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EXPLORING CORRELATIONS OF ENERGY COMPANIES ON BURSA MALAYSIA DURING THE COVID-19 PANDEMIC USING NETWORK ANALYSIS

(Meneroka Korelasi Syarikat Tenaga dalam Bursa Malaysia Semasa Pandemik COVID-19 Menggunakan Analisis Rangkaian)

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ABSTRACT

The COVID-19 pandemic has profoundly disrupted the global economy, and the energy sector has been particularly hard hit. With a sharp decline in the global economic outlook, the energy industry faced significant challenges, including a substantial drop in oil prices that reverberated throughout energy markets worldwide. In light of this unprecedented situation, our study aims to delve into the impact of COVID-19 on Shariah-compliant energy stocks listed on Bursa Malaysia between 2019 and 2020. To accomplish this, we employed the triangulated maximally filtered graph (TMFG) approach for analysing intricate datasets. By constructing networks using the TMFG technique and employing the degree centrality measure on 26 energy stocks in the pre-COVID period (2019) and during the COVID period (2020), we examined the structural changes and correlations within the networks. Notably, our findings reveal that the correlation among energy stocks became even stronger during the COVID period, highlighting the sector’s heightened interdependence. Additionally, our analysis identifies Hibiscus Petroleum Bhd (HIBI) as the most influential stock throughout both timeframes, underscoring its significance amidst the pandemic-induced market fluctuations. These research outcomes carry significant practical implications, such as offering valuable insights to market participants in navigating the energy market’s evolving landscape, which then enables informed decision-making for portfolio management and effective policy implementation.

Keywords: COVID-19; energy sector; Shariah-compliant stocks; Bursa Malaysia; triangulated maximally filtered graph; degree centrality; correlations; network analysis

ABSTRAK

Pandemik COVID-19 telah memberikan kesan mendalam terhadap ekonomi global, dan sektor tenaga terjejas teruk. Dengan kemerosotan mendadak dalam prospek ekonomi global, industri tenaga menghadapi cabaran besar, termasuk penurunan ketara dalam harga minyak yang memberi kesan kepada pasaran tenaga di seluruh dunia. Berdasarkan situasi yang belum pernah terjadi ini, kajian kami bertujuan untuk menyelidik kesan COVID-19 terhadap saham tenaga patuh syariah yang disenaraikan di Bursa Malaysia antara tahun 2019 dan 2020. Untuk mencapai matlamat ini, kami menggunakan pendekatan *triangulated maximally filtered graph* (TMFG) untuk menganalisis set data yang rumit. Dengan membina rangkaian menggunakan teknik TMFG dan ukuran pemusatan darjah ke atas 26 saham tenaga dalam tempoh sebelum COVID (2019) dan semasa COVID (2020), kami meneliti perubahan struktur dan korelasi dalam rangkaian-rangkaian tersebut. Penemuan kami mendedahkan bahawa korelasi antara saham tenaga menjadi lebih kuat semasa tempoh COVID, menonjolkan kesalingbergantungan sektor yang semakin meningkat. Selain itu, analisis kami mengenal pasti Hibiscus Petroleum Bhd (HIBI) sebagai saham paling berpengaruh sepanjang kedua-dua tempoh masa ini, menekankan kepentingannya di tengah-tengah turun naik pasaran yang disebabkan oleh pandemik. Hasil penyelidikan ini membawa implikasi praktikal seperti memberikan maklumat berkaitan pasaran tenaga, yang kemudiannya membolehkan pembuatan keputusan yang efektif serta pengurusan portfolio dan pelaksanaan dasar berkesan.

Kata kunci: COVID-19; sektor tenaga; saham patuh Syariah; Bursa Malaysia; *triangulated maximally filtered graph*; pemusatan darjah; korelasi; analisis rangkaian

1. Introduction

The coronavirus disease (COVID-19) pandemic has unleashed a multitude of challenges across various sectors, and the energy industry has been particularly affected (Hoang *et al.* 2021; Lu *et al.* 2021). The unprecedented circumstances surrounding the pandemic have disrupted global economies, leading to a sharp decline in oil prices and significant shifts in energy consumption patterns. The International Energy Agency (IEA) has projected that global energy demand will fall by 6% in 2020, the largest decline since the 1930s. It is reported that the consumption of crude oil decreased dramatically during the initial lockdown times, whereas renewable energy consumption surged during the COVID-19 pandemic (Ghabri *et al.* 2021). Liu *et al.* (2022) analysed the spillover impacts of COVID-19 on the Wilder Hill Clean Energy Index (ECO), European Renewable Energy Price Index (ERIX), and Standard & Poor Global Clean Energy Index (S&P GCE) from 2004 to 2020, including the global financial crisis period. The COVID-19 recession had a greater impact on energy stock price returns and volatilities than the global financial crisis. In addition, Wielechowski and Czech (2022) found that the stocks signifying the alternative energy sector faced a lot of substantial increases in their share prices from January 2020 to September 2021. The COVID-19 outbreak caused large energy firms to lose stock value (Huang & Liu 2021; Xiong *et al.* 2021). In particular, falling energy prices exacerbated pessimistic investment sentiment in the energy stock market, leading to increased volatility (Chundakkadan & Nedumparambil 2022).

Despite the critical importance of understanding the impacts of COVID-19 on the energy sector, there is an absence of research focusing specifically on the Malaysian market. The research problem at hand revolves around the lack of comprehensive analysis concerning the energy sector's response to the unique challenges posed by COVID-19 in the Malaysian context. Previous studies have highlighted the far-reaching effects of the pandemic on energy markets globally, including the substantial decline in crude oil consumption during lockdown measures (Le *et al.* 2021) and the subsequent rise in renewable energy consumption (Ghabri *et al.* 2021). However, these studies have largely overlooked the Malaysian energy market, leaving a crucial gap in understanding the specific dynamics and implications for this sector within the country. This is especially important considering the complex dynamics of relationships in stock markets.

There is no doubt that in this modern era and age, financialisation is becoming more widespread. Financialisation explains the growing role of financial markets in the way they affect the economy and regulatory authorities both locally and internationally (Epstein 2019). However, as financial markets grow in size to the point that they outgrow the real economy, the financial elements of the market create complex interactions that might not be sufficiently analysed quantitatively by traditional means (Bardoscia *et al.* 2021). Technically, traditional economic models do not adequately understand these financial systems and their ramifications due to the fact that they characterise systems as either a collection of entities in isolation or by aggregation (Colander *et al.* 2009). This is where financial networks, generated using network analysis methods, come into play as they are able to provide the appropriate tools to analyse complexity and interconnectedness beyond conventional boundaries (Bardoscia *et al.* 2021), besides uncovering the intricate relationships between financial elements.

Being a part of the financial market, the stock market plays a big role in the Malaysian economy, contributing to the country's well-being. Utilising network analysis methods to study the stock market is gaining traction among researchers as they are able to visualise interconnections in an easy-to-interpret manner via single-layer networks, bipartite networks, multiplex networks, and so on. It is of utmost importance that these complex connections between stocks be studied so that the appropriate measures can be taken to avoid the risk spread that could happen when a negative impact hits the stock market. If not mitigated right away, this could even lead to systemic risk, where a single entity-level event could disrupt or even cause the collapse of the entire sector or economy (Chen 2023). Due to the complex nature of financial networks, market participants tend to rely on crucial insights into the market to aid in their decision-making and strategy-planning endeavours.

