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FINANCIAL NETWORK DYNAMICS IN MALAYSIAN MARKETS: EXPLORING BURSA INDICES INTERDEPENDENCIES FROM 2019 TO 2023

(*Dinamik Rangkaian Kewangan di Pasaran Malaysia: Meneroka Kebergantungan Indeks Bursa dari 2019 hingga 2023*)

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ABSTRACT

This study examines the structural characteristics of financial networks within Malaysia's key indices from 2019 to 2023. It specifically analyzes returns and investigates the topological properties of these networks, focusing on how indices representing different sectors interact and evolve across time. By exploring these dynamics, the research aims to provide a deeper understanding of market behavior and the relative influence of each sector. Utilizing historical price data, the study calculates the returns for 13 distinct indices, employs the Triangulated Maximally Filtered Graph (TMFG) method to construct the financial networks. To capture the interrelationships and overall network structure, several important metrics are examined, including degree centrality, closeness centrality, betweenness centrality, clustering coefficients, and influence strength. The findings indicate that 2020 experienced the highest volatility, primarily attributed to the economic disruptions caused by the global pandemic. Notably, indices such as .KLCM (Consumer Products & Services) and .KLIP (Industrial Products & Services) consistently emerged as highly influential and well-connected within the network, highlighting their pivotal roles. Analysis of clustering coefficients reveals fluctuating levels of cohesion among sectors, with a notable decline in 2022, suggesting shifts in inter-sector dependencies. In summary, this study highlights the dynamic and ever-changing characteristics of financial networks, demonstrating how specific indices gain prominence over time. The findings provide a deeper understanding of market behavior and sectoral relationships as well as valuable input for enhancing risk management approaches and optimizing investment strategies.

Keywords: financial network; Bursa Malaysia; Bursa Indexes

ABSTRAK

Objektif kajian ini ialah mengkaji ciri-ciri struktur rangkaian kewangan dalam indeks utama yang tersenarai di Bursa Malaysia sepanjang tempoh 2019 hingga 2023. Secara khusus, kajian ini meneliti kadar pulangan dan mengkaji topologi rangkaian ini, dengan memberi tumpuan kepada bagaimana indeks yang mewakili pelbagai sektor berinteraksi dan berkembang dari masa ke masa. Dengan menganalisis dinamik ini, kajian ini bertujuan untuk memberikan pemahaman yang lebih mendalam mengenai tingkah laku pasaran dan pengaruh relatif setiap sektor. Dengan menggunakan data harga sejarah, kajian ini mengira pulangan untuk 13 indeks yang berbeza, dan menggunakan kaedah Triangulated Maximally Filtered Graph (TMFG) untuk membina rangkaian kewangan. Hubungan antara sektor dan struktur keseluruhan rangkaian dinilai menggunakan beberapa metrik kritikal termasuk keutamaan darjah, keutamaan kedekatan, keutamaan pengantara, pekali pengelompokan, dan kekuatan pengaruh. Penemuan kajian ini menunjukkan bahawa tahun 2020 mengalami risiko tertinggi, yang sebahagian besarnya disebabkan oleh gangguan ekonomi yang berpunca daripada pandemik global. Indeks seperti .KLCM (Produk & Perkhidmatan Pengguna) dan .KLIP (Produk & Perkhidmatan lndustri) sering muncul sebagai pempengaruh. Analisis terhadap pekali pengelompokan pula menunjukkan tahap kohesi antara sektor yang berubah-ubah, dengan penurunan ketara pada tahun 2022, mencadangkan perubahan dalam kebergantungan antara sektor. Kesimpulannya, kajian ini menekankan sifat dinamik dan berubah-ubah rangkaian kewangan, di mana indeks tertentu semakin berpengaruh dari masa ke masa. Hasil kajian ini memberikan pemahaman yang lebih mendalam mengenai tingkah laku pasaran dan interaksi antara sektor, tetapi juga memberikan input yang bernilai untuk memperbaiki amalan pengurusan risiko dan strategi pelaburan.

Kata kunci: rangkaian kewangan; Bursa Malaysia; Indeks Bursa

1. Introduction

Financial markets exhibit complex interdependencies where sectoral indices are influenced by external shocks, economic policies, and global events. Understanding these interconnections is crucial for investors, policymakers, and financial analysts to make informed decisions and mitigate systemic risks. One of the most significant disruptions in recent history, the COVID-19 pandemic, led to substantial volatility across financial markets, affecting correlations and sectoral dynamics (Dellow *et al.* 2024). The Malaysian stock market, represented by Bursa Malaysia, was no exception, it experienced heightened market synchronization during the crisis, followed by a gradual sectoral divergence during the recovery phase (Bahaludin & Syafiq 2021; Mehmood *et al.* 2021; Lee *et al.* 2020; Zuhud *et al.* 2022; Chia *et al.* 2020).

Traditional correlation-based methods for financial network analysis often fail to capture the intricate topological structures of market relationships, particularly during economic stress. To address this limitation, advanced network filtering techniques have been increasingly employed to construct robust financial networks. Among these techniques, the Triangulated Maximally Filtered Graph (TMFG) has been particularly useful in analyzing financial markets due to its ability to preserve key connections while reducing noise and maintaining a triangulated structure (Briola & Aste 2022).

TMFG is a powerful tool in financial network analysis as it constructs a maximally filtered graph while maintaining a triangulated structure, allowing for efficient computational processing and enhanced interpretability (Massara *et al.* 2016). Unlike other filtering techniques such as Minimum Spanning Trees (MST), which were introduced by Mantegna (1999) in financial networks, or Planar Maximally Filtered Graphs (PMFG), which were introduced by Tumminello *et al.* (2005), TMFG retains a higher level of information, preserving core financial relationships while eliminating weak correlations. This property is particularly advantageous in financial markets, where understanding systemic risk and market dynamics is essential (Barfuss *et al.* 2016). The ability of TMFG to extract relevant information while maintaining network coherence makes it an essential method for analyzing financial stability and sectoral dependencies (Tumminello *et al.* 2005)

Essentially, TMFG offers significant advantages over MST in financial network analysis. One of the key strengths of TMFG is its greater stability across time horizons. Unlike MST, which is highly sensitive to temporal fluctuations, TMFG maintains hierarchical consistency, allowing for more reliable tracking of financial relationships over extended periods. Additionally, TMFG ensures higher information retention by preserving a richer network structure. MST, by enforcing a tree-like topology, discards numerous significant correlations, which can result in the loss of critical insights into market interdependencies. Studies on network filtering techniques indicate that TMFG captures more comprehensive details about sectoral relationships and systemic risk factors that would otherwise be excluded using MST (Massara *et al.* 2016). Another advantage of TMFG is its enhanced representation of financial system hierarchies. MST tends to oversimplify financial connections, often failing to reflect the true hierarchical structure of asset relationships. TMFG, in contrast, provides a more robust and interpretable framework for analyzing the hierarchical organization of financial systems, allowing for a clearer understanding of market dynamics (Di Matteo *et al.* 2010).

