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Complex network analysis of global stock market co-movement during the COVID-19 pandemic based on intraday open-high-low-close data

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Abstract

This study uses complex network analysis to investigate global stock market co-movement during the black swan event of the Coronavirus Disease 2019 (COVID-19) pandemic. We propose a novel method for calculating stock price index correlations based on open-high-low-close (OHLC) data. More intraday information can be utilized compared with the widely used return-based method. Hypothesis testing was used to select the edges incorporated in the network to avoid a rigid setting of the artificial threshold. The topologies of the global stock market complex network constructed using 70 important global stock price indices before (2017–2019) and after (2020–2022) the COVID-19 outbreak were examined. The evidence shows that the degree centrality of the OHLC data-based global stock price index complex network has better power-law distribution characteristics than a return-based network. The global stock market co-movement characteristics are revealed, and the financial centers of the developed, emerging, and frontier markets are identified. Using centrality indicators, we also illustrate changes in the importance of individual stock price indices during the COVID-19 pandemic. Based on these findings, we provide suggestions for investors and policy regulators to improve their international portfolios and strengthen their national financial risk preparedness.

Keywords: Complex network, Stock market co-movement, OHLC data, Degree centrality analysis

Introduction

Stock market co-movement refers to a phenomenon in which multiple national stock markets experience the same trend of rising and falling under the deepening economic globalization and financial market integration (Forbes and Rigobon 2002). The classical theory holds that the co-movement of international stock markets stems primarily from two mechanisms. On the one hand, the economic fundamentals of various stock markets are interconnected. The core proposition of this point is that the stock market is a 'barometer' of the macroeconomy, and the macro fundamentals of various countries are interconnected, thus triggering the transnational co-movement of different stock markets (McQueen and Roley 1993). On the other hand, the market contagion mechanism leads to up-and-down linkages. This view holds that, in the event of a black swan event, such as a financial crisis, the herding effect in the financial market amplifies the speculative behavior of investors, aggravates the price volatility of the stock market, and enhances the co-movement between stock markets (King and Wadhwani 1990).

The global stock market is a complex economic system that comprises the stock markets of many countries and regions. This is an ideal testing ground for complex network analysis techniques to explore the complex co-movements of international stock markets (Wen et al. 2019). With their unique topology, complex networks can effectively capture the behavioral characteristics of various stock markets, intuitively represent their interdependence, and identify influential stock markets (Roy and Sarkar 2011). In recent years, a popular research topic in complex networks has explored the change in the topological characteristics of complex networks in black swan events (Jin et al. 2012). The co-movement of global stock markets has been investigated using the complex network during the subprime crisis and global financial crisis (Liu and Tse 2012; Li and Pi 2018), the collapse of Lehman Brothers (Roy and Saker 2011, 2013), the European debt crisis (Nobi et al. 2014; Gong et al. 2019), and Coronavirus Disease 2019 (COVID-19) (Aslam et al. 2020; Samitas et al. 2022).

In 2020, acute pneumonia COVID-19 swept the world, spread to more than 200 countries, and quickly developed into a global public health and economic disaster. Three months after the outbreak, more than 500,000 people were diagnosed with COVID-19 (Zhang et al. 2020). As of December 31, 2022, COVID-19 has caused 660.4 million infections and 6.6902 million deaths in 289 countries or territories (Dong et al. 2020). The COVID-19 pandemic has significantly increased uncertainty and volatility in global financial markets (Haroon and Rizvi 2020; Okorie and Lin 2021). In the context of uncertainty, investors become more cautious and seek safe havens to avoid possible financial losses, significantly weakening the liquidity of financial markets (Omay and Iren 2019). Global stock markets reacted quickly to the COVID-19 outbreak, and stock price indices in various countries experienced significant declines (Aslam et al. 2020). In March 2020, the United States stock market hit the circuit breaker mechanism four times in 10 days, while the last meltdown returned from 2007 to 2008 during the global financial crisis (Zhang et al. 2020). The European STOXX 600 index fell by more than 20% compared with its high index at the beginning of 2020. The day after the World Health Organization declared COVID-19 a global pandemic, March 12, was the worst day in global stock markets. The Nikkei 225 index of the Tokyo Stock Exchange plunged by more than 20% compared with its high value in December 2019. European stock markets fell by 11%, the United's stock price index fell by more than 10%, and the S&P 500 index fell by 9.5% (Samitas et al. 2022). These declines forced a halt in trading on the Asia–Pacific and New York stock exchanges. the immense black swan event of COVID-19 had a huge impact on global stock markets, complicating the international economic and financial situation.