Importantly, network analysis methods can utilise stock price data to reflect the crucial information in a system, including the way risk spreads throughout the network as it showcases interconnections (Chan-Lau 2018). This makes network analysis essential in various settings, as it is a known fact that individuals might find it rather difficult to obtain private exposure data on the relationships between companies. The Financial Stability Board (2011), which is an international body that oversees the global financial system, came out with a policy to address systemically important financial institutions (SIFIs). According to the Basel Committee on Banking Supervision (2013), 20% of an institution's systemic importance is attributed to its interconnectedness, and another 20% to its complexity, among other factors. It is mentioned that the disorderly failure of a SIFI can cause disruption to the wider financial system and dampen down the economy, which is basically a systemic risk. Network analysis methods contain tools to identify these influential institutions, or in our case, stocks, and are known for their ability to portray complexity and interconnectedness in an easy-to-understand manner. This makes network analysis even more important for this particular area of research.

In the context of the Malaysian energy sector, the Malaysian government has recently launched the National Energy Transition Roadmap (NETR), which aims to create an inclusive and sustainable energy system (Ministry of Economy 2023). The NETR focuses on increasing energy transition efforts in order to achieve a high-value green economy. Besides risk mitigation benefits, network analysis can help achieve part of the government's efforts. For example, the identification of key players in the energy sector is crucial as policymakers can implement policies to double the efforts in encouraging these specific companies to employ sustainable practices. These companies will then be able to lead the transition of the energy sector towards a greener economy in the long run. Apart from that, network visualisations are able to provide insight into the energy sector's sectorial collaborations. Policies can leverage the findings obtained to promote partnerships in fostering sustainable practices across companies from different energy subsectors, hastening the widespread adoption of these practices across the whole sector. Since, the use of current network analysis methodologies is still lacking in the Malaysian context, this paper aims to encourage further research in this field.

To bridge the identified gaps, we aim to examine the interdependencies and influences among Shariah-compliant energy stocks listed on Bursa Malaysia during the COVID-19 pandemic. Shariah-compliant stocks are said to reap many benefits, one of the most important being their ability to present lower levels of risk as compared to conventional stocks during volatile periods of time (Raza *et al.* 2023; Salvi *et al.* 2019). Salvi *et al.* (2019) also concluded that Shariah-compliant stocks tend to generate more positive returns, and this is supported by a study on the Pakistan stock market that found Shariah-compliant stocks to generate better returns because of their restricted debt levels (Khan Tareen & Siddiqui 2019). Hence, this study identifies which companies play a pivotal role during the pandemic amongst the Shariah-compliant stocks. To examine the impact of COVID-19 on energy companies, the triangulated maximally filtered graph (TMFG) method (Massara *et al.* 2017) is employed.

Several new insights are added by this research to the field of financial networks. To our knowledge, this research is the first to use the TMFG approach to analyse how COVID-19 has affected the Malaysian stock market. Secondly, this study addresses a gap in the literature by investigating the effects of COVID-19 on the energy sector of Bursa Malaysia. Despite the fact that earlier studies have examined the worldwide ramifications of energy markets as a whole, there is a considerable knowledge void about the dynamics and effects inside Malaysia. Analysing changes and correlations within this network will provide us with valuable insights into the resilience and agility of the Malaysian energy industry when faced with challenges posed by global pandemics such as COVID-19. Ultimately, our research seeks to better understand how COVID-19 specifically affects the energy industry in Malaysia, besides offering insights into the interdependencies among Shariah-compliant energy stocks. The study can potentially inform strategies for navigating similar future challenges.

The remainder of the paper continues as follows: The literature review is presented in Section 2, and the data is outlined in Section 3, as well as the elaboration of the methodology. Section 4 provides the empirical findings, and lastly, Section 5 sums up the whole paper with conclusions and suggested future work. Note that tables and figures appearing in this paper are placed following their detailed explanations.

2. Literature Review

It has been proven in many studies that the COVID-19 pandemic caused a significant impact to the energy sector. First and foremost, the pandemic has led to a decrease in the price of oil, implying a significant impact on the oil and gas sector. For example, it was reported that in Turkey, diesel consumption declined during the COVID-19 period (Ertuğrul *et al.* 2020), and the same goes for gasoline consumption (Güngör *et al.* 2021). Crude oil also experienced a sudden and dramatic decline in consumption, causing its market efficiency to be diminished (Gil-Alana & Monge 2020). The impacts of the crisis on the consumption of diesel, gasoline, and crude oil, portrays that the decline in consumers demand for energy is the most pivotal consequence of the crisis. From another perspective, the mobility restrictions put in place by the government to slow down the spread of COVID-19, have made it difficult for energy companies to acquire and supply resources. There is evidence that the pandemic status has caused a significant impact on supply and demand for energy (Kang *et al.* 2021) and has negatively influenced energy production (Chen *et al.* 2021). These studies showcase how the energy supply chain underwent challenges due to the government lockdown imposed.

Prior research has indicated that energy stock prices and volatilities were more profoundly affected by the COVID-19 pandemic (Huang & Liu 2021; Liu 2021a). These findings highlight the need to investigate and gain an overview of the effects of COVID-19 on the energy industry. Despite the aforementioned effects of COVID-19, it is still important to look into the connections between companies in the energy sector. Understanding the interconnection of companies in financial markets is crucial since it will function as a pipeline for financial turmoil. The collapse of a large, interconnected entity can spread rapidly and widely throughout the financial system, causing global financial turbulence.

Essentially, network analysis is used to present the connections of companies that are traded on the stock exchange, with the graph obtained being called a financial network. Numerous studies used the minimum spanning tree (MST) approach that was proposed by Mantegna

(1999) to get an overview of the relationships between companies. The MST is extensively employed for various scholarly endeavours, including exploring alterations in the topological characteristics of financial networks (Abbasian-Naghneh *et al.* 2020; Kazemilari *et al.* 2017) and identifying stocks to enhance portfolio strategies (Berouaga *et al.* 2023). In addition, many studies have applied this method to analyse financial markets, especially during COVID-19 (Aslam *et al.* 2020; Bahaludin & Muhammad Syafiq 2021; Mahdi *et al.* 2022; Samitas *et al.* 2022).

However, the MST method has its limitations in which it suffers from significant data loss (Massara *et al.* 2017). For example, it retains only $n-1$ edges out of $\frac{n(n-1)}{2}$ edges in a complete network. Following this, the planar maximally filtered graph (PMFG) was then introduced as a natural extension to the MST (Tumminello *et al.* 2005). Essentially, the PMFG is able to keep additional filtered information while still retaining the same hierarchical tree as the MST. It is said that this method is able to efficiently filter crucial information to showcase the structure of the whole system and within clusters. Even though the PMFG is generally larger than the MST network, it can still be considered sparse as it only retains $3n-6$ edges. Additionally, apart from being a powerful tool, the PMFG is computationally expensive and cannot be utilised on large datasets (Massara *et al.* 2017).

To address this issue, Massara *et al.* (2017) introduced the TMFG method, which can produce better results by effectively inserting vertices and edges. The TMFG method is considered an alternative approach to constructing a network that captures the underlying structure of complex datasets. Unlike older methods such as the MST and PMFG, which can suffer from significant data loss, the TMFG method seeks to construct triangulations that optimise a score function related to the network's capacity to retain information. On top of that, the TMFG method is said to be computationally cheaper as compared to its alternatives (Briola & Aste 2023), with Massara *et al.* (2017) attributing this computational effectiveness to its ability to make local topological moves as it benefits from GPU computing and parallel processing. Furthermore, TMFGs are of good quality and can be generated at a faster speed (Massara *et al.* 2017; Yu & Shun 2023). Studies also mention that, unlike the PMFG method, the TMFG method is adaptable to larger datasets (Briola & Aste 2023; Massara *et al.* 2017), making it more efficient to analyse big financial data. One of the studies employing the TMFG method discovered that this method is more capable of identifying high-order structures of stock market networks (Turiel *et al.* 2022). TMFG was also used by Xu *et al.* (2022) in their study on the new energy vehicles industry in China, and it was even employed to build a network of 25 liquid cryptocurrencies traded on the FTX digital currency exchange (Briola & Aste 2022).