A recent study by Shahzad *et al.* (2023) has considered the TMFG approach to investigate the structural properties of stock markets during the COVID-19 pandemic and evaluated systemic risk within the global energy sector from 26 countries covering the regions of the US, Europe, and Asia Pacific. Meanwhile, Liu and Yahyapour (2023) have examined the impact of COVID-19 on the Chinese medical stock market using the TMFG approach, which is computationally faster and more adaptable to enormous datasets. Moreover, empirical study on cryptocurrency networks has demonstrated that TMFG provides deeper understanding into evolving market structures across different time scales. In contrast, MST is more prone to abrupt structural shifts (Briola & Aste 2022). Additionally, the evidence shows TMFG helps track market structure evolution over time, identifying changes in correlations between assets.

Most of the existing research on financial networks has focused on major global markets such as the US, Europe and China. There are limited empirical studies that examine the Bursa index interdependencies in Malaysian financial markets based on the TMFG method. Therefore, this study attempts to map and analyse the network structure of 13 indices in Bursa Malaysia using the TMFG approach, particularly focused on the 2019 to 2023 timeframe. This period has witnessed notable market fluctuations and volatility due to the COVID-19 pandemic, particularly before, during, and after the COVID-19 crisis.

Furthermore, the motivation for this study stems from the need to systematically investigate the evolving interconnections of Bursa Malaysia's sectoral indices, particularly before, during, and after the COVID-19 crisis. While previous studies have examined financial networks using MST and PMFG, TMFG offers a more refined approach by ensuring high information retention and structural coherence (Cornaro 2023). Hence, by applying TMFG, this study aims to uncover the dynamic sectoral relationships and assess the resilience and adaptability of different industries in response to market shocks.

This study aims to achieve the following objectives. The first objective is to construct a financial network of Bursa Malaysia's sectoral indices using the TMFG and analyze its evolution from 2019 to 2023. Secondly, to examine the degree centrality, closeness centrality, clustering coefficient, and influence strength of each index, providing insights into sectoral resilience and systemic importance. Lastly, the study will assess the impact of major market disruptions, particularly the COVID-19 pandemic, on the network structure and sectoral dependencies.

The remainder of this paper is organized as follows: Section 2 presents the data and outline of the methodology. Section 3 documents the empirical results and discusses the implications of these findings for market stability and investment strategies. Finally, Section 4 concludes the study and potential directions for future research.

2. Data and Methodology

This study investigates the interconnections and dynamics of 13 sectoral indices listed on Bursa Malaysia, utilizing their daily closing prices retrieved from the DataStream financial database for the period spanning 2019 to 2023. The dataset spans from 2019 to 2023, a period marked by major financial events such as the COVID-19 pandemic and subsequent recovery. These events contributed to fluctuations in stock market networks, making this timeframe suitable for analysis (Gil-Alana & Monge 2020; Zhang *et al.* 2020; Güngör *et al.* 2021; Haroon *et al.* 2021; Riaz *et al.* 2020; Wielechowski & Czech 2022).

The indices are listed in Table 1. Data analysis was conducted in R programming, applying advanced network analysis techniques to uncover critical relationships among these indices.

2.1. *Data collection and preprocessing*

Closing price data for each index was gathered from DataStream. Before conducting network analysis, a series of preprocessing steps was applied to ensure data quality and consistency.

Table 1: Bursa Malaysia sectorial index series

No	RIC	Sector
1	.KLPL	Plantation Index
2	.KLCM	Consumer Products & Services Index
3	.KLPR	Property Index
4	.KLFI	Finance Services Index
5	.KLTE	Technology Index
6	.KLIP	Industrial Products & Services Index
7	.KLCT	Construction Index
8	.KLTC	Telecommunications & Media Index
9	.KLHC	Health Care Index
10	.KLUT	Utilities Index
11	.KLRE	REIT Index
12	.KLTP	Transportation & Logistics Index
13	.KLEN	Energy Index

Preprocessing involved checking for missing values, but no missing data were detected in the dataset. Therefore, no imputation or deletion was necessary. Additional steps included (ii) exclusion of non-trading days, (iii) normalization of log returns, and (iv) filtering indices with insufficient trading activity. It is important that the dataset excludes non-trading days (weekends and public holidays) to maintain consistency in return calculations.

2.2. *Log return calculation*

Daily log returns for each index were computed to measure percentage changes, offering a normalized scale for comparison.

$$s_i(t) = \ln \frac{m_i(t)}{m_i(t-1)} \tag{1}$$

where $m_i(t)$ is the price of stock i at time t.

2.3. *Correlation matrix computation*

Yearly correlation matrices were calculated to identify the degree of linear relationship between the indices. Pearson correlation was chosen due to its effectiveness in capturing co-movements between stock returns, a common approach in financial network analysis as seen in previous research (Mantegna 1999; Massara *et al.* 2016). The matrix served as the foundation for network construction by highlighting inter-index dynamics.

$$p_{ij} = \frac{\langle s_i s_j \rangle - \langle s_i \rangle \langle s_j \rangle}{\sqrt{(\langle s_i^2 \rangle - \langle s_i \rangle^2)(\langle s_j^2 \rangle - \langle s_j \rangle^2)}} \tag{2}$$

where i and j are indices and $\langle s_i \rangle$ is the average return of index i. The average return of indices i is calculated as:

$$\langle s_i \rangle = \frac{1}{T} \sum_{t=1}^{T} s_i \tag{3}$$

2.4. *Thresholding and adjacency matrix creation*

To build a meaningful financial network, we applied a thresholding approach using the average correlation matrix. This method effectively filters out spurious correlations while retaining the strongest connections between sectoral indices. By using the average correlation as a natural cut-off, the network structure becomes more interpretable without losing key relationships. The results confirm that this simplification enhances clarity while preserving the core structure of the network (Massara *et al.* 2016)

While thresholding does lead to some loss of information, it is a necessary trade-off to focus on stronger financial linkages that drive market behavior. Then, the adjacency matrix creation is based on the correlation values, where values below the average threshold were set to zero, while higher values were binarized to 1 (Nobi *et al.* 2014; Liang *et al.* 2024).