This study models the topology of global stock market networks before and after the COVID-19 outbreak using complex network theory to reveal the hidden information and relationships of global stock market co-movements. In the context of the COVID-19 outbreak, studying the co-movements among the world's stock markets will help policymakers take appropriate measures to resist international shocks, prevent financial risks, and maintain macroeconomic security while opening domestic capital markets (Roy and Sarkar 2013). Investors also need to clearly understand the co-movement changes in the international market to improve their investment judgment abilities and make adjustments to an internationally diversified portfolio (Samitas et al. 2022). This study provides a dynamic and visual paradigm for complex network research, which will provide policymakers and investors with a better understanding of global stock markets in the event of a black swan event. The contributions of this study to the literature on stock market co-movement are fourfold.

(1) A novel method for calculating the similarity between a pair of stock price indices was proposed. Most of the existing literature calculates stock price index similarity based solely on the return on the close price (e.g., Liu and Tse 2012; Roy and Sarker 2013; Li and Pi 2018; Zhang et al. 2020; Aslam et al. 2020). This practice may lead to the loss of important trading information, including open, high, and low prices (Huang et al. 2022a). In addition, the return-based method cannot provide a reliable measure of the similarity between two stock price indices in some cases (see Fig. 3) because the close price fails to fully reflect the intraday gaming dynamics of market buyers and sellers. By contrast, the proposed open-high-low-close (OHLC) data-based method can take full advantage of intraday trading information and guarantee a reliable similarity measure by additionally considering intraday volatility and the relative positions of open and close prices.

(2) The proposed hypothesis testing-based edge-selection approach provides new insights for building complex networks. Most existing stock price index complex networks in the literature are threshold networks, that is, when the similarity of two stock price indices is higher than the threshold. A connected edge between two corresponding nodes is revealed in the network. For example, the threshold values used by Roy and Sarkar (2011, 2013), Nobi et al. (2014), and Li and Pi (2018) are 0.6, 0.6, 0.3, and 0.9. Differences in threshold values can significantly affect the topology of the network structure. When the threshold value is significant, the network is sparse; when the threshold value is small, the network is dense. However, threshold values are often set artificially. This study examines the degree of similarity between each pair of stock price indices using t-statistics for hypothesis testing. An edge between a pair of nodes with a significant similarity coefficient was incorporated into the complex network to avoid the rigid setting of artificial thresholds.

(3) The degree centricity of the OHLC data-based network exhibited better power-law distribution characteristics than the widely used return-based network. The degree distribution of complex networks in the financial domain should follow a power-law distribution (Aiello et al. 2001; Boginski et al. 2006), which can be used as a criterion to measure whether the constructed financial complex network is reasonable. The maximum likelihood estimation for the degree of centricity of the constructed network indicates that the goodness-of-fit of the OHLC data-based network is 0.5939, which is higher than that of the return-based network (0.5369). The Kolmogorov–Smirnov statistics based on bootstrapping further prove that the

degree distribution of the OHLC data-based network has a 78.6% probability of obeying a power law distribution. By comparison, that of the return-based network was only 10.4%.