3. Materials and Methods

3.1. *Data*

The following section presents the data utilised in this study's analysis. Our research aims to delve into the correlations among stocks within Malaysia's Shariah-compliant financial market energy sector. All the stocks are listed on the main market of Bursa Malaysia, which is Malaysia's stock exchange and one of the largest bourses in ASEAN. The Shariah-compliant stocks are basically public-listed companies that have been deemed permissible for investment according to Shariah principles. These Shariah-compliant stocks are updated twice a year, in May and November, by the Shariah Advisory Council (SAC) of Securities Commission Malaysia (SC) (Bursa Malaysia n.d.a). The Shariah-compliant stocks exclude businesses involved in activities such as financial services based on interest, gaming, gambling, non-halal or tobacco-based product manufacturing, conventional insurance, and other non-permissible ventures according to Shariah (Bursa Malaysia n.d.b). As of 31 January 2024, Bursa Malaysia's energy sector possesses a market capitalisation of RM 36.08 billion (Bursa Malaysia 2024). This showcases its great contribution, albeit being one of the smaller-sized sectors.

This study compiled the daily closing prices of 26 stocks from the energy sector. To ultimately construct accurate stock market networks and further analyse these correlations, relevant data was sourced from Investing.com. The data covers a total of 494 trading days, divided into two sub-periods: pre-COVID period (January 2, 2019 to December 31, 2019) and during the COVID period (January 2, 2020 to December 31, 2020). Note that only stocks that were Shariah-compliant throughout the whole pre-COVID and during the COVID periods are considered in this study. The 26 stocks used in the analysis were further categorised into three main subsectors set by Bursa Malaysia: Energy Infrastructure, Equipment & Services; Oil & Gas Producers; and Other Energy Resources. The Energy Infrastructure, Equipment & Services subsector consists of 21 stocks, while the Oil & Gas Producers subsector includes four stocks. Additionally, one stock is classified under Other Energy Resources, namely, Techna-X Bhd. In the TMFG plots, each node is coloured according to the respective subsectors of each stock in order to provide visual clarity in understanding the relationships between stocks from different subsectors. The specific stocks included in each subsector, along with their Refinitiv Instrument Code (RIC), stock code, and node colours, can be found in Table 1 of the study.

Table 1: List of companies in the energy sector listed on Bursa Malaysia

No	Stocks	RIC	Stock Code	Sector	Node Colour
1	Hibiscus Petroleum Bhd	HIBI	5199	Oil & Gas Producers	
2	Reach Energy Bhd	RESE	5256	Oil & Gas Producers	
3	Sapura Energy Bhd	SAEN	5218	Energy Infrastructure, Equipment & Services	
4	Perdana Petroleum Bhd	PTRD	7108	Energy Infrastructure, Equipment & Services	
5	TH Heavy Engineering Bhd	THHE	7206	Energy Infrastructure, Equipment & Services	
6	Carimin Petroleum Bhd	CARM	5257	Energy Infrastructure, Equipment & Services	
7	T7 Global Bhd	TGLO	7228	Energy Infrastructure, Equipment & Services	
8	Serba Dinamik Holdings Bhd	SERB	5279	Energy Infrastructure, Equipment & Services	
9	Petron Malaysia Refining & Marketing Bhd	PTMR	3042	Oil & Gas Producers	
10	Dayang Enterprise Holdings Bhd	DEHB	5141	Energy Infrastructure, Equipment & Services	
11	Barakah Offshore Petroleum Bhd	BARA	7251	Energy Infrastructure, Equipment & Services	
12	Yinson Holdings Bhd	YINS	7293	Energy Infrastructure, Equipment & Services	
13	Wasco Bhd	WASC	5142	Energy Infrastructure, Equipment & Services	
14	Velesto Energy Bhd	VELE	5243	Energy Infrastructure, Equipment & Services	
15	Uzma Bhd	UZMA	7250	Energy Infrastructure, Equipment & Services	
16	Techna-X Bhd	TECA	2739	Other Energy Resources	
17	Scomi Energy Services Bhd	SCES	7045	Energy Infrastructure, Equipment & Services	
18	Scomi Group Bhd	SCOI	7158	Energy Infrastructure, Equipment & Services	
19	Petra Energy Bhd	PTRE	5133	Energy Infrastructure, Equipment & Services	

Table 1 (Continued)

20	Malaysia Marine and Heavy Engineering Holdings Bhd	MHEB	5186	Energy Infrastructure, Equipment & Services	
21	Icon Offshore Bhd	ICON	5255	Energy Infrastructure, Equipment & Services	
22	Hengyuan Refining Company Bhd	HENY	4324	Oil & Gas Producers	
23	Handal Energy Bhd	HDEB	7253	Energy Infrastructure, Equipment & Services	
24	Deleum Bhd	DLEU	5132	Energy Infrastructure, Equipment & Services	
25	Dialog Group Bhd	DIAL	7277	Energy Infrastructure, Equipment & Services	
26	Alam Maritim Resources Bhd	ALMT	5115	Energy Infrastructure, Equipment & Services	

3.2. *Methodology*

3.2.1. *Correlation analysis*

Before building the TMFGs, a simple correlation analysis is first carried out to gain an initial overview of the stock market's behaviour. Note that the 26 stocks' daily closing prices are used to calculate their correlations with one another. In this study, Pearson correlation coefficients are obtained in a two-step process as shown below:

(1) The first step is to compute the rate of return. For the purpose of computing the logarithmic returns of stock *i* on day *t*, $r_i(t)$, the closing price for stock *i* on day *t* is defined as $P_i(t)$.

$$r_i(t) = ln\left[\frac{P_i(t)}{P_i(t-1)}\right] \tag{1}$$

(2) We then compute the Pearson correlation matrix to determine the correlations between all pairs of stocks analysed. The Pearson correlation coefficient of stock *i* and stock *j*, C_{ij}, is given by (Mantegna 1999):

$$C_{ij} = \frac{\langle r_i r_j\rangle - \langle r_i\rangle\langle r_j\rangle}{\sqrt{(\langle r_i^2\rangle - \langle r_i\rangle^2)\left(\langle r_j^2\rangle - \langle r_j\rangle^2\right)}} \tag{2}$$

From Eq. (2), $\langle r_i\rangle$ represents stock *i*'s average return. The $N \times N$ cross-correlation matrix generated from *N* stocks contains $\binom{N}{2}$ correlation coefficients altogether. Each correlation coefficient value has a range of $-1 \leq C_{ij} \leq 1$. These values illuminate the strength and direction of the linear relationship between the two stocks, with values closer to the extremes indicating relationships of higher magnitude. The correlation matrices for the pre-COVID and during the COVID periods are presented in the form of correlograms in Section 4.2. Since the correlation matrices are symmetrical, only the upper triangular matrix is displayed (see Figure 1) to avoid redundancy.

