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Full Length Article

Network analysis of global stock markets at the beginning of the coronavirus disease (Covid-19) outbreak

Faheem Aslam [a], Yasir Tariq Mohmand [a], Paulo Ferreira [b,c,d,*], Bilal Ahmed Memon [e], Maaz Khan [a], Mrestyal Khan [a]

[a] *Department of Management Sciences, COMSATS University Park Road Tarlai Kalan, 45550, Islamabad, Pakistan*
[b] *VALORIZA - Research Center for Endogenous Resource Valorization, Portalegre, Portugal*
[c] *Instituto Politécnico de Portalegre, Portalegre, Portugal*
[d] *CEFAGE-UE, IIFA, Universidade de Évora, Largo Dos Colegiais 2, 7000, Évora, Portugal*
[e] *School of Finance and Economics, Jiangsu University, Zhenjiang, China*

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Abstract

The Coronavirus (COVID-19) outbreak has become one of the biggest threats to the global economy and financial markets. This study aims to analyze the effects of COVID-19 on 56 global stock indices from October 15, 2019 to August 7, 2020 by using a complex network method. Furthermore, the change of the network structure is analyzed in depth by dividing the stock markets into developed, emerging and frontier markets. The findings reveal a structural change in the form of node changes, reduced connectivity and significant differences in the topological characteristics of the network, due to COVID-19. A contagion effect is also identified in the network structure of emerging markets, with the nodes behaving synchronously. The findings also reveal substantial clustering and homogeneity in the world stock market network, based on geographic positioning. Besides, the number of positive correlations in the global stock indices increased during the outbreak. The stock markets of France and Germany seem to be the most relevant developed markets, while Taiwan and Slovenia have this relevance in emerging and frontier markets. The findings of this study help regulators and practitioners to design important strategies in the light of varying stock market dynamics during COVID-19.

Keywords: COVID-19; Network; Minimum spanning tree; Network topology; Stock markets

1. Introduction

According to the World Health Organization (WHO), by August 9th, 2020, COVID-19 had led to more than 19,824,060 confirmed infections and 729,910 deaths in 215 countries, and numbers continue to increase.[1] In the absence of preventative measures, this outbreak would probably infect 7.0 billion people worldwide, causing 40 million deaths (Walker et al., 2020). Besides the immediate tragedies of death and disease, indirect effects through fear are taking hold around the world. The fear associated with the number of deaths reported has fostered a sense of emergency and globally panic is spreading faster than the spread of the virus itself (Aslam, Awan, Syed, Kashif, & Parveen, 2020). The virus outbreak is becoming the most defining economic and social event in human history with far-reaching economic implications (Laing, 2020). COVID-19 represents unprecedented threats to financial stability and reduced economic activity worldwide (Boot et al., 2020). According to UN International Labor Organization estimates, nearly 25 million jobs could be lost due to COVID-

* Corresponding author. VALORIZA - Research Center for Endogenous Resource Valorization, Portalegre, Portugal.
E-mail address: pferreira@ipportalegre.pt (P. Ferreira).
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[1] https://www.worldometers.info/coronavirus/.

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19. Globally, dramatic economic impacts are noted, for example, the possible loss of $2.7 trillion in output, as referred to by Orlik or Bloomberg, the Asian Development Bank stating damages of $4.1 trillion, and an OECD report declaring global economic growth being cut by half.[2,3] Furthermore, a pandemic like COVID-19 remains unknown and presents unprecedented uncertainty, which makes it difficult for governments to formulate an appropriate economic policy response (McKibbin & Vines, 2020, p. 36). Global stock markets reacted to the rapid emergence of COVID-19. For instance, the Dow Jones Industrial Average dropped by 2353 points on March 12, 2020. Within a week, the DJIA fell by almost 3000 points, the biggest one-day plunge since the "Black Monday" crash of 1987. In just one month, the UK-FTSE fell by 29.72%, Germany's DAX by 33.37%, France's CAC by 33.63%, Japan's NIKKEI by 26.85% and the Indian SUNSEX by 17.74%.

The world has already faced other crises in the form of diseases, i.e., Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome (MERS) or Ebola, among others, with the respective negative financial impacts. There is evidence that the SARS virus in 2003 not only affected human health but also damaged business and educational activities in China (Lee, 2003). The work of Nippani and Washer (2004) examined the impact of SARS on several affected stock markets including China, Canada, the Philippines, Thailand, Singapore, Vietnam, Indonesia and Hong Kong and found an impact on those countries except for China and Vietnam. The Ebola outbreak affected investors' decisions, harming equity capital in African stock markets (Del Giudice & Paltrinieri, 2017) and also had a negative influence on the US stock market (Ichev & Marinč, 2018).

Different aspects of COVID-19 have been widely observed and commented on by governments, researchers and the public alike. Particularly, the global financial market reacted very strongly to this immense black swan event (Nicola et al., 2020). Baker et al. (2020, p. 26945) confirmed that COVID-19 is a more severe event than previous infectious disease outbreaks for US stock markets. As a consequence of COVID-19, stock indices fell drastically (McKibbin & Vines, 2020, p. 36) and stock market volatility increased during the pandemic (Ali, Alam, & Rizvi, 2020; Barro, Ursua, & Weng, 2020, p. 26866), causing huge investment losses (Zhang, Hu, & Ji, 2020). Aslam, Mohti, and Ferreira (2020) confirmed a decline in the intraday efficiency of European stock markets during this pandemic. A comparative study documented that COVID-19 has had more effect on the US stock market than on Asian and Australian stock markets (Ammy-Driss & Garcin, 2020). Somewhat similar findings are confirmed by Garcin, Klein, and Laaribi (2020). On the other hand, Topcu and Gulal (2020) find a greater impact on Asian stock markets than on European ones. From an international perspective, Ashraf (2020) confirms that stock markets react more to the number of confirmed cases than the number of deaths. Czech, Wielechowski, Kotyza, Benešová, and Laputková (2020) applied a TGARCH model to analyze the short-term impact of COVID-19 on Visegrad countries' financial markets. The authors also confirm a negative relationship between Visegrad stock market indices, and the spread of COVID-19. In a similar study, Ali et al. (2020) applied an EGARCH model to the stock markets of the 9 countries most affected by COVID-19, concluding that stock markets deteriorated when the disease changed from an epidemic to a pandemic. Commodity markets also suffered when the pandemic moved into the US.

Using network analysis, Zhang et al. (2020) analyze the impact of COVID-19 on the stock markets of the ten countries with most COVID-19 cases. The authors report that European stock markets remain connected during this pandemic and the USA stock market failed to take the leading role before and during the outbreak. Although a few studies have compared the financial impacts of COVID-19 on different regional stock markets by applying diverse statistical techniques, no comprehensive study has addressed the impacts of COVID-19 on stock market networks. From an investment and regulatory point of view the main advantage of analyzing a large sample of global stock markets is that equity valuations should include both local and global risk factors.