2.5. *Network construction using TMFG*

The Triangulated Maximally Filtered Graph (TMFG) algorithm was employed via the NetworkToolbox package, following the seminal works by Bahaludin *et al.* (2024), to construct a robust financial network. This approach retained significant connections while ensuring a triangulated structure. In the constructed financial network, nodes represents the indices and the edges represent correlations between index's returns, indicating co-movement patterns that reflect market structure.

2.6. *Centrality and clustering analysis*

Several key metrics were calculated to analyze the role and importance of each index (node) within the network:

2.6.1. *Degree centrality*

This metric quantified the number of direct connections for each index, offering insights into connectivity levels. The computation of degree centrality is as follows:

$$C_{Degree}(i) = \frac{\sum_{j}^{N} A_{ij}}{N-1} \tag{4}$$

where $A_{ij} = 1$ if a link exists between stock index i and stock index j and 0 otherwise. N represents the total number of nodes (indices) in the network.

2.6.2. *Closeness centrality*

This metric assessed the proximity of each index to others, reflecting network accessibility. The calculation of closeness centrality is as follows:

$$C_{closeness}(i) = \Big[\sum_{j=1}^{N} d(i,j)\Big]^{-1} \tag{5}$$

where $d(i,j)$ is the shortest path between stock index i and stock index j. To determine $d(i,j)$, we construct a financial network where nodes represent stock indices, and edges represent relationships based on their correlation. The edge weights are defined as:

$$d(i,j) = 1 - p_{ij} \tag{6}$$

where p_{ij} is the Pearson correlation coefficient between the log returns of stock indices i and j. A higher correlation implies a shorter distance, reflecting a stronger relationship between the indices. The shortest path between two indices is computed using Dijkstra's algorithm, which finds the minimum cumulative distance between nodes in a weighted graph. If an index pair lacks a direct connection due to thresholding, the algorithm finds the shortest indirect path or assigns an infinite distance if no path exists. This ensures that closeness centrality reflects the most efficient routes within the financial network, capturing the structural importance of each index.

2.6.3. *Clustering coefficient*

This metric evaluated the cohesiveness of an index's immediate network, revealing localized interrelations. The clustering coefficient ranges between 0 and 1, representing the proportion of actual connections between a node's neighbours to the maximum possible connections in the network. A higher clustering coefficient indicates that the node holds greater significance within the network. Considering a node i connected to k_i other nodes via k_i edges, the maximum number of possible edges between these neighbours is given by $k_i(k_i - 1)/2$. If E_i represents the actual number of edges among these neighbours, the clustering coefficient for node i is defined accordingly. The clustering coefficient can be calculated as follows:

$$C_i = \frac{2E_i}{k_i(k_i - 1)/2} \tag{7}$$

and the average clustering coefficient C of the network is:

$$C_i = \frac{\sum_{i=1}^{N} C_i}{N} \tag{8}$$

where N represents the total number of nodes (indices) in the network.

2.6.4. *Influence strength*

This metric combines degree centrality and edge weights to measure the overall influence of an index within the network as calculated as follows:

$$s_i = \sum_{j \in V} a_{ij} \tag{9}$$

where a_{ij} is the weight of the edge between nodes i and j, and V is the set of all nodes in the network. This measure captures the total strength of connections a node has by summing up the edge weights associated with it, providing insights into its relative importance within the network.

3. Results and Discussion

3.1. *Correlation analysis*

Figure 1 illustrates the correlation matrices for 13 sectoral indices on Bursa Malaysia from 2019 to 2023, capturing the dynamic interdependencies among the indices. The heatmaps utilize a color gradient where darker blue signifies stronger positive correlations, red represents negative correlations, and lighter shades indicate weak or no correlation. The correlation values range from -1 to 1, where positive values indicate co-movement in the same direction, negative values indicate opposite movement, and values near zero suggest weak or no correlation.

In 2019, moderate positive correlations were observed, particularly among the KLCT, KLCM, and KLUT indices. This suggests a stable market environment with limited clustering or extreme relationships, reflecting a segmented yet balanced behavior across sectors. However, the COVID-19 pandemic in 2020 significantly disrupted the market, leading to heightened positive correlations among several indices. This synchronization highlights the collective response of financial markets to the global economic crisis, driven by policy interventions and heightened uncertainty.

These findings align with the observations made by Dellow *et al.* (2024), who documented similar impacts of past major events on network structures within financial markets. By 2021, the correlation landscape showed greater variability. Strong positive correlations persistied in certain indices, such as KLCT and KLUT, while negative correlations began to emerge, particularly involving KLEN. This reflects the uneven recovery dynamics across sectors, as the industrial sector emerged as a primary transmitter of price return shocks, while the utilities sector was the dominant receiver (Ahmad *et al.* 2023).

In 2022 and 2023, overall correlations weakened, leading to fewer intense positive relationships and more dispersed connections. This reduction in market cohesion indicates that sector-specific factors are gaining prominence as the market transitions from synchronized dynamics of the pandemic-era to a more normalized and independent environment. These findings emphasize the importance of understanding the evolving network structure of financial indices, which provides critical understanding for investment strategies and policy interventions.

3.2. *Network analysis*

The network graphs in Figure 2 depict the financial network structure of 13 sectoral indices listed on Bursa Malaysia from 2019 to 2023. Each node represents an index, with edges indicating significant correlations derived from the correlation matrix; edge thickness reflects the strength of these relationships, while isolated nodes signify weaker or non-significant correlations in a given year.

In 2019, the network is relatively dense, with most indices forming a well-connected structure, suggesting a stable market environment characterized by moderate interdependence among sectors. The .KLHC (Healthcare Index) remains largely uncorrelated with other sectors, indicating minimal or no significant correlation within the broader market. This finding aligns with Mehmood *et al.* (2021), who observed that the healthcare sector exhibited weaker connections with other industries, suggesting a lower degree of synchronization with overall market trends. This pattern shifts in 2020, where the network becomes more centralized and clustered around key indices such as KLCM, KLPR, KLIP, KLCT and KLUTKLCM, KLPR, KLIP, KLCT and KLUT. This heightened connectivity reflects synchronized market movements during the COVID-19 pandemic, as global uncertainty and coordinated policy measures led to increased correlations across sectors (Bahaludin *et al.* 2024; Bahari *et al.* 2024)