(4) This study uses an extensive sample to describe the data accurately, and is therefore able to observe structural changes in global financial networks over the COVID-19 period. Literature on global stock market co-movement in the context of public health crises, especially during COVID-19, is limited. Only a few studies, such as that of Aslam et al. (2020), used a complex network analysis method to study the impact of the COVID-19 outbreak on 56 global stock price indices in the early stage from October 15, 2019, to August 7, 2020, while Samitas et al. (2022) investigated volatility and contagion risk in 51 major global stock markets from January 1, 2018, to June 18, 2020, based on network analysis. However, many uncertainties remain regarding the impact of COVID-19 on global stock market co-movement and the comparison of global stock market networks before and after the outbreak. This study explored a long window between January 1, 2017, and December 31, 2022, spanning the COVID-19 outbreak period. In addition, we estimate a series of stock price indices for 70 major global stock markets. A complex network analysis identifies the dynamic topological characteristics of the global financial market network before and after the COVID-19 outbreak. The findings provide an in-depth and comprehensive understanding of stock market co-movements.

The remainder of this paper is organized as follows: The "Literature review" section discusses the primary literature on complex network analyses of global stock market co-movement. The "Data and method" section provides the data and methods employed for complex networks, and the "Empirical analysis of global stock market complex network" section presents an empirical analysis of the global stock market complex network. Finally, conclusions are presented in the "Conclusions".

Literature review

Complex network analysis is a powerful tool for exploring topological relationships among actors (Scott 1988). In recent decades, complex network analysis has been widely used in various sociological research fields, such as international trade (Kim and Shin 2002), epidemic spread (Firestone et al. 2011), and smuggling networks (Huang et al. 2020). Integrating complex networks and finance involves studying stock market co-movement (Li and Pi 2018; Aslam et al. 2020). For instance, Roy and Sarkar (2011) use the Pearson correlation coefficient to measure the similarity between the returns of 93 global stock price indices from 2006 to 2010. They used the correlation coefficient as a weight to construct a complex network and a minimum-spanning tree with a correlation threshold of 0.6. The results indicate that SXXP and SXXE from Europe were the most influential stock price indices in the global stock market complex network before and after the collapse of Lehman Brothers. Liu and Tse (2012) employed a complex network analysis to examine the co-movement between the close price returns of the stock price indices of 67 member countries of the World Federation of Exchanges from 2006 to 2010. The results indicate that, before the 2008 financial crisis, the global stock market network exhibited cyclical synchronized behavior, and co-movement became pronounced after the financial crisis. In addition, developed markets are more interconnected than other ones. Roy and Sarkar (2013) conduct a complex network analysis based on 93 global stock price indices from 2006 to 2010. They detected stock market volatility in different periods through changes in the degree centrality ranking. The results indicate that the global stock market network became more interconnected during the financial crisis. Nobi et al. (2014) constructed a complex threshold network of 30 global stock price indices and 145 local Korean stocks from 2000 to 2012 based on the Pearson correlation coefficient with a threshold of 0.3. The results indicate that the average correlation of global stock price indices strengthened over time, whereas the average correlation between local Korean stocks tended to decrease.

Cao et al. (2017) construct a complex network based on the fluctuation correlations of 27 global stock price indices from January 1999 to December 2014. The dynamic evolution of the Chinese and international stock market relationships was analyzed using a sliding window approach. The results show that the connection between the Chinese and foreign stock markets became more vigorous, especially after China joined the WTO. Li and Pi (2018) construct a complex weighted network, minimum spanning tree, and threshold complex network of 38 global stock price indices from 2005 to 2010 based on the Pearson correlation coefficient. The results indicate that the United States, Southeast Asia, and European stock markets formed three clusters. Gong et al. (2019) analyzed stock market network connectivity using the transfer entropy method. The results showed that the overall connectivity of the network increased during the financial crisis. The closer the stock market is to the center of the network, the more likely it is to be affected by a financial crisis. Tang et al. (2019) applied the Granger causality test to construct a Granger causality-oriented network of 33 major global stock price indices. The results show that the United States stock price index dominates the network, with European and Asian indices not far behind. Wen et al. (2019) use tail-dependent networks to capture financial markets characterized by extreme volatility. According to the close price data of stock price indices in 73 countries from 2000 to 2016, the global efficiency of the tail-dependent network is higher than that of the Pearson's correlation coefficient network. Moreover, the European market is more influential than the Asian and African markets.

