Centrality Measures for Shariah-Compliant Securities Listed On Bursa Malaysia

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ABSTRACT

An interrelationship between each of the specified Bursa Malaysia's securities can be calculated using the correlation measure. However, there were a considerable number of these securities, thus, making it difficult to visualise their correlation. To overcome this issue, this association could be illustrated as a single network based on its correlation input. This research constructed a network between the securities listed on Bursa Malaysia, which centred on the Shariah-compliant stocks. Seven centrality measures, such as degree, betweenness, closeness, eigenvector, eccentricity, strength, and average of weight centrality, were used to determine the primary node of the network. The analysis utilised one hundred and 21 stocks from 2008 to 2018, which was divided into two periods, namely, during and after the 2008 global financial crisis (GFC). Additionally, the principal component analysis (PCA) was adopted to determine the main hub's transformations during these two intervals. Finally, this study provided the market participants with valuable information established in a network for the portfolio selection strategy.

Keywords: Bursa Malaysia, Centrality Measure, Minimum Spanning Tree

INTRODUCTION

The expanding global stock market integration is generally becoming more susceptible to shocks, which could cause a rapid ripple effect to other markets worldwide (Beine, Cosma, and Vermeulen 2010; Lehkonen 2015; Yu, Fung, and Tam 2010). For instance, distresses from pandemic Covid-19 outbreak causes financial market in volatile state as studied by numerous researcher (Aggarwal, Nawn, and Dugar 2021; Ahelegbey, Cerchiello, and Scaramozzino 2022; Ali, Alam, and Rizvi 2020; Baig et al. 2021; Chia, Liew, and Rowland 2020; Chundakkadan and Nedumparambil 2021; Emm et al. 2022; Keh and Tan 2021; Lee, Jais, and Chan 2020; Mehmood et al. 2021; Mohd et al. 2022; Riaz et al. 2020; Schell, Wang, and Huynh 2020). This rapid outbreak effect led to disasters like the global financial crisis (GFC) that once hit the financial market globally, in which economists regarded as the most severe financial crisis after the 1930's Great Depression, and among the most notable historical events (Eigner and Umlauft 2015). Specifically, in year 2007 GFC affected most of the global financial markets (Chen et al. 2018). Due to these circumstances, researchers, investors and market participants (i.e., brokers) are taking an interest in the complex correlation structure of the global financial markets. Therefore, numerous methods were utilised to analyse the financial markets, such as minimum spanning tree (MST) (Mantegna, 1999), planar

maximally filtered graph (PMFG) (Tumminello et al., 2005), random matrix theory (RMT) (Laloux et al., 1999), and many others.

Since it was first proposed, the MST method is the most favoured method to visualise and unveil the complex structure of the correlation network. According to Mantegna (1999), this method significantly reduced the correlation matrix from $M \times M$ to M(M-1)/2, where M represented the whole number of stocks and indicated the total number of links in the network. Eventually, research in the financial network adopted this method to identify the impact of numerous crisis in the financial market (Aswani 2017; Hatipoglu 2021; Kantar, Keskin, and Deviren 2011; Khoojine and Han 2019; Kumar and Deo 2012; Lee and Nobi 2018; Li and Pi 2018; Majapa and Gossel 2015; Mbatha and Alovokpinhou 2022; Nobi et al. 2015; Onnela et al. 2003; Rehman et al. 2022; Samitas, Kampouris, and Polyzos 2022; Zhao, Li, and Cai 2015).

The MST method examines the fluctuations in the financial market in terms of structure, taxonomy and clustered stocks. Specifically, Lee and Nobi (2018) revealed that France remained as a hub during the pre-GFC, GFC and post-GFC out of the 35 global indices. Similarly, Aswani (2017) compared 14 Asian stock markets during the same period, which revealed that Hong Kong, Japan, Korea, and India played crucial roles in the correlation networks. Meanwhile, the Chinese stock market during the 2015–2016 GFC revealed a star-shaped cluster with China National Chemical Engineering (Khoojine and Han 2019). In the US market, it was discovered that the financial sector played a critical role in the US economy by analysing the New York Stock Exchange (NYSE) using MST (Maman Abdurachman & Lee, 2015).

