981, implying that G19 has a weaker tendency to form a significant community. Even though G20 has the highest modularity value of 0.4895, it holds a lower average internal edge density of 0.2957 compared to G20'. This value seems to be amplified in G21' despite the lower modularity. Both networks indicate a substantial increase in the strength of community structures indicated by Q during the COVID-19 pandemic.

This suggests that modularity is relatively robust to various threshold values and a high modularity value may be a good indicator of a crisis. This is similar to another study in which the network had the highest modularity during crises (Xia et al., 2018). The stocks were more likely to group into distinct communities with relatively strong internal connections, potentially reflecting the impact of market volatility and sectoral responses to the pandemic. G21 shows a modularity value of 0.2904 with the highest average internal edge density of 0.5455. Its modularity was lower than G20 and G20', suggesting that post-pandemic, the network maintained a moderate level of community structure. Communities within G21 had the densest internal connectivity, implying that the stocks within the same community were highly interconnected.

Table 4. Community properties for G19, G20, G20', and G21.

Community properties	G19	G20	G20'	G21
Modularity, $\bar{Q}$	0.0695	0.4895	0.3357	0.2904
Average internal edge density, $f(CS)$	0.1981	0.2957	0.4268	0.5455
Number of communities (exclude isolated nodes)	4	5	4	4
Isolated nodes	9	8	2	1

Note: Community properties consist of a variety of metrics and characteristics that depict the structure of a community formed in a network.

1. Modularity, $\bar{Q}$, is a value that indicates the strength or quality of the community grouping in the network. The higher the modularity, the higher the quality.
2. Average internal edge density, $f(CS)$, is a value that reflects the connectivity structure of a community. A high $f(CS)$ means that the connectivity between stocks in each community formed in the network is high.
3. The number of communities (excluding isolated nodes) is the count of distinct groups of nodes (stocks) formed by using the Louvain algorithm.
4. Isolated nodes refer to a node that is disconnected (has no edges) in the network.

The number of communities for G19, G20', and G21 is four, while G20 has the highest number of communities (excluding isolated nodes), which is five. The increased number of communities in G20 might be due to the higher threshold, thus potentially missing out on capturing the true dynamics. This highlights the importance of considering not only the threshold but also the density of the network. Interestingly, G20' produces the same number of communities as both G19 and G21. We visualize the communities of these networks in Figure 3. The nodes of each community are colored differently except for isolates, which are all gray. The color of the edges represents the sign and magnitude of the correlation; positive edges are blue and negative edges are red. Edge thickness represents the strength of relationships (the absolute value of correlation). The thicker red edge shows a strong negative relationship (closer to -1), while the thicker blue edge shows a strong positive relationship (closer to 1). The shape of the node represents the subsector of the stocks. Note that the presence of communities sharing identical colors across different networks does not invariably imply their equivalence as identical communities in all networks. While certain stocks may be consistently assigned the same color across the three networks, it is crucial to recognize that these stocks may still pertain to different communities within each network.

The community structures in G19, G20, G20', and G21, as shown in Figure 3(a), Figure 3(b), Figure 3(c), and Figure 3(d), respectively, reveal apparent patterns of how stocks are split up and grouped together. In G19, the largest community is green and comprises 10 nodes. Within this green community, we find a mix of financial entities, including five banks, one insurance company, and four “other financial services” companies. The strength of their connections is evident in the densely thick edges that interconnect these nodes, indicating a high level of correlation among its members. Next, the purple community consists of six members, including three banks, two insurance companies, and one “other financial service” company. The blue community has only two nodes, both belonging to banks. Lastly, the orange community has three nodes, consisting of one insurance company and two “other financial services” companies.