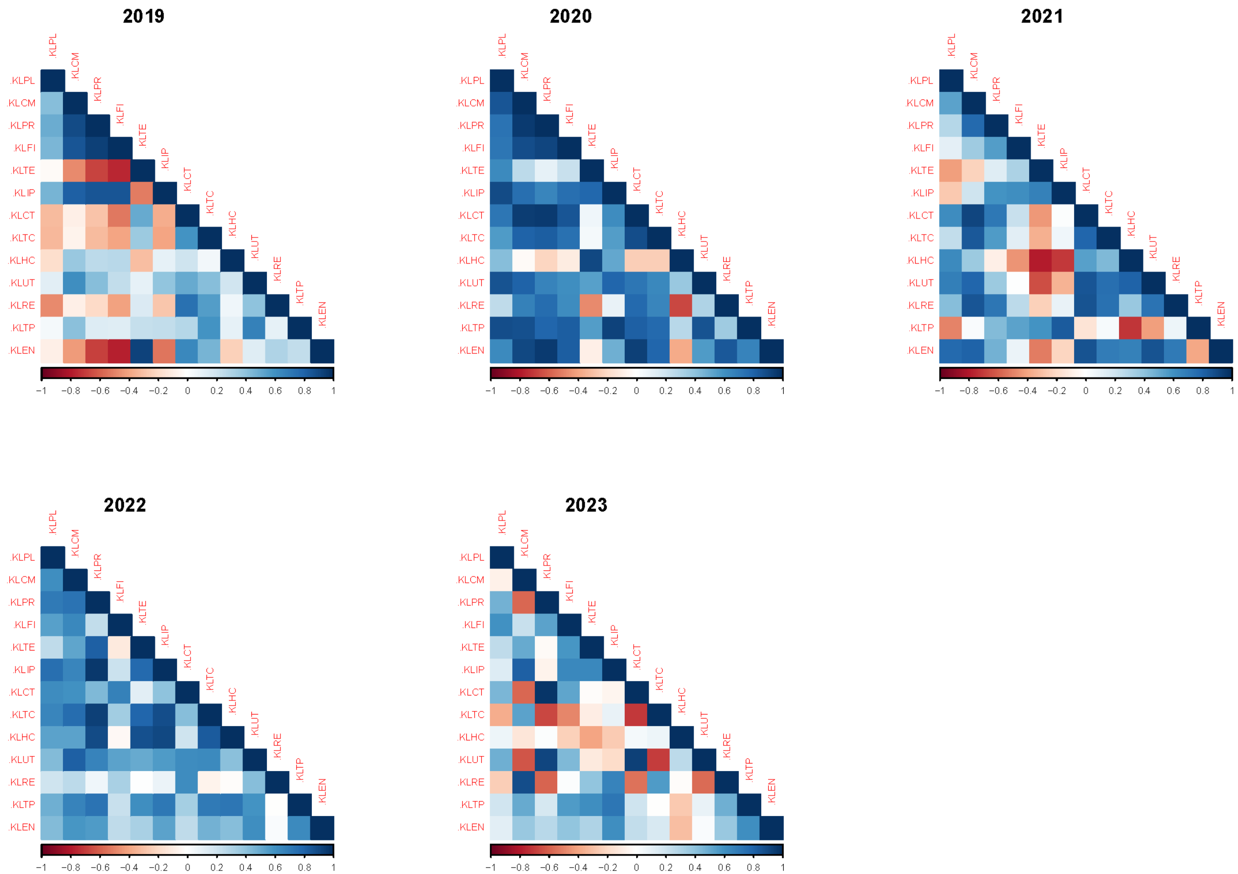

Figure 1: The correlation matrices for 13 sectoral indices on Bursa Malaysia from 2019 to 2023

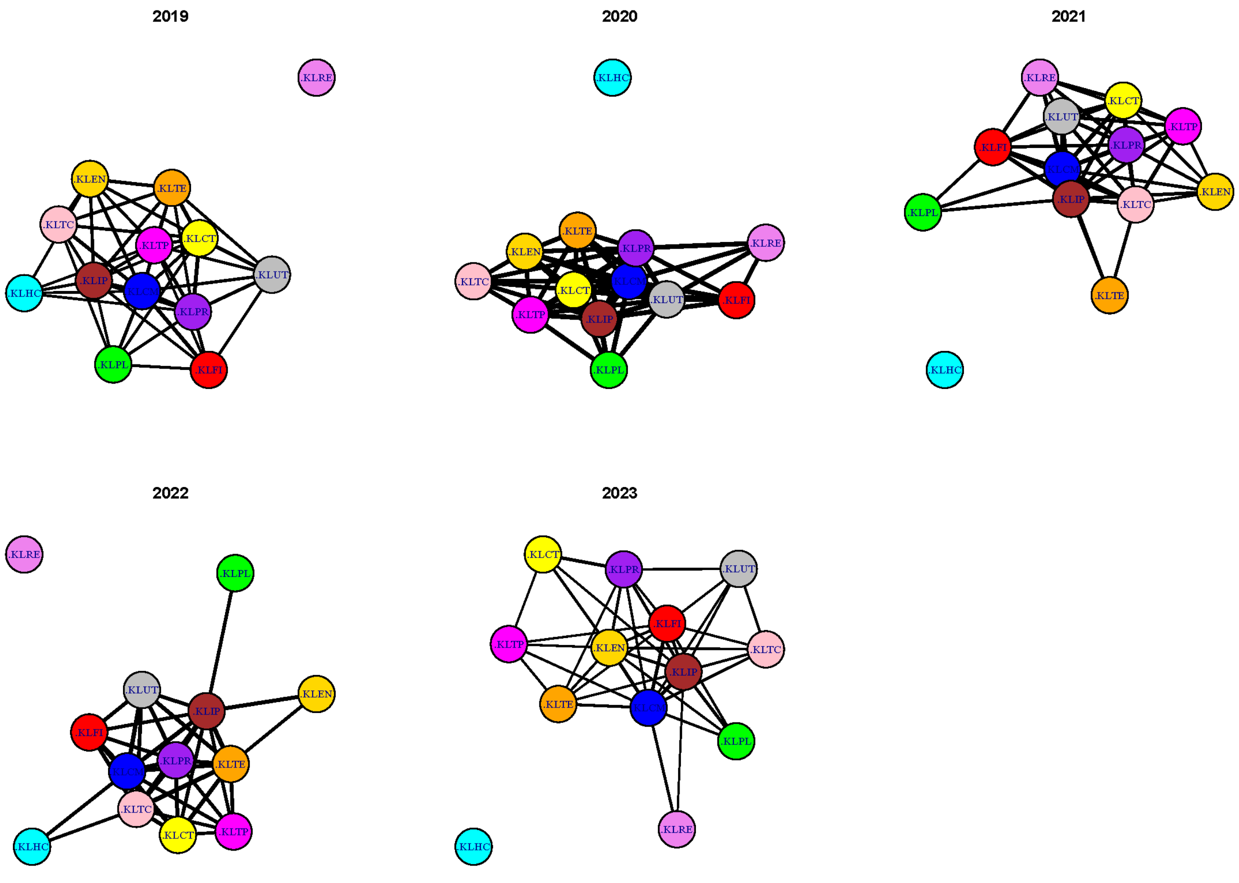

Figure 2: The financial network structure of 13 sectoral indices listed on Bursa Malaysia from 2019 to 2023