However, a network only displays the correlation of the stocks without identifying a central node. Therefore, researchers applied the method of centrality measures to determine the influential nodes (Barbi and Prataviera 2019; Coletti and Murgia 2016; Huang et al. 2017; Khoojine and Han 2019; Lee and Nobi 2018; Li and Pi 2018; Yao and Memon 2019; Zhang, Wen, and Zhu 2016). According to Freeman (1978), the centrality measure method, such as degree, betweenness, and closeness is a crucial tool to demonstrate the influential nodes in a network. Others within the centrality measure method followed, which included the eigenvector centrality (Bonacich 1987), hubs and authorities centrality (Kleinberg 1998), eccentricity (Hage and Harary 1995), information centrality (Stephenson and Zelen 1989), and total communicability (Benzi and Klymko 2013). The definition of the node's importance varied depending on its characteristics. For instance, the importance of a node is potentially dependent on the adjacency matrix, shortest path, and weightage concerning a node.

There are various previous research on the financial network. However, there are limited studies about the financial network in Shariah-compliant securities, which motivated further investigation into this subject. It is worth noting that previous studies only conducted the conventional stocks network analysis. Hence, this research investigated Shariah-compliant stocks listed in Bursa Malaysia using the MST method from 2008 to 2018. Additionally, this research also utilised the seven centrality measures, such as degree, betweenness, closeness, eigenvector, eccentricity, strength and average of weight centrality. Lastly, the PCA was evaluated to determine the most influential stock in the network. Hence, this research is divided into four chapters, with the second chapter displays the data and methodology. The third chapter presents the findings of the research and the conclusions in the fourth chapter.

DATA

Malaysia was impacted by the GFC from the fourth quarter of 2008 to the first half of 2009, as indicated by the Central Bank of Malaysia's 2009 annual report (Economic Developments 2009). The report gathered 207 daily closing prices of 121 Malaysian Shariah-compliant stocks from 1st September 2008 to 30th June 2009 during the GFC. Additionally, 2470 daily closing prices were taken from 1st July 2009 to 31st December 2018. These data were then extracted from the Eikon

Datastream, followed by the construction of MST to visualise the correlation structure of the Malaysian Shariah-compliant stocks. Subsequently, the seven centrality measures was applied to describe each stock in the networks, and later with the PCA method to compute the overall centrality measure. The next subsection demonstrates the MST procedures, centrality measures, and overall centrality method.

METHODOLOGY

Construction of a network by using a minimum spanning tree (MST)

The MST method was used to identify the stocks' correlation, which specified four steps to establish the method. The first step exhibited Equation (1), where $Q_i(t)$ represented the stock's price for i(i = 1...M) at time t and $r_i(t)$ as stock return.

$$h_i(t) = \ln Q_i(t+1) - \ln Q_i(t).$$
(1)

The second step presented Equation (2), which showed the Pearson's correlation coefficient (PCC) between stock *i* and stock *j*:

$$\chi_{ij} = \frac{\langle h_i h_j \rangle - \langle h_i \rangle \langle h_j \rangle}{\sqrt{(\langle h_i^2 \rangle - \langle h_i \rangle^2) - (\langle h_j^2 \rangle - \langle h_j \rangle^2)}}.$$
(2)

the correlation coefficient χ_{ij} represented the element of the $M \times M$ correlation matrix, *C*, where *M* was the total stocks. Meanwhile, the third step indicated the generated distance matrix using the Equation (3) as reported by Mantegna and Stanley (2000):

$$d_{ij} = \sqrt{2(1 - \chi_{ij})}.\tag{3}$$

The final step demonstrated the utilisation of Kruskal's algorithm to incorporate a network using MST entirely. This algorithm usage had several advantages, which included convenient usage (Malkevitch 2012), and limited optimality issue (Djauhari & Gan, 2013; 2014). Lastly, compared to the Prim's algorithm, Kruskal's algorithm was much simpler to utilise, albeit it was a more complex algorithm (Nesetril 1997).

Stocks characteristics

Due to the different functions of the node (stock) in a network (Lü et al. 2016), the centrality measure was applied to interpret their roles (Borgatti and Everett 2006). This research evaluated the nodes based on seven characteristics, namely, degree, betweenness, closeness, eigenvector, eccentricity, strength, and average weight. Lastly, the value of PCA was used to clarify which of the stocks exhibited the most significant function in the network.