From the literature review above, the existing literature on the complex networks of global stock markets focuses on comparing network changes before and after a black swan event, such as the mortgage, global financial, and European debt crises. Iwanicz-Drozdowska et al. (2021) investigate the impact of various economic and non-economic events on stock market spillover effects in 16 major developed and emerging countries from 2000 to 2020. The results show that viruses (e.g., the COVID-19 pandemic) were the most widespread sources of market contagion. Hence, COVID-19 can be considered a significant research event affecting global stock markets. According to the Johns Hopkins University Center for Systems Science and Engineering COVID-19 data repository, COVID-19 has caused 660.4 million infections and 6.6902 million deaths in 289 countries or territories as of December 31, 2022 (Dong et al. 2020). Figure 1 shows the cumulative number of COVID-19 cases in different continents from 22/1/2020 to 31/12/2022, which illustrates that the number of infected people maintained a rapid growth trend throughout the study period. COVID-19 poses an unprecedented threat to the economic

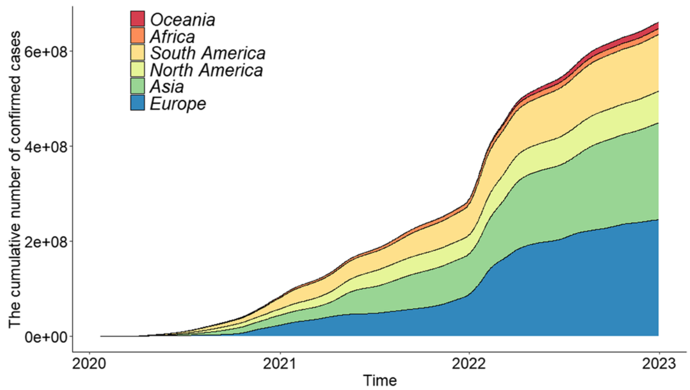


Fig. 1 Cumulative daily new COVID-19 cases by continent

functioning of countries worldwide (Altig et al. 2020; Deb et al. 2022a). An outstanding issue is severe unemployment (Aslam et al. 2020). For example, according to the Bureau of Labour Statistics, more than 22 million Americans lost their jobs between February and October 2020 (Milovanska-Farrington 2022); the South Asia Report 2020 pointed out that approximately 140 million people in South Asian countries were unemployed owing to lockdown measures (UNDP 2020). The Center for Monitoring the Indian Economy stated that approximately 38 million Indians have lost their jobs due to COVID-19 (Gururaja and Ranjitha 2022). In an economically integrated world where production and trade are closely linked, the impact of COVID-19 has long exceeded the loss of labor due to death from the disease and the inability to work due to illness. COVID-19 has led to a dramatic decline in industrial production, disruptions in global supply chain operations, restrictions on trade shipments between countries, the spread of global panic, massive business bankruptcy, halving of global economic growth, and a plunge in global stock price indices (Ashraf 2020; Gupta et al. 2020; Jackson 2021).

The existing literature based on complex networks to study stock market co-movement still lacks exploration in the global pandemic context. The literature on the economic and financial impacts of public health crisis-type shocks is scarce for two reasons. First, the spread of infectious diseases was limited in the past and the extent and severity of the infected areas were much lower than those of COVID-19. Second, global stock market correlations were weak before the 1990s (Claessens et al. 2011). When financial markets are relatively independent, public health shocks external to the economic system hardly cause significant stock market co-movement. However, studying stock market co-movement responses in the context of public health crises is essential for the development of financial globalization and the gradual increase in financial system correlation. The limited literature on global stock market co-movement in the context of COVID-19 includes Aslam et al. (2020), who use a complex network approach to analyze the impact of COVID-19 on 56 stock price indices worldwide between November 15, 2019, and August 7, 2020. They divided the 56 stock markets into developed, emerging, and frontier markets. The findings show an increase in the number of global stock price indices that are positively correlated during the pandemic. France and Germany were at the center of developed markets, whereas Taiwan and Slovenia were at the center of emerging and frontier markets. Samitas et al. (2022) investigate the impact of