By 2021, the network structure becomes more fragmented, with fewer connections between indices, suggesting greater differentiation in sectoral performance. Some indices, such as KLHC and KLTE, demonstrate distinct recovery dynamics. While KLTE showed increased independence through selective re-linking, KLHC remained structurally isolated in 2020 and 2021, reflecting the continued disconnection of the healthcare sector due to pandemic-induced constraints and policy shifts. This fragmentation continues into 2022, with the network becoming less connected overall, and several indices forming weaker or isolated links. This reduced cohesion aligns with findings that sector-specific drivers gained prominence in the post-pandemic recovery phase, leading to diversified market behavior (Lee *et al.* 2020). In 2023, the network stabilizes but remains sparse, indicating that sectors are operating more independently. This sparse structure reflects a normalized market environment, where correlations have diminished, and sectoral dynamics are driven by individual economic factors rather than broad market synchronization. The evolution of the financial network across these years highlights the interplay between external shocks, recovery, and normalization, providing critical insights into market interdependencies and sector-specific resilience.

3.3. *Topological properties of the network*

3.3.1. *Degree centrality*

Table 2: Degree centrality

No	RIC	2019	2020	2021	2022	2023
1	.KLPL	6	5	3	1	4
2	.KLCM	11	11	11	9	10
3	.KLPR	9	10	9	8	7
4	.KLFI	6	6	8	6	9
5	.KLTE	8	7	3	8	6
6	.KLIP	10	10	11	10	10
7	.KLCT	9	10	9	7	4
8	.KLTC	6	6	9	9	5
9	.KLHC	5	0	0	2	0
10	.KLUT	6	10	8	6	5
11	.KLRE	0	4	7	0	2
12	.KLTP	9	9	8	6	5
13	.KLEN	7	8	6	2	9

Degree centrality is another important indicator of network analysis which helps us to understand how different parts of an economy are affected by crises. It works by determining the extent of direct links to other indices an index has as part of the financial network. High degree centrality is suggestive of a sector that can still maintain good linkage with other sectors, and relative power and degree of centrality within the index. But centrality that is low would mean that an economy is operating in relative isolation, which illustrates a weakness in the economy's network in times of uncertainty. Most indices experienced an upward degree centrality shift amidst the 2020 COVID-19 pandemic except for the Healthcare Index (.KLHC) which fell to zero as depicted in Table 2. Noticeable synchronous market movement during crises is attributable to shocks in world economies. The use of correlation is more often appropriate in economics as sectorial movements are often associated with correlated shocks. Persistent high degree centrality was experienced by indices iincluding Industrial Products & Services (.KLIP) and Consumer Products & Services (.KLCM) with the peak hit in 2020 and 2021 (Bahari *et al.* 2024).

Sectors such as healthcare (.KLHC) and real estate (.KLRE) exhibited low and fluctuating centrality, signaling their reduced integration within the broader market network. This isolation made them particularly vulnerable during economic disruptions, as they lacked the interconnections necessary to leverage broader market stability. Research suggests that sectors with higher centrality recover more quickly and play a greater role in enhancing overall market resilience, while more isolated sectors struggle to adapt to widespread financial shocks (Dellow *et al.* 2024). A clear example of this pattern emerged during the COVID-19 pandemic, when Real Estate Investment Trusts (REITs), Transportation & Logistics, and Property sectors suffered steep declines due to social distancing measures, business closures, and movement restrictions that disrupted economic activity and supply chains (Mehmood *et al.* 2021). In contrast, while the healthcare sector demonstrated financial resilience due to increased demand for medical services and healthcare-related investments (Mehmood *et al.* 2021), our network analysis reveals that it remained structurally isolated during 2020 and 2021. This is reflected in its low degree and closeness centrality, as well as a lack of meaningful connectivity with other sectors (Hing *et al.* 2022). The persistent disconnection of the Healthcare Index (.KLHC) highlights its minimal role in propagating financial signals across the broader market network during this period, underlining the importance of enhancing its integration into the financial system.

By 2023, declining centrality across most indices, except for .KLCM and .KLIP, reflects reduced market cohesion as sector-specific factors began to dominate. This transition underscores the importance of understanding degree centrality as a measure of both resilience and vulnerability. High centrality indices play a pivotal role in maintaining market stability, particularly during crises, while low centrality indices highlight areas of fragility that require targeted strategies for strengthening sectoral linkages and enhancing overall resilience.

3.3.2. *Closeness centrality*

Table 3: Closeness centrality

No	RIC	2019	2020	2021	2022	2023
1	.KLPL	1.8360	0.9830	1.3419	0.9775	1.9072
2	.KLCM	2.2352	1.3837	1.8632	1.4909	2.4837
3	.KLPR	2.0231	1.3078	1.7851	1.4641	2.2812
4	.KLFI	1.8518	1.0617	1.7531	1.3666	2.5927
5	.KLTE	1.9531	1.0888	1.3210	1.4086	2.3132
6	.KLIP	2.3058	1.2765	1.9495	1.7172	2.6068
7	.KLCT	1.9773	1.3241	1.7965	1.4492	1.9812
8	.KLTC	1.7441	1.0724	1.8178	1.5095	2.0622
9	.KLHC	1.7970	NA	NA	1.0047	NA
10	.KLUT	1.7203	1.3406	1.6645	1.3369	2.1487
11	.KLRE	NA	0.9289	1.6236	NA	1.7112
12	.KLTP	2.1988	1.2630	1.7518	1.4479	2.1659
13	.KLEN	1.8675	1.2058	1.6629	1.0187	2.4448

Closeness centrality is a critical metric in evaluating sectoral recovery, as it quantifies the average shortest path from a specific index to all others within a financial network. Higher closeness centrality signifies greater accessibility and influence, suggesting that a sector is strategically positioned to connect with and integrate into the broader financial ecosystem. During recovery periods, such as the post-COVID-19 phase, indices with higher closeness centrality exhibit greater resilience and adaptability, often serving as stabilizing anchors within the financial network.

According to Table 3, the Property Index (.KLPR) and Technology Index (.KLTE) consistently demonstrated relatively high closeness centrality throughout the analysis period, reaching peak values of 2.281 and 2.313, respectively, in 2023. This consistent centrality underscores their pivotal role in influencing other sectors and contributing to overall market stabilization during recovery phases. Their strong network integration allowed these indices to act as hubs, facilitating the distribution of positive market trends and bolstering broader sectoral recovery.