The degree centrality, $C_D(i)$ represented the total for the node's direct links. Thus, by examining the total number of linkages to other stock using the adjacent matrix as an input (Freeman, 1978), stock could be identified as a central hub. Equation (4) presents the calculation method for this idea:

$$\mathcal{C}_D(i) = \frac{\sum_{j}^{N} P_{ij}}{M-1},\tag{4}$$

where $P_{ij} = 1$ when the stock *i* and stock *j* were connected or else $P_{ij} = 0$.

The betweenness centrality quantified the significance of a node by appearing as a bridge or a mediator in the network (Freeman 1977, 1978). Equation (5) presents the calculation for the betweenness centrality, $C_B(i)$:

$$C_B(i) = \sum_{j < k} \frac{r_{jk}(i)}{r_{jk}},\tag{5}$$

where $r_{jk}(i)$ represented the sum of the shortest distance from *j* to *k* that passed through *i*, while r_{jk} was the sum of shortest distance from *j* to *k*, where $j \neq i$ and $k \neq i$. Meanwhile, closeness

centrality $C_c(i)$ demonstrated how quick the information could be transferred in the network since $C_c(i)$ applied the weightage or the node's distance as in Equation (6):

$$C_{C}(i) = \left[\sum_{j=1}^{M} q(i,j)\right]^{-1},$$
(6)

where q(i, j) was the shortest possible distance from *i* to *j*. Eigenvector centrality measured the node's position by linking other significant nodes (^{Bonacich,1987)}, expressed as below:

$$e(i) = \lambda^{-1} \sum_{j=1}^{M} P_{ij} y_j \text{ for } i = 1, 2, \dots, M.$$
(7)

The general form of the equation can also be written as:

$$A_{ij}e(i) = \lambda e(i), \tag{8}$$

where P_{ij} was the adjacency matrix, y_j as the eigenvector of stock *j*, and e(i) as an eigenvector of the largest eigenvalue, λ .

The eccentricity measure was defined as the maximum total paths encompassed by the sum of the shortest paths to other nodes (Hage and Harary 1995). Equation (9) presents the determination of eccentric node in the network:

$$E_{c}(i) = \frac{1}{\max_{\substack{j \neq i} j \neq i} \{q(i,j)\}},$$
(9)

where q(i, j) depicted the geodesic path that connected *i* and *j*.

On the other hand, strength centrality indicated the total weight of the node's connections (Barrat et al. 2004; Yook et al. 2001). Specifically, nodes with the most substantial weight were the most significant among other nodes. Thus, Equation (10) presents the method to obtain the node's strength:

$$S(i) = \sum_{j \in \gamma(i)}^{M} o(i, j), \tag{10}$$

where $\gamma(i)$ indicated the neighbours *i* and o(i, j) as the weight of stock *i* and *j*.

Lastly, an average weight centrality was calculated to determine the average link between a particular node and the other adjacent nodes (Shamshuritawati & Maman Abdurachman, 2011; 2012). The average weight centrality was measured as follows:

$$avg(i) = \frac{\sum_{j=1}^{M} h_j(i)}{M},\tag{11}$$

where M was the total nodes and $h_i(i)$ indicated the weight of links adjacent to node i.

Overall centrality measure

The performance of the centrality measure was assessed using PCA (Lee and Maman Abdurachman 2012; Pasini 2017), which minimised the complexity of an extensive matrix and the loss of information (Jolliffe 2002). Notably, a large $M \times W$ matrix, where M represented the sum of stocks, and W as the sum of centrality measures were applied. Generally, a new set of uncorrelated variables is formed from the correlated variables, and this idea is called the principal components (PCs). The initial PCs, which included the percentage of variance, was obtained since these components contained the maximum potential information (Jolliffe 2002). Subsequently, eigenvector was determined, and each of its element was taken as a linear combination for the centrality measures of stock i.

In this case, the covariance matrix G was acquired from a matrix of 121×8 . Afterwards, the eigenvector $k = (k_1, k_2, ..., k_7)$ for the most significant eigenvalue, τ_{max} was calculated using the Equation $Gk = \tau_{max}$. Thus, Equation (12) reveals the calculation for the total centrality measure for each stock:

$$TC(i) = k_i C_D(i) + k_2 C_B(i) + k_3 C_c + k_4 e(i) + k_5 E_c(i) + k_6 S(i) + k_7 avg(i),$$
(12)

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where $C_D(i)$, $C_B(i)$, $C_C(i)$, e(i), $E_C(i)$, S(i) and avg(i) represented degree, betweenness, closeness, eigenvector, eccentricity, strength, and average weight, respectively.