The COVID-19 pandemic is creating fear of increasing global poverty levels due to lower consumer spending resulting in lower firm confidence (Lucas, 2020; Sumner, Hoy, & Ortiz-Juarez, 2020, pp. 800−809). The lockdowns and negative sentiments contributed to an increase in market illiquidity and volatility resulting in the deterioration of market stability (Baig, Butt, Haroon, & Rizvi, 2020; Chen, Liu, & Zhao, 2020). Besides this, the news regarding COVID-19 created panic sentiments which affected investor behavior and generated uncertainty and high volatility in financial markets (Haroon & Rizvi, 2020). Particularly, during bearish trends in stock markets, investors become more cautious (Lu & Lai, 2012; Omay & Iren, 2019). Similar trading behavior is reported by Allam, Abdelrhim, and Mohamed (2020), emerging during the COVID-19 outbreak. With the backdrop of ambiguity and uncertainty, investors search for safe havens to avoid possible financial losses and are reluctant to trade, which affects financial markets adversely (Epstein & Wang, 1994; Levy & Galili, 2006; Mukerji & Tallon, 2001). Moreover, the sentiments related to COVID-19 news affected the price movements of the financial market (Mamaysky, 2020) and investors' sentiments on future investments also affected the stock market during COVID-19 (Liu, Manzoor, Wang, Zhang, & Manzoor, 2020).

This study is unique and makes three main contributions to the literature. First, the study is more comprehensive. We apply a complex network approach to analyze the effects of the COVID-19 outbreak on 56 global stock indices. Second, the findings of this study are more detailed. International institutional investors have different evolving investment requirements and use different types of instruments. To address this requirement, we performed an in-depth analysis by

[2] Details are available at https://www.ft.com/content/1356af8c-5c6c-11ea-8033-fa40a0d65a98.

[3] Details are available at https://www.bloomberg.com/news/articles/2020-04-03/global-cost-of-coronavirus-could-reach-4-1-trillion-adb-says.

examining the effect of COVID-19 using developed, emerging and frontier markets. Third, this study constructs a complex network of all stock correlations and then analyzes in depth the variations in the network structure before and during COVID-19. The findings of this study will be helpful to protect stock markets by revealing the impacts of COVID-19 on global stock markets.

2. Materials and methods

2.1. Data

In the space of a few weeks, Coronavirus (COVID-19) was officially declared a pandemic and shaved off nearly a third of the global market capitalization.[4] In order to analyze the influence of this disease, this study uses daily stock index prices of 56 global stock market indices. The data is collected from Yahoo Finance from October 15, 2019 to August 7, 2020, a total of 204 observations. Stock markets are divided into developed (23 markets), emerging (22 markets) and frontier (11 markets) markets using the Morgan Stanley Capital International (MSCI) classification. The list of countries, stock market index and classification are presented in Table 1.

According to the emergence of COVID-19 and following Zhu et al. (2020), the stock data is divided into two periods of 102 trading days each. Due to the global consequence, the World Health Organization (WHO) declared the COVID-19 epidemic as a global pandemic on March 11, 2020 (Maier & Brockmann, 2020). Using the same date, the closing prices ranging from October 15, 2019 to March 10, 2020 refer to the period before COVID-19 and prices from March 11, 2020 to 7th August for the period during COVID-19.

2.2. Building the network

To build the network, we started by defining the traditional log returns:

$$R_i(t) = lnp_i(t) - lnp_i(t-1) \tag{1}$$

where the closing price of the index at moments *t* and *t-1* are represented respectively by $p_i(t)$ and $p_i(t-1)$.

To measure the dependence between stock market indices, the long-run correlation coefficient is estimated based on the heteroskedasticity and autocorrelation consistent variance−covariance matrix introduced by Andrews (1991). This choice was guided by the fact that return series are subject to mild levels of autocorrelation and to excess volatility during crises (Výrost, Lyócsa, & Baumöhl, 2019).

For a given sample size T, Andrews' (1991) estimate takes the following form:

$$\widehat{\Omega}_T = \begin{bmatrix} \widehat{w}_{i,i} & \widehat{w}_{i,j} \\ \widehat{w}_{j,i} & \widehat{w}_{j,j} \end{bmatrix} = \sum_{m=-T+1}^{T-1} k\left(\frac{m}{B}\right)\widehat{\Gamma}(m) \tag{2}$$

where,

$$\widehat{\Gamma}(m) = \begin{cases} T^{-1}\sum_{t=m+1}^{T} [Z_t Z_{t-m}], & m \geq 0 \\ T^{-1}\sum_{t=m+1}^{T} [Z_{t+m} Z_t], & m < 0 \end{cases} \tag{3}$$

and where $t = 1,2, \ldots,T$, $Z_t = [r_{i,t}, r_{j,t}]^T$, and k (.) is the quadratic spectral kernel weighting function that together with bandwidth parameter B weighs lagged variances and co-variances. In our empirical work, we choose automatic choice for the bandwidth parameter which is 4, corresponding to 4 working days that attain the greatest weight. The quadratic spectral kernel function is defined as:

$$k\left(x = \frac{m}{B}\right) = \frac{25}{12\pi^2 x^2}\left(\frac{sin(6\pi x/5)}{6\pi x/5} - cos(6\pi x/5)\right) \tag{4}$$

Finally, the long-run correlation $\widehat{\rho}_{i,j}$ is estimated as:

$$\widehat{\rho}_{i,j} = \frac{\widehat{w}_{i,j}}{\sqrt{\widehat{w}_{i,i}\widehat{w}_{j,i}}} \tag{5}$$

The correlations for the two different periods are represented in Fig. 1 for the whole set of stock markets and in Figs. 2−4, respectively, for developed, emerging and frontier stock markets. The lower triangle of the plot shows the correlation coefficients before COVID-19, whereas the upper triangle shows the coefficients during COVID-19. The blue color means positive correlations, red means negative correlations and the vertical and horizontal axes represent each of the indices. The comparisons clearly show changes in the correlation structure during COVID-19 in all types of stock markets.

Fig. 2 shows the correlogram for all 56 stock markets before and during COVID-19. Overall, the number of positive correlations in the global stock indices increased during the outbreak. In the whole set of pairs of correlations (3136) we observed a total of 2900 positive correlations, about 92.4%, while the remaining 7.5% were negative, in the period before COVID-19. However, during COVID-19, the number of positive correlations increased to 2944 (93.88%) and only 192 (6.12%) remained negative. From a total of 3136 (56 × 56) correlations, the direction of 384 correlations changed during the COVID-19 outbreak, with a significant impact on the stock markets in China, Pakistan, Tunisia, Serbia and Vietnam. The results show a significant change in the correlation direction of Vietnam (HNX 30) with 45 global stock indices, and Tunisia (Tunindex) with 24 global stock indices. It is noted that both Vietnam and Tunisia belong to frontier markets but show strong correlation changes with all 56 stock markets. For instance, the direction of Vietnam with Canada (Developed) and Pakistan (Emerging) changes from −0.37 to 0.30 and −0.30 to 0.31 respectively. However, the correlation direction

[4] The details are available at https://economictimes.indiatimes.com/wealth/invest/stock-market-hit-by-coronavirus-reasons-for-turmoil-what-equity-investors-should-do-now/articleshow/74623291.cms?from=mdr.