In contrast, sectors with low or fluctuating closeness centrality, such as the Healthcare Index (.KLHC), experienced slower recovery rates. The absence of centrality data for .KLHC in 2020 and 2021 highlights its isolation and diminished influence during those years. This trend aligns with the disruptions in the healthcare sector caused by the COVID-19 pandemic, which led to supply chain constraints, reduced elective medical procedures, and a decline in private healthcare spending (Hing *et al.* 2022). However, its re-entry into the network in 2022 (1.005) marks the gradual reintegration of previously isolated sectors into the financial system as markets normalized. This progression underscores the importance of improving closeness centrality for sectors aiming to recover, as enhanced connectivity enables greater benefits from inter-sectoral synergies.

Overall, the findings highlight that sectors with higher closeness centrality are better equipped to navigate and recover from market disruptions, leveraging their strong connections and influence within the financial network. Conversely, sectors characterized by isolation must prioritize strategies to enhance their centrality, thereby strengthening their resilience and adaptability in the face of future crises.

3.3.3. *Clustering coefficients*

Table 4: Clustering coefficients

No	RIC	2019	2020	2021	2022	2023
1	.KLPL	0.8000	1.0000	1.0000	0.0000	1.0000
2	.KLCM	0.6364	0.6727	0.6364	0.6944	0.5333
3	.KLPR	0.6944	0.7333	0.8611	0.8571	0.7143
4	.KLFI	0.8000	0.8667	0.7857	0.9333	0.6389
5	.KLTE	0.7857	1.0000	1.0000	0.7143	0.8667
6	.KLIP	0.6667	0.7556	0.6364	0.5556	0.5111
7	.KLCT	0.7222	0.7556	0.8611	0.9048	0.6667
8	.KLTC	0.8667	1.0000	0.7500	0.6944	0.9000
9	.KLHC	0.9000	0.0000	0.0000	1.0000	0.0000
10	.KLUT	0.8667	0.7111	0.9286	0.9333	0.9000
11	.KLRE	0.0000	1.0000	0.9524	0.0000	1.0000
12	.KLTP	0.7222	0.8333	0.8929	1.0000	0.7000
13	.KLEN	0.8095	0.9286	1.0000	1.0000	0.6111

The clustering coefficient evaluates the extent to which nodes in a network form tightly interconnected clusters, providing a measure of cohesion within a financial system. High clustering coefficients indicate that a sector is embedded within a robust sub-network, promoting resilience during economic disruptions by enabling efficient information flow and risk-sharing among interconnected entities. Conversely, low clustering coefficients suggest network isolation, which can hinder a sector's ability to recover promptly from external shocks. During the COVID-19 pandemic, sectors with higher clustering coefficients exhibited greater resilience, as their interconnectedness facilitated the absorption and diffusion of economic shocks, as highlighted in prior studies (Cornaro 2023).

Table 4 presents the clustering coefficients of 13 sectoral indices on Bursa Malaysia from 2019 to 2023, offering insights into the cohesion of their respective sub-networks. A clustering coefficient of 1.000 signifies a perfectly interconnected sub-network, whereas lower values point to weaker local connectivity. The trends reveal that external shocks, such as the

COVID-19 pandemic, and subsequent recovery phases significantly influenced the structure of sectoral networks. Notably, certain indices achieved perfect clustering coefficients during the study period, including .KLPL (Plantation) and .KLTE (Technology), which recorded coefficients of 1.000 in both 2020 and 2021. These results underscore their pivotal roles within tightly interconnected sub-networks during a period of heightened market synchronization. Similarly, .KLRE (REIT) displayed strong clustering in 2021 (0.952), reflecting improved integration into the financial network during the recovery phase.

The market uncertainty induced by the pandemic in 2020 drove synchronized sectoral behavior, resulting in elevated clustering coefficients for several indices, including .KLPL and .KLTE. This trend indicates a temporary increase in network cohesion, as sectors responded uniformly to external shocks, a pattern consistent with global studies of financial networks during crises (Bahari *et al.* 2024). However, some sectors, such as Property (.KLPR) and Construction (.KLCT), which initially exhibited steady clustering coefficients, experienced a decline by 2023 (0.714 and 0.667, respectively). This decline reflects weakening cohesion within their local networks, likely driven by sector-specific challenges and a reduction in market interdependencies as recovery progressed.

The Healthcare Index (.KLHC) exhibited intermittent clustering throughout the period, with high coefficients in 2019 (0.900) and 2022 (1.000), but zero clustering in 2020, 2021, and 2023. These fluctuations underscore its sporadic integration into the financial network, exposing vulnerabilities to market disruptions and challenges in maintaining consistent linkages with other sectors. Conversely, the Energy Index (.KLEN) demonstrated consistent performance, maintaining relatively high clustering coefficients throughout the study period, peaking at 1.000 in 2021 and 2022.

By 2023, clustering coefficients for indices such as .KLPL, .KLTE, and .KLRE remained high, reaffirming their roles in well-integrated sub-networks. However, other sectors, such as .KLPR and .KLCT, exhibited reduced cohesion, reflecting a fragmented and increasingly independent post-pandemic market environment. These findings emphasize the dynamic nature of sectoral networks, with clustering coefficients revealing the underlying cohesion and interdependencies across indices. Indices such as .KLPL, .KLTE, and .KLEN demonstrated resilience and maintained strong clustering, highlighting their capacity to adapt to disruptions. Conversely, sectors like .KLHC, with intermittent connectivity, underscored the vulnerabilities present in less cohesive networks during times of market turbulence and recovery.

3.3.4. *Influence strength*

Table 5: Influence strength

No	RIC	2019	2020	2021	2022	2023
1	.KLPL	13.6203	17.1015	3.9254	0.4847	5.5160
2	.KLCM	54.1333	87.4442	64.9425	47.1529	38.4580
3	.KLPR	36.1372	70.7157	39.7273	35.5711	16.8907
4	.KLFI	14.4501	23.6636	30.0004	18.6494	26.9333
5	.KLTE	27.9217	33.8637	3.7347	36.6812	11.1706
6	.KLIP	40.4801	73.0782	62.0658	53.7624	36.6394
7	.KLCT	36.7835	70.7810	39.5611	25.3997	5.5148
8	.KLTC	15.0816	23.0662	38.9338	46.0549	8.4144
9	.KLHC	8.9705	0.0000	0.0000	1.83223	0.0000
10	.KLUT	15.3132	69.5751	31.8286	19.8809	7.6994
11	.KLRE	0.0000	10.6027	23.4763	0.0000	1.2999
12	.KLTP	31.4724	54.6714	28.9661	17.3579	7.3958
13	.KLEN	20.5635	42.4324	14.7362	2.0222	28.7132

Table 5 highlights the shifting relative strength of 13 sectoral indices in Bursa Malaysia from 2019 to 2023, showcasing their evolving roles within the financial network during and after crises. Influence strength, calculated from an index's degree centrality and edge weights, measures both the number and intensity of connections, providing an overall impact score for each index.