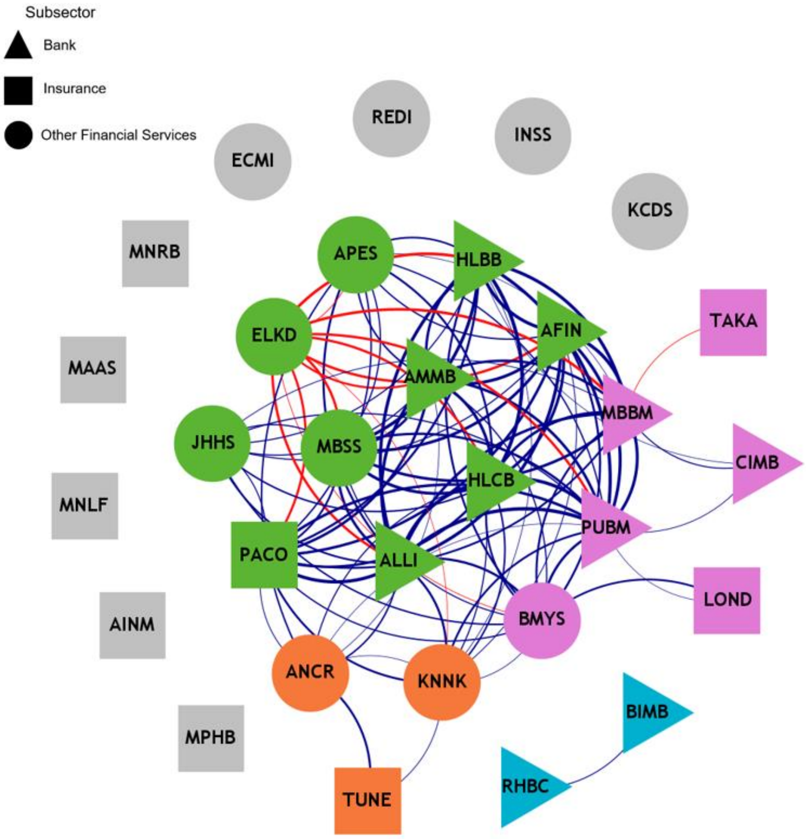
Meanwhile, G20 depicts several smaller communities. The largest community in this network is shown in blue and comprises 10 nodes, five banks, two insurance companies, and three “other financial services” companies. The orange community has four nodes, all belonging to banks. The green community consists of three nodes, all representing “other financial services” companies. Lastly, the red community consists of two nodes, one insurance company, and one “other financial service” company. G20 exhibits distinct community structures that are disconnected from each other, forming five components. This results in a high modularity value (0.4895) due to the strong separation between these communities.

However, G20’, with two components, produces four communities. It identifies three communities within one big component, yet still exhibits a considerably high modularity value, suggesting a significant underlying community structure. The largest community in G20’ is colored green and comprises 11 nodes, five banks, three insurance companies, and three “other financial services” companies. The orange community has six nodes, consisting of four insurance companies and two “other financial services” companies. The purple community also has six nodes, comprised of five banks and one insurance company. Lastly, the blue community has five nodes, and all are “other financial services” companies.

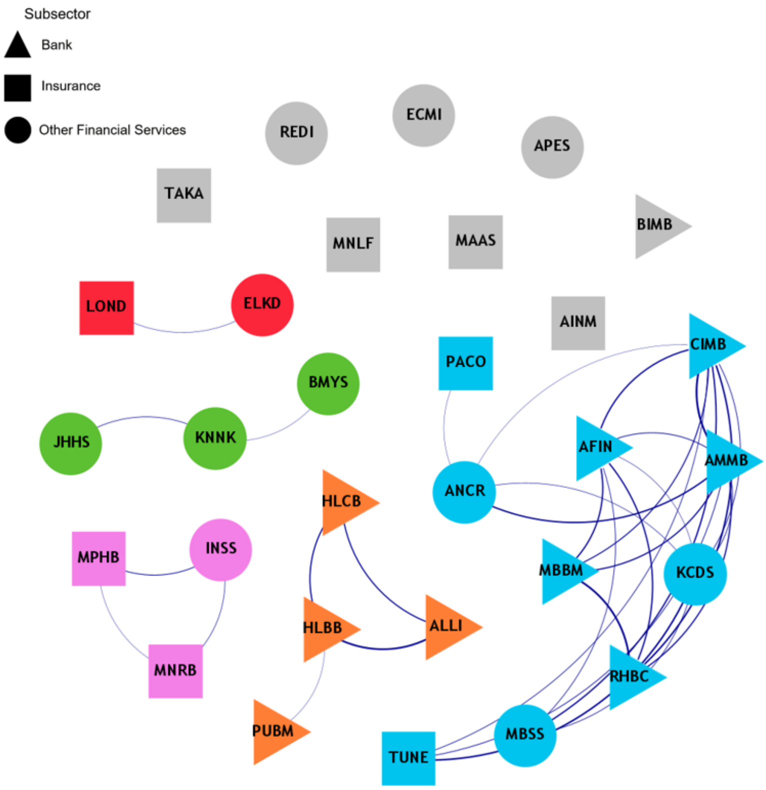
For G21, the largest community is the green one comprising 11 nodes, five banks, five insurance companies, and one “other financial services” company. The purple community has 10 nodes, including one bank, three insurance companies, and six “other financial services” companies. The blue community has only two nodes, representing banks. The orange community has six nodes, two banks, one insurance company, and three “other financial services” companies. These community structures in G21 reflect the evolving dynamics in the post-COVID-19 period, highlighting the interconnectedness of various financial entities within each community.