Table 1
List of countries with the corresponding stock index, split by market classification.

Developed Markets			Emerging Markets			Frontier Markets		
S.No.	Country	Index Name	S.No.	Country	Index Name	S.No.	Country	Index Name
1	Australia	ASX 200	1	Argentina	S&P Merval	1	Croatia	CROBEX
2	Austria	ATX	2	Brazil	Bovespa	2	Kazakhstan	KASE
3	Belgium	BEL 20	3	Chile	S&P CLX IPSA	3	Kenya	Kenya NSE 20
4	Canada	S&P/TSX	4	China	Shanghai Composite	4	Mauritius	Semdex
5	Denmark	OMXC20	5	Colombia	COLCAP Global X	5	Morocco	Moroccan All Share
6	Finland	OMX Helsinki 25	6	Czech Republic	FPXAA.PR	6	Nigeria	NSE 30
7	France	CAC 40	7	Greece	Athens General Composite	7	Romania	BET
8	Germany	DAX	8	Hungary	Budapest SE	8	Serbia	Belex 15
9	Hong Kong	FTSE China 50	9	India	S&P BSE SENSEX	9	Slovenia	Blue-Chip SBITOP
10	Ireland	ISEQ All Share	10	Indonesia	JSE Composite Index	10	Tunisia	Tunindex
11	Israel	TA 35	11	Malaysia	KLCI	11	Vietnam	HNX 30
12	Italy	FTSE MIB	12	Mexico	S&P/BMV IPC			
13	Japan	Nikkei 225	13	Pakistan	KSE-100			
14	Netherlands	AEX	14	Peru	S&P Lima General			
15	New Zealand	NZX 50	15	Philippines	PSEi Composite			
16	Norway	OSE Benchmark	16	Poland	WIG20			
17	Portugal	PSI 20	17	Russia	MOEX			
18	Singapore	STI Index	18	South Africa	South Africa Top 40			
19	Spain	IBEX 35	19	South Korea	KOSPI			
20	Sweden	OMXS30	20	Taiwan	Taiwan Weighted			
21	Switzerland	SMI	21	Thailand	SET			
22	United Kingdom	FTSE 100	22	Turkey	BIST-100			
23	United States	Dow 30						

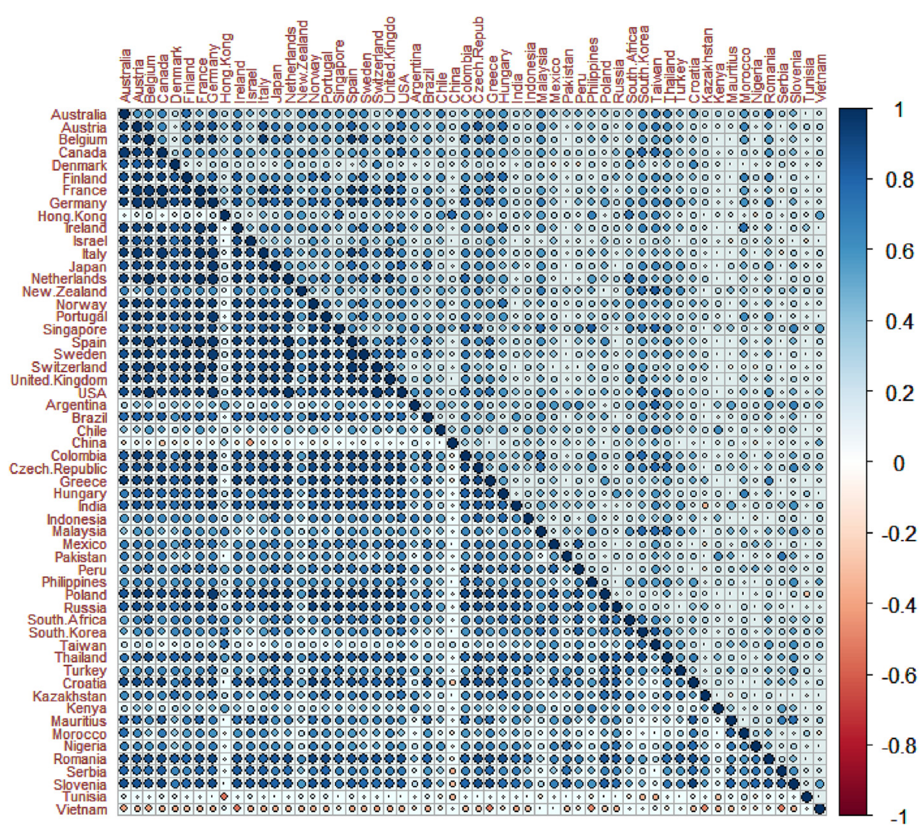

Fig. 1. Correlogram for all stock markets before and during COVID-19. This is the correlation coefficient matrix representing the relationships before and during COVID-19 for all 56 stock market indices. The lower triangle of the plot shows the correlation coefficients before COVID-19 whereas the upper triangle shows the coefficients during COVID-19. Blue means positive correlations and red means negative correlations. The vertical and horizontal axes represent the whole set of 56 international stock indices.