A significant surge in influence strength was observed in 2020 for several indices, notably .KLPR (Property) and .KLCT (Construction), which reached values of 70.716 and 70.781, respectively. These indices were pivotal during the pandemic, likely benefiting from policies supporting infrastructure and property development. Similarly, .KLTE (Technology) and .KLEN (Energy) gained substantial influence, underlining their critical roles during heightened market volatility and sectoral shifts.

By 2021, the influence strength of .KLPL (Plantation) and .KLTE saw substantial fluctuations, whereas .KLRE (REIT) displayed resilience with a rising influence strength of 23.476. This growth reflected its increasing integration into the financial network as the market sought stability.

In 2022, the financial network experienced widespread disintegration, with declining influence strength across most indices. Although .KLCT (25.400) and .KLPR (35.571) retained moderate influence, their values fell well below their 2020 peaks. The diminished influence of .KLHC (Healthcare) and .KLRE (REIT), the least connected indices during this period, underscored their weak roles and limited connectivity within the network.

In 2023, the .KLCM (Consumer Products & Services) index emerged as the most influential, with an influence strength of 38.458, followed closely by the .KLIP (Industrial Products & Services) index at 36.639. This highlights the continued dominance of consumer-driven and industrial sectors in shaping post-pandemic market dynamics. The .KLEN (Energy) index also maintained substantial influence with a strength of 28.713, reflecting its growing relevance amid ongoing global energy supply and demand adjustments. Meanwhile, the .KLTE (Technology) index showed a noticeable rebound, with its influence strength increasing from 3.735 in 2022 to 11.171 in 2023. Although this value remains modest compared to the top-performing indices, the upward shift signifies renewed demand for digital technologies and innovation in the post-pandemic recovery. These developments underscore the dynamic nature of economic conditions and the adaptability of critical sectors.

Conversely, the .KLHC (Healthcare) sector remained consistently isolated, with no measurable influence strength in 2020, 2021, or 2023. This persistent disconnect highlights its minimal integration and marginal role in shaping broader market trends.

The findings emphasize influence strength as a key indicator of a market segment's significance within the financial structure. While sectors like Property, Construction, and Energy demonstrated robust influence during the pandemic, others, such as Healthcare, struggled with isolation. This sectoral analysis underscores the need for diversification strategies to enhance network integration and bolster sectoral resilience during periods of economic disruption and recovery.

3.4. *Summary of the performance of Bursa Malaysia sectoral indices (2019–2023)*

Over the five-year period from 2019 to 2023, the financial network of Bursa Malaysia's sectoral indices exhibited significant structural changes, largely influenced by external shocks such as the COVID-19 pandemic, global economic recovery, and shifts in sectoral investment trends. The correlation analysis showed that during the early pandemic phase (2020), sectoral indices became highly synchronized, reflecting market-wide panic and coordinated policy responses. This finding aligns with Dellow *et al.* (2024), who observed a similar increase in correlation across global markets during economic crises. However, by 2023, correlations weakened as different industries regained independence, marking a return to sector-driven market movements, consistent with the post-pandemic analysis by Lee *et al.* (2020).

The network centrality analysis highlighted key sectors driving market connectivity. In 2020, Consumer Products & Services (.KLCM) and Industrial Products & Services (.KLIP) had the highest degree centrality, indicating their pivotal roles in linking the market. In contrast, Healthcare (.KLHC) and REIT (.KLRE) became isolated, with their degree centrality values approaching zero. This observation aligns with Mehmood *et al.* (2021), who found that the healthcare sector, despite its critical role during COVID-19, remained disconnected due to policy-driven funding shifts. By 2023, the Energy Index (.KLEN) became the dominant node, exhibiting the highest centrality values. This dominance reflects the global energy sector's resurgence, consistent with the findings of Ahmad *et al.* (2023) regarding energy stocks as key drivers of economic recovery.

The closeness centrality metric further emphasized sectoral resilience and reintegration patterns. The absence of centrality data for .KLHC in 2020 and 2021 underscores its isolation, likely due to government prioritization of pandemic control over private healthcare investment (Hing *et al.* 2022). For certain years, such as 2019 and 2022, the closeness centrality for the .KLRE (REIT) index was recorded as NA due to its structural isolation from the financial network, meaning it lacked viable connections to other indices. The high closeness centrality of .KLEN in 2023 suggests its role in shaping market dynamics, similar to global trends in energy sector investments (Cornaro 2023).

Lastly, clustering coefficients and influence strength revealed deeper insights into sectoral cohesion. The Technology (.KLTE), Energy (.KLEN), and Consumer Products (.KLCM) indices consistently exhibited strong clustering coefficients, suggesting the presence of well-connected sub-networks that enhance sectoral stability. In contrast, Property (.KLPR) and Construction (.KLCT) indices showed fluctuating influence strength, likely due to policy-driven investments and infrastructure development patterns (Bahari *et al.* 2024). By 2023, most sectoral indices exhibited declining influence strength. The .KLEN index was the only one to register a substantial increase, while .KLTE experienced a decline from 36.681 in 2022 to 11.171 in 2023, despite maintaining relevance in the digital economy. These patterns signal a shift toward sector-specific market movements rather than broad interconnectivity.

4. Conclusions

This study analyzed the evolving financial network structure of Bursa Malaysia's sectoral indices from 2019 to 2023, revealing key shifts in market connectivity, sectoral resilience, and systemic influence. The results highlight that sectoral correlations strengthened during the COVID-19 crisis, creating a highly interconnected market in 2020. However, post-pandemic recovery led to a decline in correlations, returning the market to a more independent sectoral structure by 2023. The Energy (.KLEN) and Technology (.KLTE) indices emerged as the most central and influential sectors in the post-pandemic period, whereas Healthcare (.KLHC) and REIT (.KLRE) indices displayed fluctuating connectivity, reflecting external shocks and policy-driven investment shifts.

These findings provide valuable insights for investors and policymakers in understanding sectoral resilience and systemic risk within financial networks. The study confirms that sectors with higher centrality metrics tend to recover faster, reinforcing the importance of maintaining strong market linkages. Additionally, the observed decline in overall influence strength suggests that markets may become less interdependent over time, highlighting the need for adaptive investment strategies in evolving financial conditions.