3.2.2. *Construction of network using TMFG*

The construction of the network based on the TMFG method involves identifying three vertex cliques in the original network and inserting a new vertex at their centre. A complete subgraph where all the *p* elements in it are connected to one another is called a clique of *p* elements or simply a *p*-clique (Tumminello *et al.* 2005). The goal of the TMFG method is to maximise the total edge weights of the three vertices that are linked to the new vertex. This process is repeated until all cliques have been exhausted, resulting in a subnetwork that preserves the fundamental geometry of the original network while allowing for chordal properties. A chordal network is essentially when a 4-node clique contains a chord that links two non-adjacent edges to form two triangles (Briola & Aste 2023; Massara *et al.* 2017). In this study, computational analysis was performed using RStudio, with the usage of relevant packages, including *NetworkToolbox* and *igraph*. Specifically, the `TMFG()` function from the *NetworkToolbox* package was utilised to apply the TMFG method that was proposed by Massara *et al.* (2017), and the *igraph* package was used to construct the network. The steps to construct the TMFG are as follows:

(1) Load the price data and select the date range.
(2) Define a function called **corr** to calculate the rate of return and correlation matrix of the price data.
(3) Call the **corr** function and store the rate of return matrix in a variable called **ret**.
(4) Calculate the average return for each column of the **ret** matrix and store it in a data frame called **avg_ret**.
(5) Calculate the correlation matrix and store it in a variable called **rho**.
(6) Convert the correlation matrix to an adjacency matrix by thresholding at a certain level. This study considers the average of the correlation matrix.
(7) Construct the TMFG using the adjacency matrix and store it in a variable called **tmfg**.
(8) Create a graph from the adjacency matrix using **graph_from_adjacency_matrix** and store it in a variable called **g**.
(9) Simplify the graph by removing multiple edges and loops using **simplify**.
(10) Match the subsectors of the companies with the graph vertices.
(11) Assign colours to the subsectors.
(12) Plot the graph with vertices coloured by subsector, besides the size of the nodes being proportional to their degree centrality.

The general code to construct the TMFG using RStudio, based on the previously specified steps, can be found in Appendix A. Note that, this study considers thresholding the correlation matrix to filter for more prominent connections and to produce a network visualisation that is sparser and easier to interpret. The threshold value is set as the average of the correlation matrix, that is, determining the threshold value based on a statistical measure as seen in a study on the consumer products and services sector of the Malaysian stock market (Dellow *et al.* 2024) and on the Korea Composite Stock Price Index 200 (Nobi *et al.* 2014).

3.2.3. *Degree centrality measure*

To further analyse the TMFG, the degree centrality measure is applied. The degree centrality of a node is defined as the total number of connections (edges) it has (Freeman 1978). Nodes with higher degree centrality values are considered to be more important than nodes with lower degree centrality values. For a node *e*, its degree centrality is set by:

$$Deg(e) = \sum_{k=1}^{n} A_{ek}, \tag{3}$$

where A_{ek} is the *ek*-th element of the adjacency matrix, *A*, of the graph, and *n* is the total number of nodes in the graph. It is worth noting that degree centrality is one of the simplest and most easily comprehensible centrality measures that is utilised in a wide range of studies employing network analysis. Essentially, this centrality measure is of great importance due to the scale-free power-law distribution property found by Barabási and Albert (1999) in random or large networks. This simply means that real-world applications of financial networks tend to have scale-free properties in which only a small number of nodes, called hubs, have a large number of connections. Degree centrality is then a great measure to determine stocks with the greatest number of interactions with other stocks, that is, identifying the hubs of the network across different time periods.

4. Results and Discussion

4.1. *Descriptive analysis*

Table 2 presents the descriptive statistics of closing prices for various companies. These statistics provide important insights into the distribution, variability, and shape of the closing prices within each company. By examining the mean values, we observe that YINS has the highest mean closing price of 5.725, followed by PTMR with a mean of 5.001. This indicates that, on average, YINS and PTMR have relatively higher closing prices as compared to the other companies in the table. Conversely, SCOI and BARA have the lowest mean closing prices, 0.051 and 0.049, respectively.

Table 2: Overview of the descriptive analysis of each company's closing price over the years 2019 and 2020

RIC	Mean	SD	Min	Max	Skewness	Kurtosis
YINS	5.725	0.906	4.060	7.240	-0.211	1.770
WASC	0.746	0.263	0.385	1.433	0.990	2.954
VELE	0.240	0.092	0.095	0.400	0.078	1.489
UZMA	0.717	0.189	0.330	1.110	0.131	1.954
THHE	0.077	0.025	0.030	0.150	0.750	2.945
TGLO	0.432	0.056	0.240	0.550	-0.331	2.844
TECA	0.139	0.051	0.040	0.290	0.591	2.734
SERB	1.835	0.219	1.130	2.430	0.534	3.630
SCES	0.271	0.171	0.035	0.650	0.221	1.622
SCOI	0.051	0.024	0.010	0.115	0.661	2.626
SAEN	0.211	0.093	0.065	0.359	-0.212	1.291
RESE	0.165	0.084	0.030	0.345	0.410	2.020
PTRE	0.897	0.315	0.350	1.790	0.515	2.372
PTRD	0.278	0.109	0.110	0.535	0.237	1.745
PTMR	5.001	1.219	2.500	7.490	-0.038	1.802
MHEB	0.631	0.207	0.285	0.955	-0.244	1.461
ICON	0.189	0.105	0.035	0.815	1.078	5.044
HIBI	0.807	0.236	0.260	1.210	-0.339	1.742
HENY	4.272	1.109	2.290	6.700	0.188	1.932
HDEB	0.309	0.083	0.165	0.475	-0.281	1.540
DLEU	0.829	0.213	0.355	1.280	-0.245	1.668
DIAL	3.419	0.244	2.800	3.990	-0.042	2.521
DEHB	1.404	0.559	0.490	2.950	1.128	3.783
CARM	0.831	0.253	0.335	1.470	0.593	2.437
BARA	0.049	0.028	0.010	0.145	0.997	3.403
ALMT	0.099	0.025	0.030	0.185	0.783	4.450

The standard deviation (SD) values reflect the degree of variability or dispersion around the mean closing prices. A higher SD suggests greater volatility or fluctuations in the closing prices. In this regard, PTMR has the highest SD of 1.219, indicating relatively larger price fluctuations than other companies. On the other hand, SCOI has the lowest SD of 0.024, indicating relatively less variability in its closing prices. Here, it implies that more expensive stocks tend to face greater price fluctuations and be more volatile than cheaper stocks that possess more stable prices. This can also be seen through the analysis of the minimum and maximum values, where we find that the smallest minimum closing price is 0.010 for SCOI and BARA, while the highest maximum closing price is 7.490 for PTMR. These values highlight the range within which the closing prices fluctuate for each company.

The skewness measures the symmetry of the distribution of closing prices. Negative skewness values, such as that of TGLO (-0.331) and HIBI (-0.339), indicate a longer left tail, suggesting that these companies have a slightly skewed distribution with more closing prices that are lower in value. Positive skewness values, like that of DEHB (1.128) and ICON (1.078), indicate a longer right tail, suggesting a distribution skewed towards higher closing prices. Kurtosis measures the "tailedness" of the distribution. Higher kurtosis values indicate more extreme values or outliers in the distribution. In this table, ICON stands out with a kurtosis value of 5.044, suggesting a distribution with heavy tails and potentially more extreme closing prices as compared to the other companies. Overall, the descriptive statistics provide a comprehensive overview of the closing prices for each company. These statistics can be useful in understanding the characteristics, volatility, and distributional properties of closing prices, enabling investors and analysts to make informed decisions based on the observed patterns and trends within the market.