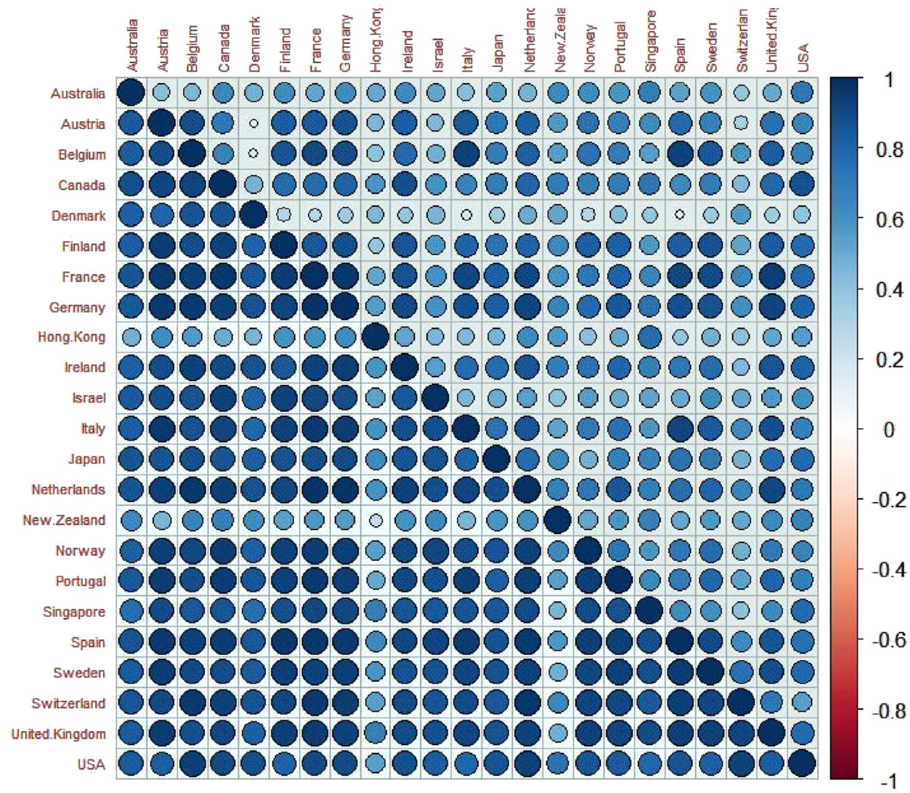

Fig. 2. Correlogram for developed stock markets before and during COVID-19. This is the long-run correlation coefficient matrix representing the relationships before and during COVID-19 for the 23 developed stock market indices. The lower triangle of the plot shows the correlation coefficients before COVID-19 whereas the upper triangle shows the coefficients during COVID-19. Blue means positive correlations and red means negative correlations. The vertical and horizontal axes represent the 23 developed stock indices.

between the USA (Developed) and Kazakhstan (Frontier) changed from −0.06 to 0.21. Likewise, the correlation direction becomes positive between the USA and China from −0.14 to 0.31 during COVID-19.

It is important to note that COVID-19 has varying impacts on developed, emerging and frontier markets. Overall, the largest number of changes in correlations is found among the frontier markets during COVID-19, rather than in developed and emerging markets.

As shown in Fig. 2, the direction of correlations did not change significantly among developed stock markets. However, the strength of the relationship changes significantly. From a total of 529 correlations (23 × 23), the strength of 462 (87%) correlations become weaker among developed stock markets during the COVID-19 outbreak. The most significant change in correlation strength is identified in Norway, Israel, Spain, Switzerland and Denmark. For example, the correlation value for Israel (TA 35) and Denmark (OMXC 20) declines against all other 22 stock markets during the COVID-19 outbreak. On the other hand, the correlation of New Zealand became stronger with 15 stock indices during the outbreak.

Fig. 3 shows that the correlation structure among emerging markets changed more than in developed markets. Before COVID-19, emerging markets showed positive correlations and only 10 out of 484 correlations (22 × 22) changed direction during the COVID-19 outbreak. The stock markets of Pakistan, Poland, China, Argentina and Taiwan showed major significant changes during the COVID-19 outbreak. The correlation direction of Poland changed with 4 stock markets. For example, the correlation between Poland and China changed from positive (0.38) to negative (−0.07). Although only two percent of the relationships changed sign, the strength of relationships changes significantly among emerging markets during this pandemic. The stock markets of Brazil, the Philippines, Poland, Indonesia and Mexico showed a significant change in the strength of correlations with other stock markets. For example, Brazil's correlation with other 21 stock markets became weaker during the COVID-19 outbreak, but that of Chile with other stock indices became stronger during the crisis.

Finally, the biggest changes can be observed in frontier markets, as shown in Fig. 4. Frontier markets showed a change of about 10% in correlation directions, with a total of 12 changes out of 21 (11 × 11) correlations. The most significant changes are found in the stock markets of Kazakhstan, Morocco, Nigeria and Vietnam. The Vietnamese stock market (HNX 30) showed major significant changes in correlation direction with four other markets during the COVID-19 outbreak. For example, the correlation direction between Vietnam and Morocco becomes −0.15 from 0.008 during COVID-19. However, the direction of the correlation between Vietnam and Kazakhstan changed from −0.01 to 0.11,

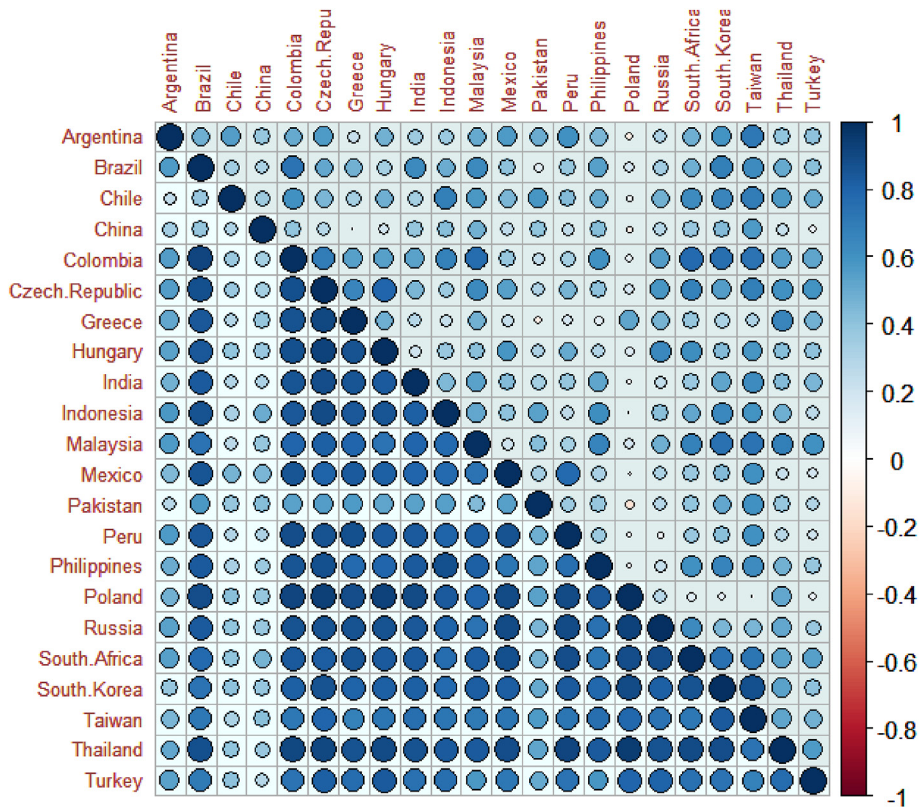

Fig. 3. Correlogram for emerging stock markets before and during COVID-19. This is the long-run correlation coefficient matrix representing the relationships before and during COVID-19 for the 22 emerging stock market indices. The lower triangle of the plot shows the correlation coefficients before COVID-19 whereas the upper triangle shows the coefficients during COVID-19. Blue means positive correlations and red means negative correlations. The vertical and horizontal axes represent the 22 emerging stock indices.

Otherwise, correlations become weaker in the frontier markets during COVID-19.