To strengthen sectoral resilience and market stability, policymakers should prioritize integrating isolated sectors, such as Healthcare, into the financial network by providing targeted support and fostering inter-sectoral collaboration. Regular monitoring of network metrics, such as clustering coefficients and influence strength, can help detect emerging risks and inform strategic interventions. Additionally, leveraging high-centrality sectors like energy and technology to drive growth and innovation can ensure a balanced and resilient financial ecosystem. Tailored recovery strategies and investments in infrastructure, sustainable energy, and technological advancements will be crucial for building a robust and interconnected financial network that can withstand future economic disruptions.

4.1. *Limitations and future research*

This study effectively captures linear dependencies through correlation-based network construction. However, it does not account for nonlinear relationships that exist in financial markets. Therefore, future research should explore alternative methods such as mutual information and copula-based approaches to uncover complex dependencies between sectoral indices. Additionally, a rolling-window analysis could provide deeper insights into how market structures evolve dynamically over time. Expanding the dataset to include international market interactions could also enhance the robustness of financial network modeling.

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References

Ahmad N., Shahiri H., Nor S.M. & Azman Aziz M.I. 2023. Connectedness analysis of price return index among Malaysian economic sectors. *International Journal of Islamic and Middle Eastern Finance and Management* **16**(4): 856–872.

Bahaludin H., Dellow A.A. & Abdullah M.H. 2024. Exploring correlations of energy companies on Bursa Malaysia during the COVID-19 pandemic using network analysis. *Journal of Quality Measurement and Analysis* **20**(3): 1–22.

Bahaludin H. & Syafiq S.N.A.M. 2021. The impact of COVID-19 on industrial products and services sector of Bursa Malaysia by using minimum spanning tree. *Menemui Matematik (Discovering Mathematics)* **43**(2): 111–120.

Bahari N.N., Bahaludin H., Ismail M. & Razak F.A. 2024. Network, correlation, and community structure of the financial sector of Bursa Malaysia before, during, and after COVID-19. *Data Science in Finance and Economics* **4**(3): 362–387.

Barfuss W., Massara G.P., Di Matteo T. & Aste T. 2016. Parsimonious modeling with information filtering networks. *Physical Review E* **94**(6): 062306.

Briola A. & Aste T. 2022. Dependency structures in cryptocurrency market from high to low frequency. *Entropy* **24**(11): 1548.

Chia R.C.J., Liew V.K.S. & Rowland R. 2020. Daily new COVID-19 cases, the Movement Control Order, and Malaysian stock market returns. *International Journal of Business and Society* **21**(2): 533–568.

Cornaro A. 2023. Financial resilience of insurance network during COVID-19 pandemic. *Quality & Quantity* **57**(Suppl 2): 151–172.

Dellow A.A., Ismail M., Bahaludin H. & Razak F.A. 2024. Comparing the impacts of past major events on the network topology structure of the Malaysian consumer products and services sector. *Journal of the Knowledge Economy* **16**: 925–967.

Di Matteo T., Pozzi F. & Aste T. 2010. The use of dynamical networks to detect the hierarchical organization of financial market sectors. *The European Physical Journal B* **73**: 3–11.

Gil-Alana L.A. & Monge M. 2020. Crude oil prices and COVID-19: Persistence of the shock. *Energy Research Letters* **1**(1).

Güngör B.O., Ertuğrul H.M. & Soytaş U. 2021. Impact of COVID-19 outbreak on Turkish gasoline consumption. *Technological Forecasting and Social Change* **166**: 120637.

Haroon O., Ali M., Khan A., Khattak M.A. & Rizvi S.A.R. 2021. Financial market risks during the COVID-19 pandemic. *Emerging Markets Finance and Trade* **57**(8): 2407–2414.

Hing N.Y.L., Leong C.T., S K.R., Lim A.W.Y., Loo C.E. & Woon Y.L. 2022. Impacts of the COVID-19 pandemic on healthcare services in Malaysia from the perspective of healthcare providers: A cross-sectional analysis. https://www.preprints.org/manuscript/202203.0378/v1 (10 June 2024).

Lee K.Y.M., Jais M. & Chan C.W. 2020. Impact of COVID-19: Evidence from Malaysian stock market. *International Journal of Business and Society* **21**(2): 607–628.

Liang K., Li S., Zhang W., Wu Z., He J., Li M. & Wang Y. 2024. Evolution of complex network topology for Chinese listed companies under the COVID-19 pandemic. *Computational Economics* **63**(3): 1121–1136.

Liu Q. & Yahyapour R. 2023. Forecast stock price based on GRA-LoGo model of information filtering networks. *J. Intell. Fuzzy Syst.* **45**(6): 12329–12339.

Mantegna R.N. 1999. Hierarchical structure in financial markets. *The European Physical Journal B-Condensed Matter and Complex Systems* **11**: 193–197.

Massara G.P., Di Matteo T. & Aste T. 2017. Network filtering for big data: Triangulated maximally filtered graph. *Journal of Complex Networks* **5**(2): 161–178.

Mehmood W., Mohd-Rashid R., Aman-Ullah A., Shafique O. & Tajuddin A.H. 2021. The reaction of the Malaysian stock market to the COVID-19 pandemic. *Journal of Contemporary Eastern Asia* **20**(2): 63–84.

Nobi A., Maeng S.E., Ha G.G. & Lee J.W. 2014. Effects of global financial crisis on network structure in a local stock market. *Physica A: Statistical Mechanics and its Applications* **407**: 135–143.

Riaz S., Ahmed R., Parkash R. & Ahmad M.J. 2020. Determinants of stock market investors' behavior in COVID-19: A study on the Pakistan Stock Exchange. *International Journal of Disaster Recovery and Business Continuity* **11**(3): 977–990.

Shahzad S.J.H., Ferrer R. & Bouri E. 2023. Systemic risk in the global energy sector: Structure, determinants and portfolio management implications. *The Energy Journal* **44**(6): 211–243.

Tumminello M., Aste T., Di Matteo T. & Mantegna R.N. 2005. A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences* **102**(30): 10421–10426.

Wielechowski M. & Czech K. 2022. Companies' stock market performance in the time of COVID-19: Alternative energy vs. main stock market sectors. *Energies* **15**(1): 106.

Zhang D., Hu M. & Ji Q. 2020. Financial markets under the global pandemic of COVID-19. *Finance Research Letters* **36**: 101528.

Zuhud D.A.Z., Musa M.H., Ismail M., Bahaludin H. & Razak F.A. 2022. The causality and uncertainty of the COVID-19 pandemic to Bursa Malaysia financial services index's constituents. *Entropy* **24**(8): 1100.

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