RESULTS

This section is divided into two subsections, in which the result of the constructed financial discussed in the first subsections. The main hub of the network based on the centrality measure is elaborated in the second subsection.

Network of Shariah-compliant stocks by using the MST method

The visualisation of the correlation structure in Shariah-compliant stocks during the GFC was realised by using the MST method. Five dominant clusters originated from GENP, UNIM, MG, WCT, and WTK are presented in Figure 1. The figure reveals that GENP and UNIM comprised a similar number of ten adjacent stocks. Correspondingly, MG and WCT consisted of six stocks each and WTK with only five stocks. Based on Figure 2, fluctuations are evident in the topological arrangement of stocks after a financial turmoil. Hence, this idea established seven primary clusters that were dominated by MLH, MUHIB, KMB, WTK, IJMC, TNB, and LBA. Notably, an estimated half of the dominant stocks originated from the industrial sector, thus, confirmed the vital role of the industrial sector after the GFC.

In particular, Figure 1 and Figure 2 reveal that the stocks' sectors were scattered across the network during and after GFC. These findings were consistent with previous results by Lee and MamanAbdurachman (2012), and Yee and Rohayu (2018), which revealed stocks from similar sectors on the network did not cluster together. Although these data were derived from conventional stocks, a similar structure was found for the network of Shariah-compliant stock. In contrast, other studies revealed that clustered stocks stemmed from the same sectors. Specifically, the clustered network structure of Shariah-compliant stocks registered in Bursa Malaysia, which contradicted with the findings from the foreign financial network (Hatipoğlu 2017; Kantar et al. 2011; Tabak, Serra, and Cajueiro 2010; Tang et al. 2018). This research proved that the Shariahcompliant stocks from similar sectors did not possess a strong correlation between them. However, upon closer observation on the network, the stocks from the plantation sector were clustered together during the GFC. Subsequently, these clustered stocks turned to the industrial sector, as illustrated in According to Lee and Maman Abdurachman (2012) and Yee and Rohavu (2018), two clusters belonged to construction and finance sectors dominated the network of conventional stocks in Bursa Malaysia. Meanwhile, the most dominated sectors for Shariah-compliant securities in the Malaysian market for the GFC and post-GFC was the industrial sector.



Figure 1: Financial network of Shariah-compliant stocks for the duration between 1st September 2008 and 30th June 2009

Stocks characteristics

The importance of nodes on the network was determined with the different characteristics defined in centrality measures. The analysis was presented in the highest five scorers for each centrality.

Degree centrality

Degree centrality measured the importance of the stock, which depended on the total links of the network. Based on Table 1, the data revealed that GENP and UNIM possessed the highest degree centrality value of 0.0833 each, followed by MG, WCT, and WTK. Specifically, UNIM shared the same degree centrality scores with GENP with each stocks acquired ten links that were connected to other stocks. GENP, for instance, was related to KULK, MUHIB, SOP, KWANT, FARH, SIME, JTH, THRE, APM, and UMW. Conversely, UNIM was connected to KMB, CHOO, HOCK, VS, BDA, WEC, SCIE, CREC, PLSP, and TELM, as illustrated in Figure 1.

Table 1 reveals that the degree centrality suggested that MLH and MUHIB acquired the maximum degree centrality values after the crisis. Similarly, the other top five stocks were KMB, WTK, and IJMC. Notably, the findings suggested that only WTK persevered as the highest ranking for both during and after a crisis. Additionally, the degree centrality value of WTK increased from 0.0417 to 0.0992, as presented in Table 1 indicated that WTK possessed more significant stocks connected after the crisis compared to during the crisis.