To calculate the weight in the network, we calculate the distance between all pairs of correlation coefficients, as proposed by Mantegna (1999) and Stanley and Mantegna (2000). The transformation function for the distance can be expressed as:

$$d_{ij} = \sqrt{2\left(1-\rho_{ij}\right)} \tag{6}$$

Based on Equation (4), we obtain different distance matrices with dimensions of 56 × 56 (considering all markets), 23 × 23 (for developed markets), 22 × 22 (for emerging markets) and 11 × 11 (for frontier markets).

2.3. Minimum spanning tree

Due to the mutual flow of information and synchronization among investors, stock returns show high cross-dependence, even across countries. Since the seminal study by Mantegna (Mantegna, 1999), devoted to correlation-based networks, it has been observed that the structures of such networks contain significant economic information and also important independent information (Buonocore et al., 2016). A network is a collection of nodes or vertices connected by arcs or edges referred to as G with N nodes and M edges. A directed network is a collection of directed edges or arcs representing the flow or direction of information from one node to another. An undirected network, however, is where the edges are bidirectional, and instead of showing the directional flow, it represents the connection between two nodes. The connection between those nodes can be weighted or unweighted. So, along with an adjacency matrix A, weighted networks also have a weight matrix W.

However, a stock market cannot be illustrated by complex networks as the market is completely connected, representing an interconnection among all nodes. Such a representation will not yield insightful network statistics. Instead, stock markets can be better explained with a Minimum Spanning Tree (MST). This network methodology is applied to analyze numerous economic and financial crises (Mahamood, Bahaludin, & Abdullah, 2019; Majapa & Gossel, 2016; Memon, Yao, Aslam, & Tahir, 2019; Yang, Li, & Zhang, 2014). Particularly regarding stock markets, the minimum spanning tree (MST) methodology is adopted to analyze the interdependency of stock markets (Han, 2019; Mantegna, 1999; Memon & Yao, 2019; Nguyen, Nguyen, & Nguyen, 2019). The MST also provides a proper visualization of a complex network and market relation (Rešovský, Horváth, Gazda, & Siničáková, 2013). Mantegna (1999) reported a topological arrangement of stocks traded in S&P500 which was associated with a meaningful economic taxonomy. The finance

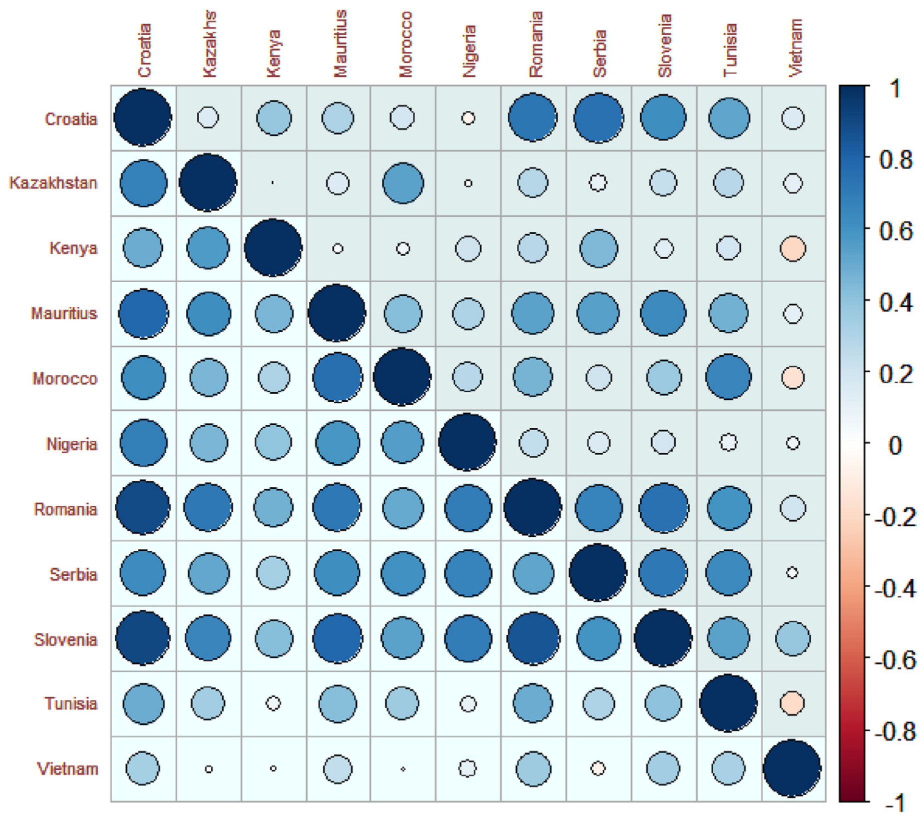

Fig. 4. Correlogram for frontier stock markets before and during COVID-19. This is the long-run correlation coefficient matrix representing the relationships before and during COVID-19 for 11 frontier emerging stock market indices. The lower triangle of the plot shows the correlation coefficients before COVID-19 whereas the upper triangle shows the coefficients during COVID-19. Blue means positive correlations and red means negative correlations. The vertical and horizontal axes represent the 11 frontier stock indices.

network literature has been extended to study the network topology of 56 global stock indices before and during the COVID-19 outbreak.

A spanning tree is a sub-graph which contains all the nodes of the network but with fewer edges. Different algorithms exist for the extraction of MST from a network, with the Kruskal and Prim algorithm (Kruskal, 1956) being the most popular. In this paper, the stock markets' MSTs are created using the Kruskal algorithm for an undirected graph $(G = N,E,W)$ in forming MST (Kruskal, 1956). Following this, communities are identified using the Girvan-Newman algorithm (Girvan & Newman, 2002).

Several topological properties are used to calculate the most important node in a network. The most common include degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. In this study, betweenness and closeness centralities are used. Betweenness detects the nodes acting as bridges for the flow of information from one end to another. It can be expressed mathematically as

$$B_c(i) = \sum_{a,b \in V} \frac{\lambda(a,b|i)}{\lambda(a,b)} \tag{7}$$

where V being the node set, $\lambda(a, b)$ represents the number of shortest paths and $\lambda(a, b|i)$ is the shortest path passing through i. On the other hand, closeness is the average shortest distance from node i to all the other nodes, which reflects the importance of the node relative to other nodes in the network. Mathematically:

$$C(V_i) = \frac{(N-1)}{\sum_{j=1}^{n} d(V_i V_j)} \tag{8}$$

where $d(V_iV_j)$ is the shortest distance between V_i and V_j and is equal to the minimum stations from V_i to V_j in the network, whereas $(N-1)$ is the normalization factor. The average shortest path length is also studied, characterized by the minimum number of edges passing through one node to another, defined as:

$$a = \sum_{s,t \in V} \frac{d(s,t)}{n(n-1)} \tag{9}$$

where V is the set of nodes in G, $d(s,t)$ is the shortest path from s to t and n is the number of nodes in MST.