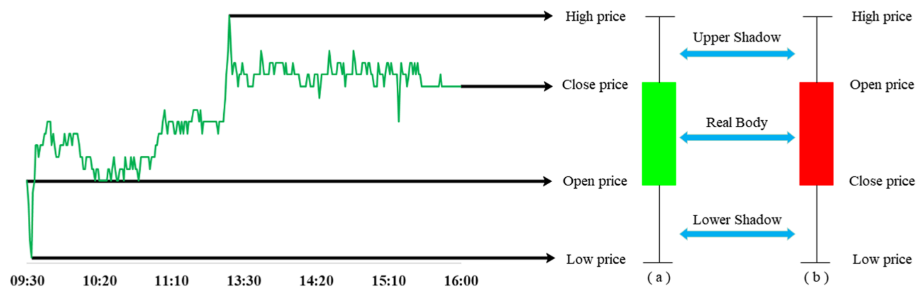


Fig. 2 A graphical representation of OHLC data

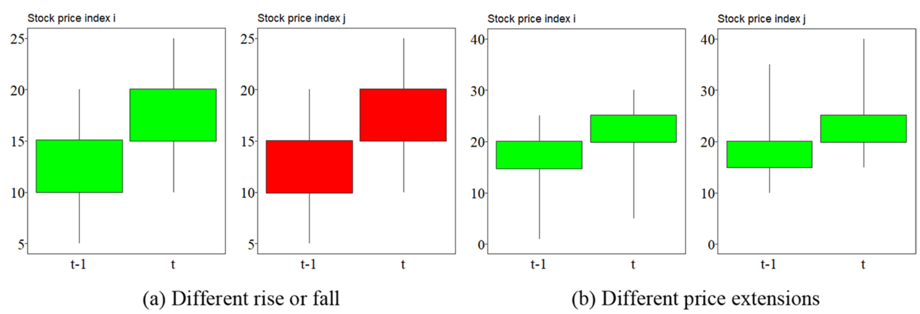


Fig. 3 Toy cases for the inadequacy of similarity measure based only on returns

the COVID-19 pandemic on 51 major stock markets based on dependence dynamics and network analysis.

The study was conducted from January 1, 2018, to June 18, 2020. Evidence suggests that the lockdown and coronavirus transmission led to an immediate financial contagion. They provide investors and policymakers with important information on the use of financial networks to improve portfolio selection. Yuan et al. (2022) construct a nonlinear financial contagion network for 26 major global stock markets during the COVID-19 pandemic using a dynamic hybrid copula-extreme value theory (EVT) model. The investigation spanned from January 1, 2019, to March 27, 2022. Investor behavior, including investor attention, sentiment, and fear, was measured using Google search volumes. They found that investor behavior plays an important role in explaining pandemic-driven financial contagions.

Although the above studies examined global stock market co-movement during the COVID-19 epidemic using a complex network approach (Aslam et al. 2020; Samitas et al. 2022), they only utilized the return information of the close price. However, in the financial market, stock price index data take the form of OHLC data (see Fig. 2). In addition to close price, other intraday trading information includes open, high, and low prices (Huang et al. 2022a).

The correlation coefficient measure that considers only the close price loses essential trading information. In many situations, it does not accurately reflect the similarity between pairs of stock price indices. Figure 3 shows two toy cases. In Fig. 3a, b, the returns of stock price indices i and j are the same in period t. However, Fig. 3a shows that stock price index i is a bull market in periods $(t-1)$ and t, while stock price index j belongs to a bear market in the same period. In Fig. 3b, the stock price index i surges and then falls back, while there is a sharp dip in the stock price index j and then a rebound. Additional intraday trading information provides evidence of the significantly different gaming dynamics between market buyers and sellers. There should be similarity differences between the two stock price indices i and j in period t in both situations, as illustrated in Fig. 3, where the stock price indices i and j show the potential for rising and falling trends, respectively. In contrast, the two stock price indices have perfect similarities if the calculation is solely based on returns, which does not align with the economic implications. In contrast, the other method can measure the difference between i and j.