When stocks from the same subsector, such as banks, are the only ones that group together in the same community, it can indicate a concentration of risk. Particularly during market stress and turbulent periods, if adverse events or market shocks affect that subsector, all the stocks within that community could be simultaneously vulnerable, potentially leading to amplified losses. In our analysis, G20 exhibits two such homogenous communities, while G20’ shows one, highlighting the potential vulnerability of these sectors within the network. In addition, G20 and G20’ are only composed of positive edges, which makes the communities particularly sensitive to external factors affecting their subsector. They may respond similarly to news, economic trends, or regulatory changes, making them vulnerable to systemic risks (Hu et al., 2015). This community structure analysis provides valuable insights into how stocks are grouped during each period, potentially driven by sectoral similarities and shared market responses.

(a)



(b)



Continued on next page

(c)

(d)

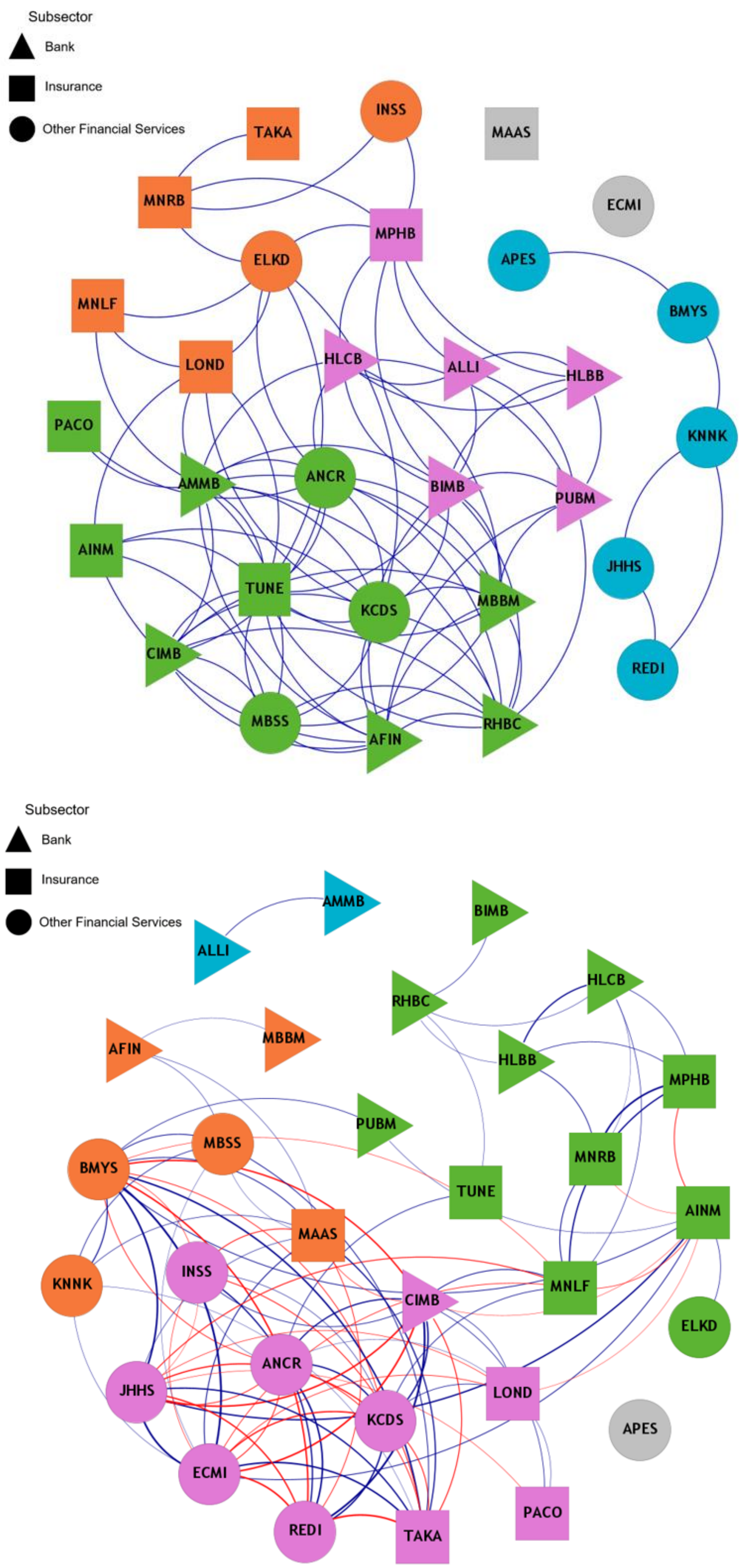


Figure 3. Communities in (a) G19, (b) G20, (c) G20', and (d) G21. The shape of the nodes represents the subsector of stocks, a triangle is a bank, a square is an insurance company, and a circle is an "other financial services" company. The color of the nodes represents their respective community given by the Louvain algorithm for community detection except for isolated nodes in gray.