3. Results and discussion

With the transformation of daily closing prices of stock indices in log returns and with the distance performed in Equation 4, we built a weighted graph G with N nodes and M edges, an associated adjacency matrix $A = [a_{i,j}]$ and a weight matrix $W = [w_{i,j}]$ representing the correlation between stocks. Using the Kruskal algorithm, MSTs were extracted from the graph taking the form $T\ (V,\ E)$, where T is the MST with $V = \{Vertex_1,\ Vertex_2,\ ....\ Vertex_n\}$ a set of vertices and $E = \{Edge_1,\ Edge_2,\ ...Edge_n\}$ representing the edges with weights $W = [w_{i,j}]$ as shown in Figs. 5−8.

Fig. 5 shows the comparative minimum spanning tree of all the 56 stock market indices before and during COVID-19 with the upper MST showing the financial network before and the lower one the network during COVID-19 (the color of the node represents the community belonged to). Through a comparative analysis of the minimum spanning tree of all 56 stock markets before COVID-19 (All-MST19) and during COVID-19 (All-MST20), we can see that before the emergence of COVID-19, there was a cluster of Asian countries with South Korea in the center. European countries such as France, Germany, Italy, Poland and the Netherlands occupied a central position before the epidemic and more connected with Europe (cluster in the middle of the MST). In terms of connectivity, there are two principal nodes of Germany and France having six degrees of connection. This possibly reflects the concentration of the world stock market network around these two hub nodes before COVID-19. This is in line with the findings of J. W. Lee and Nobi (2018) where France is the central node in the MST in all periods, and due to its global positioning a hub for numerous corporations. In addition, strong reliance and connectivity of European stock market nodes with the rest of the nodes is observed. Moreover, the MST represents strong stock market clustering and homogeneity based on geographical distribution of stock market regions.

However, the structure of the stock market has changed since the spread of the virus. The lower MST (panel b) during COVID-19 shows one dominant hub node of Germany having seven degrees of connection, followed by Taiwan having five

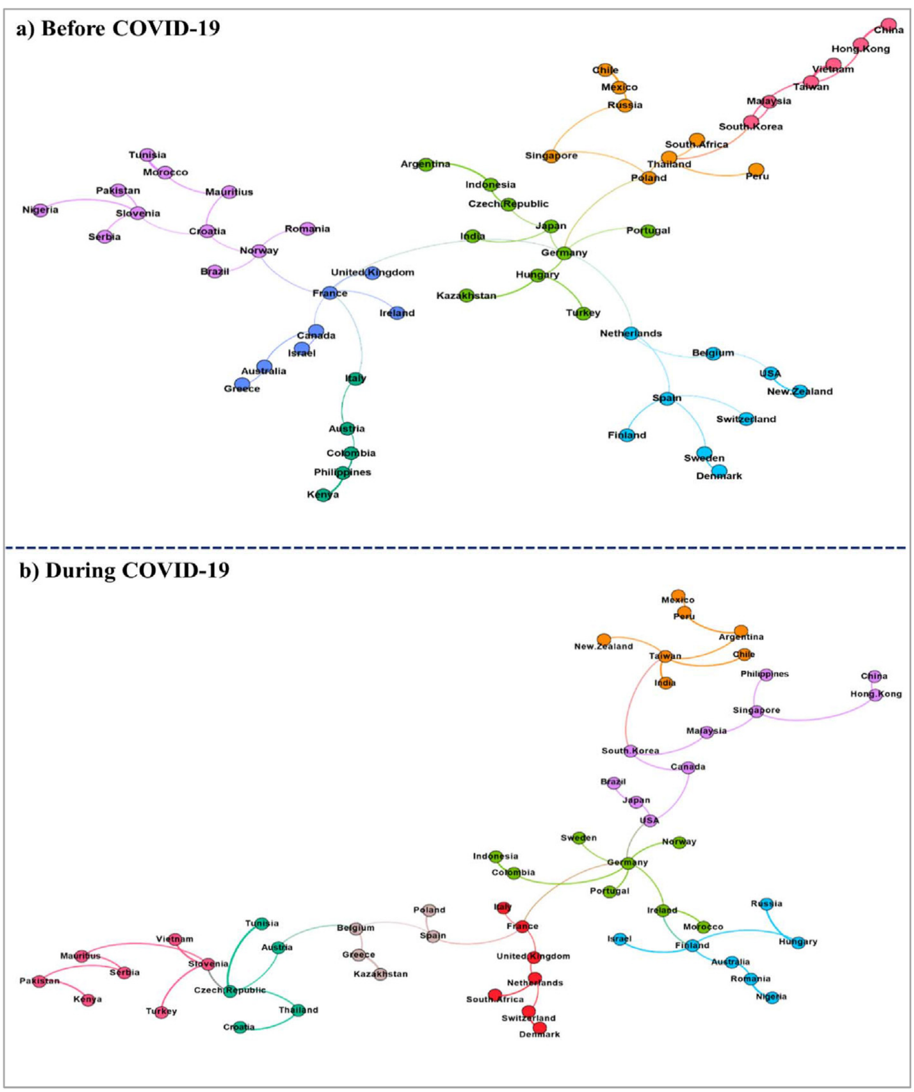

Fig. 5. Comparative community structure for the whole set of stock markets before (Panel a) and during (Panel b) COVID-19. Vertices are colored to indicate different communities.

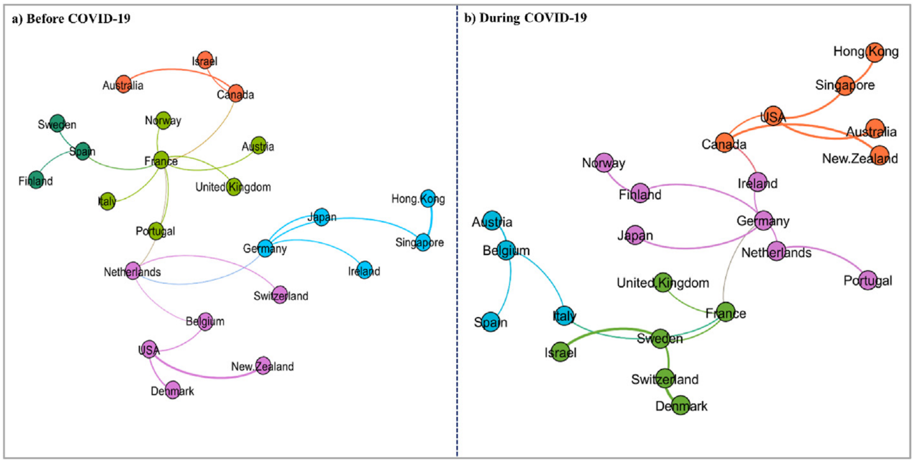

Fig. 6. Comparative community structure for the 23 developed stock markets before (panel a) and during (panel b) COVID-19. Vertices are colored to indicate different communities.