Table 3: Mean rate of return for each stock in the years 2019 and 2020

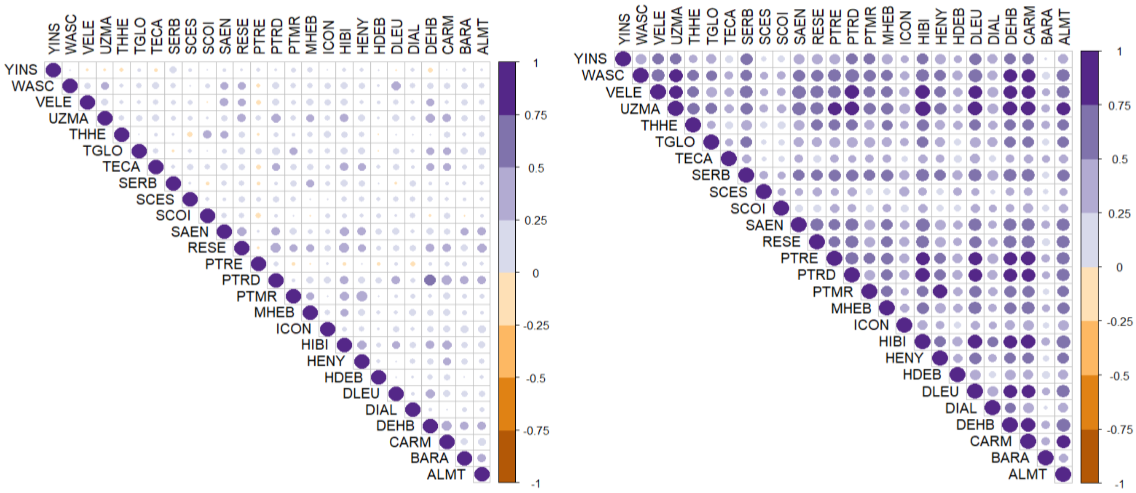
No	RIC	2019	2020	Sparklines	No	RIC	2019	2020	Sparklines
1	YINS	0.18%	-0.05%		14	PTRD	0.25%	-0.34%	
2	WASC	0.26%	-0.16%		15	PTMR	-0.09%	0.02%	
3	VELE	0.31%	-0.40%		16	MHEB	0.19%	-0.27%	
4	UZMA	0.21%	-0.22%		17	ICON	-0.14%	-0.17%	
5	THHE	0.45%	0.00%		18	HIBI	0.05%	-0.19%	
6	TGLO	0.14%	-0.02%		19	HENY	-0.04%	0.14%	
7	TECA	-0.06%	0.08%		20	HDEB	0.05%	-0.12%	
8	SERB	0.09%	-0.09%		21	DLEU	-0.01%	-0.18%	
9	SCES	-0.07%	-0.53%		22	DIAL	0.04%	0.00%	
10	SCOI	-0.13%	-0.12%		23	DEHB	0.65%	-0.30%	
11	SAEN	-0.02%	-0.31%		24	CARM	0.48%	-0.28%	
12	RESE	-0.24%	-0.20%		25	BARA	-0.36%	0.32%	
13	PTRE	0.50%	-0.10%		26	ALMT	0.22%	-0.17%	

Overall, the data presented in Table 3 sheds light on the performance of energy stocks in the face of the COVID-19 pandemic by presenting their average rates of return over the years 2019 and 2020. This table also includes small graphics of line charts without axes, called sparklines, to provide a quick representation of the general trend of the mean rate of return for each stock from 2019 to 2020. The data reveals interesting insights into the performance of these stocks during these challenging times. The diverging patterns observed in 2019 and 2020 underscore the difficulties and instability witnessed in the energy industry over these periods. In 2019, a majority of the 26 energy stocks demonstrated positive mean rates of return, indicating a generally favourable performance for most companies within the energy sector. However, the scenario took a downturn in 2020, as most of the stocks faced negative mean rates of return. Out of the 26 stocks, six of them, namely, TECA, SCOI, RESE, PTMR, HENY, and BARA, experienced increases in their mean rates of return. Still, only four of these six stocks (TECA, PTMR, HENY, BARA) generated positive returns. With only six stocks experiencing positive growth, this suggests a significant depreciation in the value of the majority of stocks and an overall loss in the sector. Notably, the four stocks exhibiting positive returns during the pandemic demonstrate their ability to weather adverse market conditions in 2020 and emerge with successful performances as compared to their counterparts.

Noteworthily, the wide range of rate of return values observed in Table 3 reflects the heightened volatility within the energy sector of the Malaysian market during the COVID-19 pandemic. This discovery aligns with prior research indicating that the global health crisis has resulted in increasing market volatility (Chundakkadan & Nedumparambil 2022; Liu 2021b) and has negative effects on energy stock prices, particularly in countries like China (Huang & Liu 2021; Liu 2021a). The results emphasise the impact of external factors, such as the pandemic, on the energy sector and underscore the importance of analysing the performance of individual stocks within this dynamic market environment.

4.2. *Correlation analysis*

The correlation matrices of energy stocks for two separate periods are distinctly presented in Figure 1. Each security is displayed on both the horizontal and vertical axes. Purple dots denote positive correlations, while negative correlations are represented by orange dots. It is crucial for market participants to grasp these correlations, as they disclose the interrelations between different stocks. Generally, investors seek to select stocks with negative correlations, as they tend to exhibit inverse movements, resulting in a well-diversified portfolio. On the other hand, stocks with extremely positive correlations would stumble simultaneously if a negative impact were to hit them as they move in homogenous directions. A thorough comparison of the correlations prior to and during the COVID-19 pandemic can be observed in Figure 1. The analysis reveals that the strength of correlations has shifted between these timeframes, with a darker purple dot indicating a stronger relationship. Investors should be vigilant in such circumstances, as a considerable number of stocks display positive relationships. The correlograms supply market participants with a holistic overview of the relationships among stocks, simplifying the identification process for stocks with positive or negative correlations.



(a) (b)

Figure 1: Correlograms for the year (a) 2019; (b) 2020

In 2019, a majority of the stocks showed relatively low positive correlations, indicated by correlation coefficients ranging from 0.01 to 0.1. This suggests that there was limited similarity or interdependence in price movements among these stocks during that year. However, in 2020, there was a notable shift, where a majority of the stocks showed significant increases in their positive correlations with one another. Only six specific stocks, namely, BARA, HDEB, ICON, SCES, SCOI, and TECA, exhibited correlation coefficients of less than 0.2 with nearly all the other stocks in the energy sector, which is still generally higher than the correlation values of most of the stocks in the previous year. This highlights a distinct pattern, where these six stocks have weaker associations with other stocks in the sector than the rest.

Diving into the details provided in Table 4, we gather crucial information regarding changes in average correlation values across different years for the energy sector stocks. The analysis shows that in 2019, the average correlation value recorded was relatively low at 0.178. However, this figure underwent a substantial surge and reached an intriguingly higher level of approximately 0.492 during the subsequent year (2020). This increase in average correlation indicates a greater degree of co-movement and dependency between energy sector stocks in 2020, which may be influenced by external events such as the COVID-19 pandemic. Notably, when considering all years as a whole dataset and calculating an overall average correlation value based on multiple data points taken from different time periods, we obtain a result of approximately 0.384. This figure is higher than the 2019 average correlation but lower than the 2020 average correlation. These findings strongly allude to a noticeable shift within the dynamics of energy sector stocks over time and suggest that the correlation levels among the stocks rose generally. The significant increase observed in the average correlation value for the year 2020, affected by extraordinary circumstances such as the COVID-19 pandemic, raises intriguing possibilities regarding external influences impacting these dynamics within this specific period.

The phenomenon of significant average correlation increases, is common in the investment scene, in that periods of highs and lows often cause herding behaviour to take place. This is when stocks become highly correlated with one another as investors simultaneously buy or sell stocks to reduce their losses (Pozzi *et al.* 2013). Essentially, investors react irrationally to the heightened risk and uncertainty of the market conditions by moving in a synchronised manner. We can relate this increase in positive correlations as a flight to safety measure by investors, relating this to the increase in negative average returns for most of the energy stocks across the year 2020. It is important for market participants to take note of this rapid integration of correlations between energy stocks over the course of the COVID-19 pandemic, as it can cause serious negative spillovers if not well taken care of.