Betweenness centrality

Betweenness centrality was calculated to determine the prominence of stock in a network. To establish the stock's significance, a mediator was established to utilise the movement of information in a network (Freeman, 1977; 1978). Table 2 reveals that KMB was at the uppermost rank with a value of 0.6420, followed by MUHIB, UNIM, GENP, and CHOO. In other words, these stocks presumably acted as the "bridge" in the network, which coordinated the flow of information in the network such as crisis and price fluctuation. Hence, the downturn of these stocks could affect other stocks. Additionally, MUHIB acted as the intermediary stock with betweenness centrality value of 0.7063 in the recovery period. Similarly, MLH, KMB, WTK, and FAJ were the other five significant stocks. KMB became less significant after the crisis period, while MUHIB presented otherwise. The results revealed that the betweenness centrality value for KMB decreased

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from 0.6420 to 0.4455 after the crisis. Hence, this observation deduced that KMB was more influential during the crisis compared to after the crisis.

Closeness centrality

Table 3 showcases the five crucial values of closeness centrality during and after GFC. Similar to the betweenness centrality, KMB scored the highest in closeness centrality followed by MUHIB, UNIM, GENP, and MLH. These five stocks possessed numerous stocks that were adjacent to them. The three closest stocks to KMB were MLH, MUHIB, and UNIM with distance values of 0.789, 0.933, and 0.998, respectively. Since the distances were based on the correlation among stocks, KMB exhibited a strong correlation with the three stocks. Hence, the crisis could potentially be escalated by KMB to the three stocks vis-à-vis other stocks in the network. Table 3 also presents the five crucial stocks during the post-crisis period, which were MUHIB, MLH, KMB, WTK, and TNB. The outcomes indicated that WTK and TNB exhibited a small distance with other stocks after the crisis compared to the ongoing crisis period. In other words, WTK and TNB transmitted the information more rapidly after the crisis compared to during the crisis, while UNIM and GENP showed the opposite results.

Eigenvector centrality

To create a prominent stock, a specific stock that can be similarly linked to other crucial stocks must be realised (Bonacich 1987). Table 4 presents the five most significant eigenvector centrality measure scores to which UNIM revealed the highest score of 0.5788 during the crisis. Meanwhile, KMB showed a score of 0.2582, 0.0072 for GENP, while CHOO and HOCK at 0.2173 and 0.2172, respectively. Notably, UNIM was linked with the crucial stock like KMB, which was the five leading stocks in degree and was consistently the highest as well as at the top three degrees in betweenness and closeness centrality measure. Table 4 shows that MUHIB was the uppermost prominent stock with the most significant value in eigenvector centrality, which was 0.5142 after the crisis. This outcome was followed by MLH with a value of 0.4076, 0.3155 for KMB, and 0.2126 for WTK. Particularly, this idea provided evidence that the stocks were linked with other prominent stocks in the network. For instance, Figure 2 showed that MUHIB was linked to the prominent stocks such as WTK, KMB, and MLH, in which the stocks were consistently listed in the top five in degree, betweenness, and closeness centrality measures. However, only KMB was consistently listed as the top five stocks concerning the GFC period. Conversely, the other four stocks were substituted by the new stocks in the period post-GFC, such as MUHIB, MLH WTK, and TNB. The results elucidated that UNIM, GENP, CHOO, and HOCK lost their connectivity with prominent stocks in the recovery period.

Eccentricity centrality

Eccentricity centrality calculated the maximum total paths among all the shortest paths (Hage and Harary 1995). A node was likely to be the centre of a network due to the higher value of eccentricity centrality. In the context of the Malaysian Shariah-compliant stocks, Table 5 indicates that KMB and UNIM exhibited the two most eccentric stocks in the network during the catastrophic period with each value displayed at 0.1429. Additionally, AJN, CHOO, and SCIE shared the same scores of 0.1250 each. These results explained that the stocks with identical values exhibited the same number of the shortest paths. Table 4 depicts that KMB and FAJ being in the uppermost rank in the post-crisis with a value of 0.1429. Crucial stocks such as HWA, KHEE, and KUAN were observed by the eccentricity centrality, which played an essential role in the network post-crisis. However, although these vital stocks were not at the top five stocks in degree, betweenness, closeness, and eigenvector centrality, they were still essential for the eccentricity centrality measure by having a small number of the shortest paths. Eccentricity centrality

investigated the number of shortest paths a stock could grasp throughout the network, as opposed to the total shortest distance in closeness centrality. An evaluation between these centrality measures produced different results, in which KMB and FAJ corresponded to eccentricity centrality, while, MUHIB corresponded to closeness centrality post-crisis. The results indicated that KMB and FAJ had a small number of shortest paths with a sizeable total distance; however, it was the opposite for MUHIB.