In conclusion, the existing literature has three main shortcomings related to stock market co-movement based on complex networks. First, the existing literature lacks an analysis of stock market co-movement in the context of the COVID-19 pandemic, and the sample countries and time horizons investigated are inadequate. Second, the complex global stock market networks constructed in the literature solely consider close prices. This approach essentially loses important intraday trading information (e.g., open, high, and low prices). This does not correctly reflect the similarity between pairs of stock price indices in some cases (see Fig. 3). Third, existing literature uses artificially specified thresholds for selecting edges incorporated in complex networks that lack credibility. To fill these gaps, this study constructs complex networks of 70 worldwide stock markets from 2017 to 2019 as the pre-COVID-19 outbreak period and from 2020 to 2022 as the post-COVID-19 outbreak period. A new network construction method was proposed based on OHLC data and hypothesis testing for edge selection. A complex network analysis was conducted to investigate global stock market network changes according to the network basis and centrality indicators. Stock market conditions by year, market segmentation, and continent are discussed separately to provide different analytical perspectives. This study provides a new approach for studying global stock market co-movement using complex networks that can fully use intraday trading information, enrich the relevant literature, and have broad applications. Government regulators can use this analysis to monitor the core nodes and ensure a stable overall market. Government regulators can also consider the national stock market's ability to resist epidemics and develop relevant response mechanisms. Investment institutions and individual investors can use this analysis to improve portfolio allocation and make better investment decisions.

Data and method

Data

This study uses OHLC data for major stock price indices worldwide from January 1, 2017, to December 31, 2022. The data covered 70 countries and regions from six continents and were sourced from the Wind database (https://www.wind.com.cn/). These countries were selected based on data availability and GDP size. The countries selected for this study account for more than 98% of global GDP. The dataset considered in this study examines a larger number of countries. It has a longer time horizon than most existing studies and provides detailed and reliable insights into global stock market co-movement observations during COVID-19.

Table 1 lists the specific countries and regions and the corresponding stock price index codes in the Wind database. Among the selected stock price indices, 2 were

Table 1 Summary of selected stock price indices

Continent	Country/region	Code	Continent	Country/region	Code
Oceania	Australia	AS51	South America	Brazil	IBOVESPA
	New Zealand	NZ50		Argentina	MERV
North America	the United States	SPX		Chile	IPSA
	Canada	GSPTSE		Colombia	COLOM20
	Mexico	MXX		Peru	960400.MI
	Venezuela	IBVC	Africa	Egypt	CASE
Europe	the United Kingdom	FTSE		Nigeria	NGSEINDX
	France	FCHI		Morocco	WIMAR
	Germany	GDAXI		South Africa	JALSH
	Italy	FTSEMIB		Kenya	136,643.MI
	Russia	IMOEX		Mauritius	136,644.MI
	Spain	IBEX		Tunisia	136,646.MI
	Switzerland	SSMI	Asia	China	000300.SH
	Portugal	BVLX		Hong Kong	HSI
	Ireland	ISEQ		Taiwan	TW50
	Netherlands	AEX		Japan	N225
	Belgium	BFX		South Korea	KOSDAQ
	Luxembourg	LUXXX		Singapore	STI
	Denmark	KAX		India	SENSEX
	Finland	HEX		Thailand	SETI
	Norway	OSEAX		Indonesia	JKSE
	Sweden	OMXS30		Malaysia	KLSE
	Austria	ATX		Philippines	PSI
	Greece	ASE		Vietnam	VNINDEX
	Poland	WIG		Jordan	940000.MI
	Czech	PX		Pakistan	WIPAK
	Hungary	BUX		Sri Lanka	914400.MI
	Ukraine	UX		Bahrain	133712.MI
	Turkey	XU100		Kuwait	133713.MI
	Croatia	CRO		Qatar	133715.MI
	Estonia	TALSE		Kazakhstan	136637.MI
	Slovenia	SBITOP		Israel	TA125
	Bulgaria	SOFIX		Lebanon	BLOM
	Romania	BET		Saudi Arabia	SASEIDX
	Serbia	BELEXLIN		the United Arab Emirates	DFM