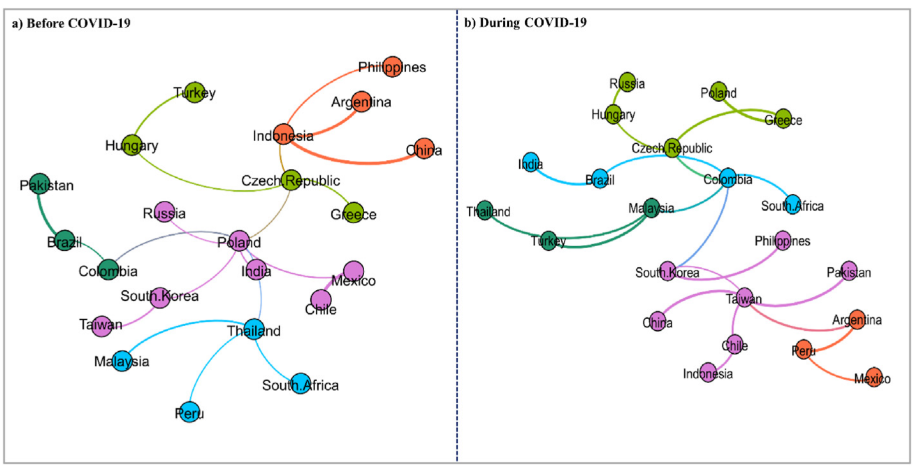

Fig. 7. Comparative community structure for the 22 emerging stock markets before (panel a) and during (panel b) COVID-19. Vertices are colored to indicate different communities.

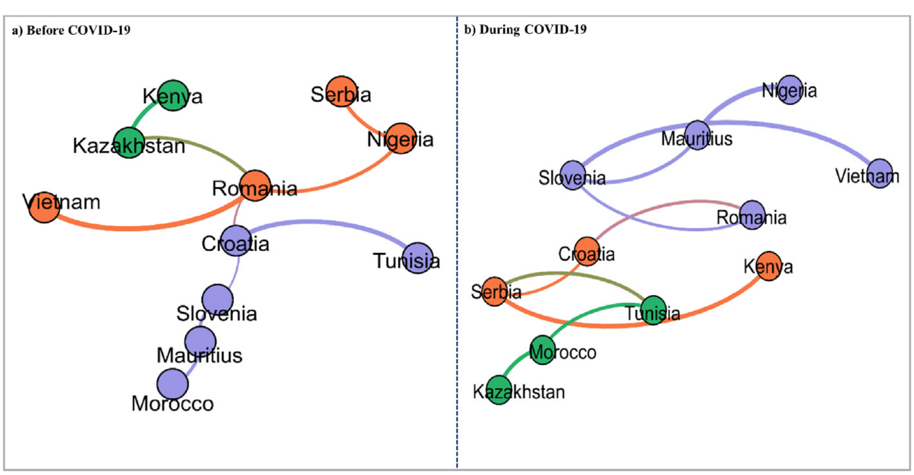

Fig. 8. Comparative community structure for the 11 frontier stock markets before (panel a) and during (panel b) COVID-19. Vertices are colored to indicate different communities.

degrees of connection during COVID-19. Apart from these two nodes, the rest of the tree in the MST has a decreased level of connectivity. Thus, the MST has a star-like structure, which is commonly found during crisis periods (Memon & Yao, 2019). Before COVID-19, Germany and France were the most connected markets. However, Germany remains in the leading nodes during COVID-19, but Taiwan replaces France as the most connected market. The number of communities also increased from 7 to 8. Looking at the Asian markets, Taiwan emerges as the central hub followed by South Korea. Before, these two markets were part of same community, but after the pandemic, the community changes. Taiwan is no longer connected to the Asian markets.

The USA, which was a member of the European cluster, is now connected to the Asian market along with Canada, Brazil and Japan. The hard-hit countries of Italy and Spain are less connected now than before. It is also worth noting that the US stock market is not a hub node in either MST. Similar findings about the US stock market emerged in Coelho, Gilmore, Lucey, Richmond, and Hutzler (2007) and Wang, Xie, and Stanley (2018) in the MST, due to strong correlation among European stock market indices that lessens the influence of the US stock market. The results also present strong geographical clustering with Europe and Asia being prominent, which could be explained by the fact that the pandemic started in Asia and then moved to Europe. In addition, the Chinese stock market is connected directly to the Hong Kong stock market in both MSTs, representing the coronavirus effect which started in China and affected the Hong Kong stock market directly.

For a detailed insight, we also created separate MSTs with communities in Figs. 6–8. The MSTs before and during COVID-19 of developed markets are presented in Fig. 6 and show a reduction in the number of communities from five before COVID-19 to four during COVID-19. Furthermore, the community changed significantly.

Before COVID-19, most connected nodes remain with European stock market indices dominating the developed countries market with high degree of connections. France holds a key central position in the MST of developed countries stock market with eight degrees of connection, followed by Germany and the Netherlands with four connections each. In addition, the shortest distance is observed among European stock markets, representing the highest correlation among developed stock markets before COVID-19. However, after the COVID-19 outbreak the connections of major hub nodes of France and Germany drop, which may be due to turbulence in the financial markets. Before COVID-19, Spain was connected to Sweden and Finland, but during COVID-19 it is connected to Belgium only.

Fig. 7 shows the comparative community structure for the 22 emerging stock markets before (panel a) and during (panel b) COVID-19. Although the number of communities remained the same (i.e. 5), the community membership changes significantly. The outbreak's epicenter, China, was connected with Indonesia before COVID-19. However, after COVID-19, the Chinese stock market formed a connection with that of Taiwan. The possibility of a contagion effect is noted among emerging stock markets in the form of re-configuration of key nodes before and after COVID-19. The principal nodes before COVID-19 are recorded as follows: Poland with seven degrees of connections, followed by the Czech Republic, Indonesia and Thailand having four direct connections each. However, during COVID-19 the nodes are less connected and form a chain-like structure, with Colombia and Taiwan connecting directly with five other nodes of the network. Investors' vulnerability is shown, in the rearrangement and reconfiguration among key nodes before and during COVID-19. Other significant nodes include Malaysia, the Czech Republic and South Korea, with three connections. Fig. 3 shows that the correlation structure among emerging markets changed more than in developed countries.

Finally, Fig. 8 shows the comparative community structure for the 11 frontier stock markets before (panel a) and during (panel b) COVID-19. As in the case of emerging markets, community membership changed without changing the number of communities. It is evident from Fig. 8 that before COVID-19, the Romanian stock market occupied a central position. However, Slovenia emerged as a central hub during the pandemic.

Our results reveal that the correlation between stock markets is positive before COVID-19. Of a total of 484 correlations (22×22), 10 (2%) changed the direction of correlations in the emerging market during the COVID-19 outbreak. The stock markets of Pakistan, Poland, China, Argentina and Taiwan showed major significant changes during the COVID-19 outbreak. The correlation direction of Poland changed with 4 stock indices in the emerging market during the COVID-19 outbreak. For example, the correlation direction between Poland and China changed from positive (0.38) to negative (-0.07).