Strength centrality

A strength centrality measured the total weights of its connections, which indicated prominent nodes. In this study, a total distance of adjacent node was used, which suggested that a node with the highest score in strength centrality was the most prominent node in a network. Table 6 displays that during the crisis, UNIM scored the highest at 11.5399, followed by GENP with a value of 10.7893, which was slightly lower than that of UNIM. MG, WCT, and WTK were the other three critical stocks during the crisis.

Since the strength centrality was extended from the degree centrality (Barrat et al. 2004), the results of degree centrality and strength centrality were compared. A different result showed that UNIM was less important compared to GENP in terms of degree centrality as displayed in Table 1. However, based on the strength centrality, the result was vice versa as UNIM obtained lower connectivity with other stocks but had a more considerable total distance. Additionally, other stocks remained in the same rank for both centrality measures.

For the post-crisis period, MLH had the highest value, while MUHIB, KMB, WTK, and TNB were the top five stocks, as shown in Table 4. In addition, WTK remained as the highest stocks for both crisis and post-crisis period with an increased strength centrality value post-crisis period. This result was due to WTK possessing more adjacent stocks in the post-crisis period, which was twelve stocks compared to five stocks during the crisis period. Thus, the distinctive number of adjacent links affected the total distance of WTK.

Average of weight centrality

According to Shamshuritawati and Maman Abdurachman (2011; 2012), the average weight centrality was computed to measure the average correlation set by a particular node to other adjacent nodes. Table 7 shows the score centrality based on the average of weight during and postcrisis. During the crisis period, ZEC had the highest average correlation in the network, with a score of 1.3079. The second important stock was EMICO with a score of 1.3046, followed by AMTEK, SHCM, and KHIND. Nevertheless, the stocks in the average of weight centrality were crucial as they comprised a prominent total distance with a small denominator, known as the number of adjacent links.

During the post-crisis period, GRH was the most important stock, followed by FARH, COM, and MENT as demonstrated in Table 7. The results showed that GRH had the highest value in the average influence over other adjacent stocks. Similar to the crisis period, findings from Table 7 revealed that the stocks were positioned at the periphery of the network as presented in Figure 2, albeit played an essential role with the average of weight centrality measure. Additionally, this research also found that each stock had a similar average of weight centrality values at 1.37. This was due to the stocks having approximately the same total distances with the same number of adjacent stocks.

Overall centrality measure

The PCA was used to identify the stocks that played a crucial role in the network based on different centrality measures. The first principal component for crisis and post-crisis period was 99.6% and 99.5%, respectively based on the cumulative proportion of variance adequate to identify the overall centrality measure. Table 8 shows the top five overall centrality measure values in the network for both periods. UNIM exhibited the highest value in the overall centrality, which showed that UNIM was the most important stock during the GFC with a score of 9.2020. GENP was in second place with a score of 8.4389, followed by MG, WCT, and WTK. The findings depicted that UNIM ranked at the top five stocks in all centrality measures except in average of weight centrality. In other words, UNIM played the most important role in the network during GFC that impacted the Malaysian market. Figure 3 illustrates the network of Shariah-compliant stocks during the crisis period with the dominated stock based on the PCA values.

Post-crisis, this study identified that the most important stock in the network was MLH with the highest overall centrality value, followed by MUHIB, KMB, WTK, and TNB, as provided in Table 8. The dominated stocks based on PCA value for post-crisis was illustrated in Figure 4. MLH has consistently listed as the top five scorer for each centrality measures except for the eccentricity. It is worth noting that WTK consistently played as top five stocks in the overall centrality for the crisis and post-crisis period. Therefore, it can be said that WTK was also a significant stock.

During crisis		Post-crisis	•
Stock	Degree centrality	Stocks	Degree centrality
GENP	0.083	MLH	0.132
UNIM	0.083	MUHIB	0.132
MG	0.050	KMB	0.124
WCT	0.050	WTK	0.099
WTK	0.042	IJMC	0.041

Table 1: Degree centrality measures during crisis and post-crisis period

 Table 2: Betweenness centrality measures during crisis and post-crisis period

During crisis		Post-crisis	
Stock	Betweenness centrality	Stock	Betweenness centrality
KMB	0.642	MUHIB	0.796
MUHIB	0.600	MLH	0.514
UNIM	0.569	KMB	0.446
GENP	0.468	WTK	0.302
CHOO	0.262	FAJ	0.212