Table 4: Average correlation coefficient for energy stocks

Year	2019	2020	2019-2020
Average Correlation	0.178	0.492	0.384

4.3. *Network based on TMFG*

This study aims to explore the changes in the structure of financial market networks amidst the COVID-19 pandemic. The noteworthy alteration in the network structure becomes evident upon examining Figure 2 and Figure 3, which portray the TMFGs for 2019 and 2020 respectively. In 2019, all stocks were interconnected, signifying a cohesive network of financial entities. However, in 2020, six companies (ICON, HDEB, BARA, TECA, SCOI, SCES) became isolated from the network, indicating a transformation in the relationships among these entities. The isolation of these stocks suggests a lack of significant correlations with other stocks in the network. This implies that the price movements of these isolated stocks may be independent of overall market or sector trends. Consequently, these stocks hold potential value for diversification purposes, as they may help to reduce overall portfolio risk by mitigating the impact of broader market fluctuations. Investing in peripheral stocks is also recommended by previous research, as seen in Mo and Chen (2021), Peralta and Zareei (2016), and Pozzi *et al.* (2013). Past studies have agreed that portfolios composed of peripheral stocks tend to fare better than central stocks due to the reduced investment risk (Peralta & Zareei 2016; Pozzi *et al.* 2013) and improved average returns (Mo & Chen 2021). Notice as well that the six isolated stocks in 2020 coincide with the six stocks possessing the lowest correlation values from the correlation analysis subsection. It can be said that stocks of low correlations tend to be positioned at the peripheries of the network and are ideal for diversification strategies.

In 2019, that is in the pre-COVID period, the most connected nodes in the network were HIBI and PTRD. This indicates that these nodes were pivotal in transmitting price fluctuations. Furthermore, the fact that HIBI and PTRD hail from different subsectors implies that they are leading companies within their respective subsectors. These observations highlight their potential influence and significance within the network. However, as the pandemic unfolded in 2020, the structure of the TMFG experienced notable changes. The COVID-19 outbreak particularly impacted the energy sector's stock networks. Figure 3 reveals a shift in the central stock, where DEHB assumes a highly correlated position with other stocks. This indicates that DEHB played a crucial role in transmitting and absorbing market information during the pandemic. Simultaneously, HIBI maintained its position as a central hub within the network, suggesting its ongoing importance and influence despite the challenges posed by the pandemic.

In summary, the outcomes of this study demonstrate that the COVID-19 outbreak had discernible effects on the energy sector's stocks, as exemplified by the changes in stock structure illustrated in Figure 2 and Figure 3. The structural transformations in the TMFG during this period reflect the unique circumstances and challenges faced by financial entities during the pandemic. Understanding these changes contributes to our comprehension regarding the resilience, vulnerabilities, and interconnectedness of different sectors amidst crises such as COVID-19. These insights can assist investors, regulators, and policymakers in developing effective risk management strategies and policies to mitigate future systemic risks.