6. Discussion

Our correlation analysis across three periods (before, during, and after COVID-19) reveals significant shifts in stock market dynamics. We observed a surge in positive correlations during the pandemic, tighter interdependence among stocks, and reduced correlation dispersion. These changes may have been influenced by the Malaysian government's implementation of several measures to support the financial sector during COVID-19, such as immediate cashflow relief and an economic stimulus package, including a loan moratorium (Bank Negara Malaysia, 2020). Since the relationship between the stocks can be seen from the price movement of the stocks, represented as correlations between the stocks, we use networks to visualize this relationship. We built four networks, which represent three periods.

The networks revealed dynamic changes through various network properties. Especially during the COVID-19 pandemic, we observed heightened connectivity and an overwhelming dominance of positive correlations in the network, indicating synchronized stock movements amidst market uncertainties. These shifts highlight the profound impact of the pandemic on stock market network dynamics and connectivity. It is crucial to highlight the limitations of the threshold method during market crises. While it efficiently generates sparse networks, it can inadvertently omit crucial connections, misrepresenting the underlying network structure and failing to accurately reflect the complex relationships between stocks in the market during COVID-19. Thus, the novelty of our method in choosing a threshold is that we suggest using density as a counterbalance to only using the mean and standard deviation.

The connectivity of the networks was analyzed using average weighted degree, average clustering coefficient, and transitivity as global metrics of the network. A high average weighted degree, specifically in the networks during COVID-19 that only have positive edges, indicates that many stocks are moving together in the same direction, which is a sign of increased systemic risk in the financial system. A higher average weighted clustering coefficient indicates tighter clusters with strong relationships, implying potentially amplified herding. During a crisis like the COVID-19 pandemic, a surge in the average weighted clustering coefficient supports the notion of herding behavior in such turbulent times (Huang et al., 2024) and has a positive effect on collective behavior in the financial market (Kumar & Deo, 2012). However, this metric alone does not fully capture the dynamics between stocks. Transitivity, a complementary concept, asks if their shared connections amplify correlations, potentially leading to information cascades or herding. High transitivity before and after crises suggests collective behavior within clusters, while low transitivity during COVID-19 for G20 and G20' indicates independent decisions based on shared economic factors; this metric is sensitive to COVID-19-induced crises (Miśkiewicz & Bonarska-Kujawa, 2022). Moreover, the cyclical nature of business activity, intertwined with the presence of economic uncertainty during crises, directly influences the observed patterns of herding behavior in stock returns (Ahn et al., 2024).

Modularity is used to evaluate the existence of structure or patterns within a network, as it measures the degree to which the network can be partitioned into distinct clusters or communities. In other words, it quantifies how well the nodes in a network can be grouped into subsets that are more densely connected with each other than with the rest of the network. The community structure during COVID-19 exhibited the highest modularity and it is high both for G20 and G20', indicating that it is somewhat robust to varying thresholds, indicating stronger community structures during the pandemic but also vulnerable to the risk posed by the pandemic.

7. Conclusions

In this research, we propose a new pipeline to analyze and visualize stock interdependencies and the dynamics of the financial crisis, i.e., COVID-19, with a particular emphasis on using correlation to obtain networks and modularity in the financial sector of Bursa Malaysia. Our correlation analysis across three periods (before, during, and after COVID-19) reveals significant shifts in stock market dynamics. By applying graph theory and network science to correlation-based networks and community analysis, we have unraveled significant insights into the evolving connectivity patterns among stocks, highlighting moments of crisis-induced turbulence and post-pandemic recovery. Moreover, for future research, we can include more sectors of the stock market in Malaysia to explore the network of other sectors and their communities, or cross-country comparisons of global correlations, networks, and communities. Additionally, delving deeper into the structural changes within communities and their implications for systemic risk management offers promising avenues for further investigation. This research aims to give a better understanding of the impact of financial crises, specifically COVID-19, on the network and community of stock markets in Malaysia.

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Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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