During crisis		Post-crisis	
Stock	Closeness centrality	Stock	Closeness centrality
KMB	0.249	MUHIB	0.305
MUHIB	0.244	MLH	0.268
UNIM	0.234	KMB	0.262
GENP	0.220	WTK	0.246
MLH	0.213	TNB	0.228

 Table 3: Closeness centrality measures during crisis and post-crisis period



Figure 3: Overall centrality network during the crisis period

During crisis	-	Post-crisis	
Stock	Eigenvector centrality	Stock	Eigenvector centrality
UNIM	0.5788	MUHIB	0.5142
KMB	0.2582	MLH	0.4076
GENP	0.2272	KMB	0.3155
CHOO	0.2173	WTK	0.2126
HOCK	0.2172	TNB	0.1335

Table 4: Eigenvector centrality measures during crisis and post-crisis period

 Table 5: Eccentricity centrality measures during crisis and post-crisis period

During crisis		Post-crisis	
Stock	Eccentricity centrality	Stock	Eccentricity centrality
KMB	0.143	KMB	0.143
UNIM	0.143	FAJ	0.143
AJN	0.125	HWA	0.125
CHOO	0.125	KHEE	0.125
SCIE	0.125	KUAN	0.125



Figure 4: Overall centrality network post-crisis period.

During crisis		Post-crisis	<u> </u>
Stock	Strength centrality	Stock	Strength centrality
UNIM	11.540	MLH	20.682
GENP	10.789	MUHIB	20.346
MG	7.435	KMB	19.449
WCT	6.740	WTK	15.226
WTK	5.855	TNB	6.479

Table 6: Strength centrality measures during crisis and post-crisis period

Table 7: Average of weight centrality measures during crisis and post-crisis period

During crisis		Post-crisis		
Stock	Average of weight centrality	Stock	Average of weigh centrality	nt
ZEC	1.308	GRH	1.372	
EMICO	1.305	FARH	1.371	
AMTEK	1.301	COM	1.369	
SHCM	1.299	MENT	1.369	
KHIND	1.298	KUAN	1.367	

Table 8: Overall centrality measures during crisis and post-crisis period

During crisis		Post-crisis	
Stocks	Overall centrality	Stocks	Overall centrality
UNIM	9.202	MLH	18.101
GENP	8.439	MUHIB	17.775
MG	5.066	KMB	16.865
WCT	4.382	WTK	12.639
WTK	3.496	TNB	3.889

CONCLUSION

The impact of the GFC towards Shariah-compliant stocks listed on Bursa Malaysia was demonstrated using a financial network. The MST was employed to construct a network and centrality measure was used to extract the information that embedded in the network, while PCA was applied to generalise the findings and identify the central hub for the Shariah-compliant stocks' network. This study found several significant outcomes. Firstly, the existence of structural changes of the network during and post-crisis found that the number of clusters changed from five clusters during the crisis to seven clusters post-crisis. Secondly, the networks exhibited that the stocks under the same sector were not clustered together. Thirdly, the impact of GFC changed the stocks that played a crucial role in a network as UNIM, GENP, MG, and WCT were no longer significant stocks post-crisis period. These stocks were replaced by MLH, MUHIB, KUB Malaysia, and TNB. However, only WTK Holding remained as an essential stock for both periods. Thus, this study enhanced the understanding of the correlation between Shariah-compliant stocks to assist the market participants in their portfolio selection strategy.

ACKNOWLEDGEMENTS

This paper is funded by the grant of IIUM-UMP-UiTM Sustainable Research Collaboration Grant 2020 (SRCG20-047-0047).