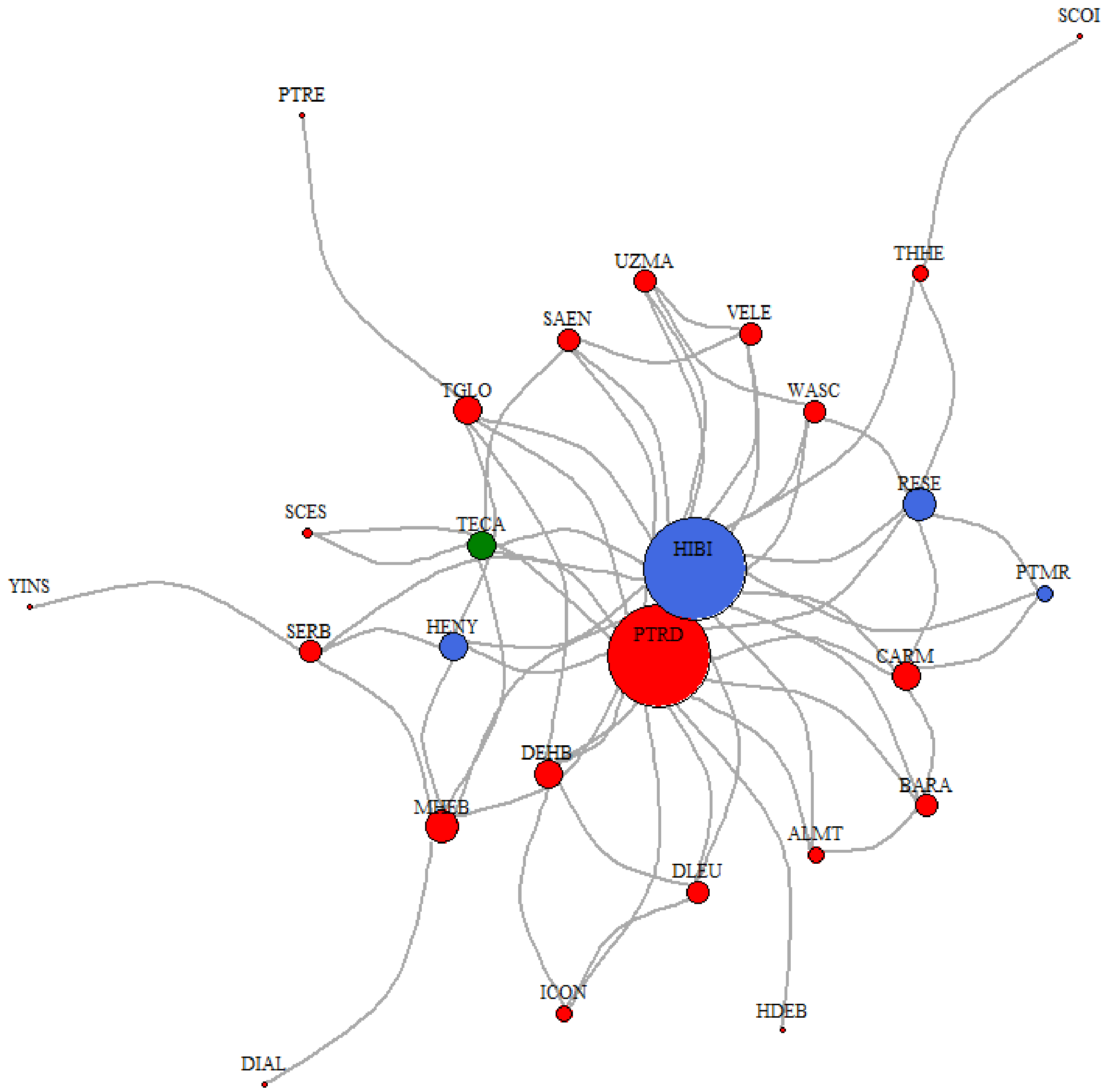


Figure 2: Network based on degree centrality for the year 2019

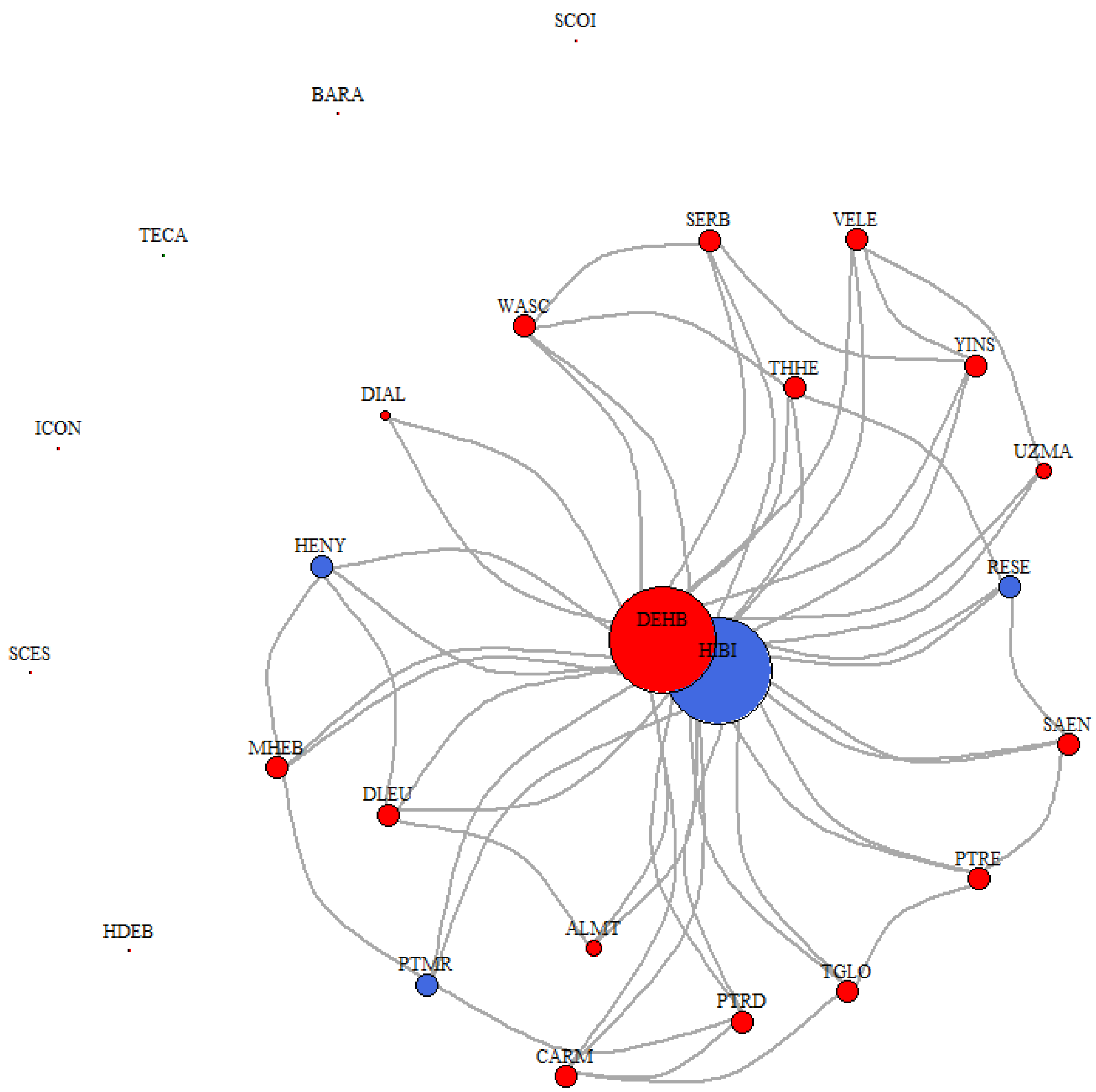


Figure 3: Network based on degree centrality for the year 2020

4.4. *Degree centrality*

Degree centrality is a metric used to measure the number of edges a node has within a network (Freeman 1977). In this study, the total number of edges in the pre-COVID period is 60, which declines to 53 during the COVID period. Table 5 offers an overview of the degree centrality for both the years studied, 2019 and 2020. This presentation enables us to comprehend not only their prominence but also their importance within a given network. By looking at these nodes' degrees of centrality, we can obtain a good idea of how influential they are and what they might be able to do as key players in this network structure.

Table 5: Degree centrality

No	RIC	2019	2020	No	RIC	2019	2020
1	YINS	1	4	14	PTRD	18	4
2	WASC	4	4	15	PTMR	3	4
3	VELE	4	4	16	MHEB	6	4
4	UZMA	4	3	17	ICON	3	0
5	THHE	3	4	18	HIBI	18	19
6	TGLO	5	4	19	HENY	5	4
7	TECA	5	0	20	HDEB	1	0
8	SERB	4	4	21	DLEU	4	4
9	SCES	2	0	22	DIAL	1	2
10	SCOI	1	0	23	DEHB	5	19
11	SAEN	4	4	24	CARM	5	4
12	RESE	6	4	25	BARA	4	0
13	PTRE	1	4	26	ALMT	3	3

In 2019, the nodes PTRD and HIBI stood out with high degree centralities, signalling their prominence and wide-ranging connections of 18 each in the network. Next in line, RESE and MHEB come in third and fourth place as stocks with the highest degree values of 6, although they are far off from PTRD and HIBI. This underscores PTRD and HIBI's substantial connections within the network. As we transition to the year 2020, it is apparent that the degree centrality values for the majority of nodes show a sense of stability with minimal fluctuations observed. This implies that the significance of these nodes in terms of their connections remained unchanged throughout this timeframe. Notably, HIBI continues to exhibit a high degree centrality value, even increasing by one connection, signifying its ongoing influence and extensive relationships within the network. On the other hand, PTRD's reign is, however, taken over by DEHB, as DEHB increases from a degree value of 5 to 19, while PTRD's degree value drops from 18 to only 4. This implies that PTRD was significantly affected by the pandemic, causing it to lose its influence in the energy sector. This helps us to conclude that not all stocks in the energy sector are resilient, even central stocks. It is important to keep tabs on the changes in central stocks due to their ability to spread risks.

Aside from DEHB, YINS and PTRE display an upward trend in their degree centrality from the year 2019 to 2020, with an increase of three connections each. This signifies a notable enhancement in their connections and a potential surge in their influence within the network. On the other hand, PTRD, TECA, BARA, and ICON witness a decline in their degree centrality values of three or more connections, which indicates a potential diminishment in influence. In terms of prominence and influence within the network, the degree centrality analysis demonstrates that certain nodes stand out. It is worth emphasising once again that HIBI consistently exhibits high degree centrality values across both years, suggesting its key role in the network. This stock potentially serves as a hub for information flow and facilitates connections between other stocks.

The observed changes in degree centrality for certain nodes highlight the dynamic nature of the network, where the prominence and connections of nodes evolve over time, although there are also many of the stocks remaining resilient in their standings. This analysis provides valuable insights into the network structure, key nodes, and potential areas of focus for further investigation and analysis. Stocks exhibiting the lowest degree centrality values hold considerable importance in asset allocation strategies, as they signify a peripheral position within the network (Clemente *et al.* 2021; Peralta & Zareei 2016). This peripheral status is crucial for portfolio selection and can impact investment choices. In 2019, YINS, SCOI, PTRE, HDEB, and DIAL were situated on the outskirts of the network. In 2020, six companies became isolated from the network, displaying degree centralities with a value of 0. These isolated stocks are recommended for consideration when constructing a portfolio during that year.

4.5. *Insights and implications*

As seen throughout this study, analysing financial markets using a combination of correlation analysis, network visualisations, and degree centralities can help deepen our understanding of the dynamics and embedded structures of complex financial networks. These network analysis methods have helped us to capture structural network differences as the market evolves over a volatile period of time, aiding in the processing of complex information and relationships that might otherwise be difficult to pin down. Network analysis methods are able to visualise a stock market's social network, while the identification of central stocks can provide additional insights to market participants from a different angle (Hua *et al.* 2019). TMFGs, which are said to retain more details without significant data loss as seen in MST networks and PMFGs, can be considered a tool to showcase the relationships between the Shariah-compliant energy stocks in this study. We generate TMFGs along with the usage of network analysis methods to identify the specific interconnections, besides central and peripheral stocks, to help mitigate risks that may arise during turbulent periods.