However, in emerging markets, Brazil, Philippines, Poland, Indonesia and Mexico showed a significant change in the strength of correlations with other stock markets. For example, Brazil's correlation became weaker with 21 stock markets during the COVID-19 outbreak, but Chile's has become stronger with other stock indices during the crisis. Furthermore, the correlation between Russia and Chile became stronger, from 0.39 to 0.47, meaning a general increase of common risk. Regarding the frontier stock markets, their MST maps are presented in Fig. 8, showing a similar pattern of reduced connectivity during COVID-19. As can be seen, two significant nodes before COVID-19 are Romania and Croatia, containing four and three degrees of connections. However, during COVID-19, both nodes have dropped their degree of connections and are directly connected with two other nodes of the network. Additionally, the results identify no direct connection between many frontier stocks markets, when comparing both periods. Hence, these changes can be seen as varied reactions to the risks posed by COVID-19 for these specific stock markets. The COVID-19 situation is unlike previous events for all markets.

The topological properties of the MSTs are presented in Table 2, identifying several measures for the MST of the network for the whole set of indices (AllMST), for developed

Table 2
Lists of the topological properties of the MSTs considering the whole set of countries.

Network	Nodes	Edges	Avg. Degree	Path length	Betweenness Centrality	Closeness Centrality	Power Law[a] $p(k) \sim k^{-\beta}$
AllMST19	56	55	1.97	5.47	0.66	0.25	−1.47
AllMST20	56	55	1.97	6.75	0.6	0.17	−1.87
DevMST19	23	22	1.91	3.36	0.65	0.36	−1.16
DevMST20	23	22	1.91	4.12	0.58	0.28	−1.59
EmMST19	22	21	1.91	3.23	0.74	0.43	−1.25
EmMST20	22	21	1.91	3.73	0.61	0.3	−1.09
FrMST19	11	10	1.82	2.87	0.58	0.37	–
FrMST20	11	10	1.82	3.42	0.36	0.22	–

[a] The degree distributions of the MSTs (except Frontier) follow power law fit of the form $p(k) \sim k^{-\beta}$.

indices (DevMST), for emerging indices (EmMST) and for frontier indices (FrMST). The identification of "19" refers to the period before COVID-19 and "20" to the period during COVID-19. As shown in Table 2, the average shortest paths of all markets during the pandemic have increased when compared to before. This means that before COVID, markets were closely connected. Similarly, betweenness and closeness centralities of the minimum spanning tree of all 56 stock markets during COVID-19 have decreased compared to the minimum spanning trees of the period before COVID-19. The degree distributions of all the markets hold true to power law distribution given by $p(k) \sim k^{-\beta}$ (except frontier), meaning a few nodes having highest degree centrality (a few markets such as Germany, France, Poland and South Korea are highly connected, whereas others such as China, Hong Kong and Pakistan are less so).

One of our interesting findings was that Germany remained in the leading nodes during COVID-19 and Taiwan became one of the most connected markets, which could be related to some measures adopted in these countries. For instance, in Germany, the first COVID-19 death was reported on March 9, 2020. Thereafter, Germany imposed very strict actions to control the spread which included closing its borders. By 22nd March, curfews were imposed in some German states, while others prohibited physical contact with more than one person from outside households. By the first week of April, the number of confirmed cases started to decline in Germany. Additionally, the German parliament introduced economic stabilization funds with the main purpose of supporting the real economy. Regarding Taiwan, this is a country with a very small number of COVID-19 cases, just 481 confirmed cases and only 7 deaths. Taiwan has been admired for its relatively successful control of the first wave of the epidemic. For example, the country started COVID-19 RT-PCR tests at the start of the outbreak and tried to control the emerging virus through science, technology and democratic governance. Several measures were adopted to preserve economic and financial market stability. This could be seen as a sign of confidence by investors, making Taiwan the center of the emerging markets during COVID-19. In agreement with Zhang et al. (2020), the findings confirm that the US index (DOW 30) has failed to lead global stock markets before and during the COVID-19 period.

4. Conclusions and recommendations

Coronavirus (COVID-19) has had a devastating effect on world economies, with many of them going into lockdown in order to contain the spread of the virus. Besides the economic impacts, it has also had a significant impact on financial markets. The purpose of this study is to provide a perspective of global stock markets during the turbulence caused by this new disease.

This study compares the network properties of 56 global stock markets before and during the coronavirus (COVID-19) outbreak by applying a complex network approach. To address institutional investors and regulators' requirements, we performed an in-depth analysis by examining the effect of COVID-19 on developed, emerging and frontier markets.

Stock network MSTs were created using the Kruskal Algorithm from a long run correlations distance matrix. The findings show that COVID-19 had a significant impact on financial networks with a structural change in the form of node changes and reduced connectivity, along with significant differences in the topological characteristics. Furthermore, the impact of COVID-19 varies with respect to the level of stock market development. In the case of emerging stock markets, a contagion effect is also identified in the network structure, with the nodes behaving synchronously. Based on geographic positioning, substantial clustering and homogeneity is found in the world stock market network. Besides, COVID-19 changes the sign and intensity of the correlation structure among global stock markets. The community structure reveals that the stock markets of France and Germany seem to be crucial for developed, Taiwan for emerging and Slovenia for frontier markets.

Although developed markets remain positively correlated before and during COVID-19, the strength of the relationship declines during COVID-19. For less mature markets, such as emerging and frontier ones, their returns are naturally lower. Normally, this could also be considered as a possibility for diversification, but our results show that for these indices in many cases the correlations became positive. This means these markets are now positively correlated with other markets, which was not the case in the past, implying less possibility of diversification and increased risk for investors. During COVID-19, market risk has increased substantially due to the great uncertainty of the pandemic. This market risk is raised by economic losses and is highly volatile during COVID-19 (Zhang et al., 2020).

The main limitation of this study is the relative unavailability of data after COVID-19, as it is still spreading. Despite this limitation, the study has important theoretical and managerial implications. For example, policies and regulations depend on better understanding of the topological network structures of financial markets (Tang, Xiong, Jia, & Zhang, 2018).

In the light of these findings, this study suggests integrated policy-making to cope with the financial impacts of the COVID-19 outbreak. Particularly, the regulators of stock markets in the same community should design combined policies to improve stock market stability. Individual and institutional investors can design their portfolios and risk management strategies in the light of these findings. The results suggest that diversification opportunities could be lower now, which should be considered by investors. On the other hand, using the information about stock market communities, the investor can design pair trading strategies by considering the movement of correlated indices (Elliott, Van Der Hoek, & Malcolm, 2005; Gatev, Goetzmann, & Rouwenhorst, 2006). Furthermore, optimal portfolio optimization could be achieved using the topology of networks (Tang et al., 2018). In order to address the limitations of this paper, future research could use a longer sample of the COVID-19 period, and obviously, information after COVID-19, to investigate how the networks behave after the end of the pandemic.

Declaration of competing interest

None.

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