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APPENDIX

No.	Stocks	Code	No.	Stocks	Code
1	Ajinomoto	AJN	38	Southern Acids (M)	SA
2	Amtek Holdings	AMTE K	39	Subur Tiasa Holdings	SUB
3	Cck Consolidated Hdg.	CCK	40	Timberwell	TIM
4	Cwg Holdings	CWG	41	Tong Herr Resources	THRE
5	Emico Holdings	EMICO	42	Vs Industry	VS
6	Federal International Holdings	FED	43	White Horse	WHITE
7	Hwa Tai Industries	HWA	44	Wong Engineering Corporation	WEC
8	Khee San	KHEE	45	Woodlandor Holdings	WOOD
9	Khind Holdings	KHIND	46	Wtk Holdings	WTK
10	Kuantan Flour Mills	KUAN	47	Kumpulan Jetson	KUM
11	Lay Hong	LAY	48	Ipmuda	IP
12	Ltkm	LTKM	49	Kub Malaysia Berhad	KMB
13	Mintye	MINT	50	Ums Holdings	UH
14	Nestle (Malaysia)	NEST	51	Ideal United Bintang International	IUB
15	Paragon Union	PARA	52	Amverton	AMV
16	Pccs Group	PCCS	53	Ark Resources Holdings	ARKH
17	Rex Industry	REX	54	Bina Darulaman	BDA
18	Sand Nisko Capital	SAND	55	Crescendo Corporation	CREC
19	Shh Resources Holdings	SHH	56	Grand Hoover	GRH
20	Sinotop Holdings	SIN	57	Mk Land Holdings	MLH
21	Umw Holdings	UMW	58	Oriental Interest	ORI
22	Yee Lee Corporation	YEE	59	Tiger Synergy	TIGS
23	Brahim's Holdings	BH	60	Genting Plantations	GENP
24	Fiamma Holdings	FIAM	61	Batu Kawan	BATU
25	Konsortium Transnasional	KONS	62	Far East Holdings	FARH
26	Mesb	MESB	63	Jaya Tiasa Holdings	JTH
27	Ocb	OCB	64	Kuala Lumpur Kepong	KULK
28	Permaju Industries	PER	65	Kwantas Corporation	KWAN T
29	Petronas Dagangan	PETD	66	Pls Plantations	PLSP
30	Sime Darby	SIME	67	Sarawak Oil Palms	SOP
31	Alcom Group	ALC	68	Sin Heng Chan (Malaya)	SHCM
32	Amalgamated Indl.Steel	AMAL	69	Innoprise Plantations	INP
33	Anzo Holdings	ANZ	70	United Plantations	UPS
34	Apm Automotive Hdg.	APM	71	Ta Ann Holdings	THL
35	Atta Global Group	ATTA	72	Mtd Acpi Engineering	MTAE
36	Central Industrial Corporation	CENT	73	Fajarbaru Builder Group	FAJ
37	Chin Well Holdings	CHIN	74	Ho Hup Construction	HOHUP

List of 121 shariah-compliant companies from the year 2008 until 2009

75	Choo Bee Metal Inds.	CHOO	99	Hock Seng Lee	HOCK
76	Cme Group	CME	100	Ijm Corporation	IJMC
77	Computer Forms (Mal.)	COM	101	Mercury Industries	MERC
78	Concrete Engr.Prds.	CEP	102	Merge Energy	MERG
79	Ata Ims	ATA	103	Mitrajaya Holdings	MITH
80	Fima Corporation	FIMA	104	Muhibbah Engineering (M)	MUHIB
81	Golden Pharos	GOLD	105	Vizione Holdings	VIZ
82	Kia Lim	KIA	106	Wct Holdings	WCT
83	Kim Hin Industry	KIM	107	Zecon	ZEC
84	Kumpulan H&L High-Tech	KUMH	108	Pdz Holdings	PHLG
85	Kym Holdings	KYM	109	See Hup Consolidated	SEHC
86	Lb Aluminium	LBA	110	Boustead Heavy Industries Corporation	BOUST
87	Master-Pack Group	MG	111	Mesiniaga	MESIN
88	Mce Holdings	MCE	112	Unisem (M)	UNIM
89	Mentiga Corporation	MENT	113	Turiya	TURH
90	Mieco Chipboard	MIE	114	Bimb Holdings	BIMB
91	Minho (M)	MIN	115	Syarikat Takaful Malaysia Keluarga	STMK
92	Perstima.Mal.(Perstima)	PERS	116	Telekom Malaysia	TELM
93	Poly Glass Fibre (M)	POLY	117	Utusan Melayu (Malaysia)	UMM
94	Public Packages Hdg.	PPH	118	Mega First Corporation	MFCB
95	Quality Concrete Hdg.	QCH	119	Tenaga Nasional	TNB
96	Sarawak Cons.Inds.	SCD	120	Kpj Healthcare	KPJH
97	Scientex	SCIE	121	Yinson Holdings	YH
98	Seacera Group	SEA			