Notice how stocks with low correlations are found to be on the peripheries of the network plots, indicating their weaker or lack of connections with other stocks. In contrast, central stocks tend to be positioned at the centre of the plots and possess high correlation values, as seen via the correlation analysis, showcasing their wide net over the whole energy sector system. The plots aid in making conclusions from the quantitative data obtained, such as adding insights into the stocks that have direct significant links with one another. The results show an obvious change in network structure during the pandemic. For example, there are decreased mean returns, increased correlations between stocks, changes in the network plot structure, and central stocks as the COVID-19 pandemic hits the energy market. This makes network analysis a good indication of market volatility or major events in which the authorities should intervene when something looks to be out of character. Investors could also be notified of significant market fluctuations so as to be extra cautious in making any investment decisions.

Even though risk cannot be avoided all at once, steps can still be taken to reduce the widespread risks throughout the financial system. Therefore, the identification of central stocks, as done in this study, can provide great benefits, as the authorities can focus their support and aid on these influential stocks (Abdul Razak & Expert 2021). A central stock is essentially connected to many other stocks, and in some way, their movements, whether negative or positive, will reflect on their neighbours as well. During times of crisis like the COVID-19 pandemic, the increase in correlations combined with the irrational behaviours of investors can cause central stocks to carry larger risks (Pozzi *et al.* 2013). As such, policies could be implemented to identify these central stocks in real-time, with increased checks during volatile periods of time as indicated by the change of market structures. Providing financial aid to central stocks when the stock market is unstable would help to regulate and reduce the domino effects of super spreader events on the whole network. For example, targeted financial support such as providing low-interest loans, subsidies, tax relief or even incentives to central stocks, could help reduce their financial burden. This would then increase their chances to maintain operations during challenging periods, thus stabilising these influential stocks. Although controlling stock prices directly is a challenging task, such financial measures can reduce the overall volatility of the market by dampening down the risk spread emerging from central stocks.

In the case of this study, help should be provided to HIBI and PTRD in the pre-COVID period and HIBI and DEHB during the COVID period. Doing so will reduce the negative risk spread to other stocks from all three subsectors as they are highly interconnected. Additionally, past research has shown that the optimal portfolio should consist of low-central stocks since stocks that are highly central tend to cause large variances (Peralta & Zareei 2016). The optimal portfolio for 2019 should then consist of YINS, SCOI, PTRE, HDEB, and DIAL, while portfolios for 2020 should consist of ICON, HDEB, BARA, TECA, SCOI, and SCES, since they are located at the peripheries of the network and are of low degree centrality values. From an investor's point of view, those who have a big appetite for risks can include central stocks in their portfolio, while those who have a low-risk tolerance can invest in peripheral stocks. This suggested strategy will help maximise their profits or minimise their risks according to their investment style.

5. Conclusion and Future Work

The intricate relationships among financial elements can be simplified by employing a filtration method. Although the MST is frequently utilised by researchers, it is associated with certain limitations. Consequently, the TMFG has been introduced to yield improved results. This paper is driven to examine the Malaysian energy sector's stock network using the TMFG method in light of the COVID-19 disruption. Shariah-compliant stocks for 2019 and 2020 are extracted and incorporated into this study. Furthermore, the TMFG's degree centrality measure is assessed. HIBI and PTRD emerged as central stocks in the network in 2019. However, the central stocks shifted to HIBI and DEHB in 2020 due to the impacts of the COVID-19 shock. These findings indicate that the COVID-19 outbreak has influenced energy stocks, as the topological structure of the networks changes with respect to dominant stocks from 2019 to 2020. Market participants such as investors and policymakers can gain insights into the overall activity of the energy sector and the impact of COVID-19 on the industry. This analysis may assist and guide market participants in making informed decisions to optimise portfolio returns. Additionally, these findings can help investors choose stocks based on their investment preferences. Risk-seeking investors may opt for central stocks, while risk-averse investors may pursue the opposite strategy.

Future research in this area could focus on several aspects. For instance, further investigation could explore the long-term effects of the COVID-19 pandemic on the Malaysian energy sector and its stock network. By examining data beyond the years 2019 and 2020, researchers could gain a more comprehensive understanding of the sector's resilience and recovery from the pandemic's impact. This could include comparisons between the pre, during, and post-COVID periods, over longer time intervals. Choosing the right timeframes for each period would enable somewhat of an isolation between the pandemic's effects and other internal or external factors. It is worth noting that there are a myriad of interactions taking place between stocks, from the aspect of stock prices, common shareholders, shared board of directors, intercompany lending, and so on. These various interactions, influenced by different factors or risks can be modelled via a multilayer network. Instead of a single layer network, future studies can generate multilayer networks that visualise many data aspects to understand the topology of the energy sector according to different factors. Multilayer networks involve a more complex methodology and data collection process. To the best of our knowledge, it has not been employed on Malaysian financial networks to date. Future studies can employ this method to study the long-term effects of the pandemic, looking at different angles other than the interactions between stocks based on stock prices.

It is also important to take note of the many other centrality measures that can be employed to identify central stocks. As an example, the degree, eigen vector, closeness, and betweenness centralities, are frequently used to identify influential nodes in a network (Dimitrios & Vasileios 2015) and have been implemented on Malaysian financial networks by past researchers (Bahaludin & Muhammad Syafiq 2021; Surantharan *et al.* 2024). Since each measure offers a unique perspective based on its definition, employing different centrality measures would likely lead to different influential nodes. As such, information on influential stocks can be gathered based on their various roles in the market. Last but not least, future research can consider the whole fleet of energy stocks, including Shariah and non-Shariah compliant stocks to obtain a fuller picture of energy stock interrelationships.

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Appendix A.

```
#Call the libraries
library(NetworkToolbox)
library(igraph)
# Load data and select date range
price <- read_excel("Data.xlsx")

# Calculate rate of return and correlation matrix
corr <- function(price_data) {
  n <- nrow(price_data)
  u <- ncol(price_data)
  ror <- signif(log(price_data[2:n, 2:u]/price_data[1:n-1, 2:u]), 6)
  ror<- as.matrix(ror)
  corr_mat <- cor(ror, method = "pearson")
  return(list(ror = ror, corr = corr_mat))
}

# Call the price and use correlation function
B <- corr(price)
ret <- as.matrix(B$ror)
rho <- as.matrix(B$corr)

# Calculate average correlation matrix and convert to adjacency matr
ix
avg <- mean(rho)
adj_matrix <- as.matrix(rho > avg)
```

```r
# Construct TMFG using adjacency matrix and plot
tmfg <- TMFG(adj_matrix, normal = TRUE, na.data = c("none"), depend
= FALSE)
g <- graph_from_adjacency_matrix(tmfg$A, mode = "undirected")
g_simp <- simplify(g)

# Assign sector colours
gp <- rep(1:3, length.out = length(V(g_simp)))
my_colour <- c("#E41A1C", "#377EB8", "#4DAF4A")[gp]

# Plot graph with degree centrality
l <- layout.kamada.kawai(g_simp)
deg <- degree(g_simp)
plot(g_simp, edge.width = 2, vertex.label.color = "black",
     vertex.label.cex = 0.6, vertex.label.dist = 0.6,
     layout = l, vertex.size = 1.1*deg, vertex.color = my_colour,
     vertex.shape = "circle", vertex.label.degree = -pi/2)
```

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