from Oceania, 4 were from North America, 5 were from South America, 7 were from Africa, 23 were from Asia, and 29 were from Europe. The sample countries are concentrated in Asia and Europe because of their different levels of geographical aggregation and economic development.

Method

Correlation coefficient based on OHLC data

The existing literature tends to measure the similarity between different stock markets based on close price returns, with the close price return of the i-th stock price index in period t calculated according to the following formula (Liu and Tse 2012; Roy and Sarkar 2013; Nobi et al. 2014; Li and Pi 2018; Aslam et al. 2020).

$$R_{it} = \ln x_{it}^{(c)} - \ln x_{i(t-1)}^{(c)} = ln\frac{x_{it}^{(c)}}{x_{i(t-1)}^{(c)}}, \tag{1}$$

where $x_{it}^{(c)}$ and $x_{i(t-1)}^{(c)}$ represent the close price of the $\underline{i}$th stock price index in periods t and $(t-1)$, respectively.

The similarity between stock markets $\underline{i}$ and j is then measured based on the Pearson correlation coefficient (Liu and Tse 2012; Roy and Sarkar 2013; Li and Pi 2018).

$$\begin{aligned}\rho_{ij} &= \frac{Cov(R_i, R_j)}{\sqrt{Var(R_i)Var(R_j)}} = \frac{E(R_iR_j) - E(R_i)E(R_j)}{\sqrt{Var(R_i)Var(R_j)}} \\ &= \frac{T\sum_{t=1}^{T}(R_{it}R_{jt}) - \sum_{t=1}^{T}R_{it}\sum_{t=1}^{T}R_{jt}}{\sqrt{\left(T\sum_{t=1}^{T}R_{it}^2 - \left(\sum_{t=1}^{T}R_{it}\right)^2\right)\left(T\sum_{t=1}^{T}R_{jt}^2 - \left(\sum_{t=1}^{T}R_{jt}\right)^2\right)}}\end{aligned} \tag{2}$$

Stock price indices are available as OHLC data for financial markets. Therefore, measuring the similarity between stock price indices using only close-price returns may lead to a loss of intraday trading information. To utilize information from a full range of financial data, this study measured the similarity between different stock price indices based on OHLC data. For the OHLC data of the $\underline{i}$-th stock price index in period t, that is, $\boldsymbol{x}_{it} = \left(x_{it}^{(o)}, x_{it}^{(h)}, x_{it}^{(l)}, x_{it}^{(c)}\right)'$, this study first divides its portions by the previous day's close price to obtain the normalized data:

$$\boldsymbol{x}_{it}^{*} = \left(x_{it}^{(o*)}, x_{it}^{(h*)}, x_{it}^{(l*)}, x_{it}^{(c*)}\right)' = \left(\frac{x_{it}^{(o)}}{x_{i(t-1)}^{(c)}}, \frac{x_{it}^{(h)}}{x_{i(t-1)}^{(c)}}, \frac{x_{it}^{(l)}}{x_{i(t-1)}^{(c)}}, \frac{x_{it}^{(c)}}{x_{i(t-1)}^{(c)}}\right)', \tag{3}$$

where * is the mark of the normalized data; $x_{it}^{(o)}$, $x_{it}^{(h)}$, $x_{it}^{(l)}$ and $x_{it}^{(c)}$ represent the open, high, low, and close prices of the $\underline{i}$th stock price index in period t, respectively; $x_{i(t-1)}^{(c)}$ stands for the close price of the $\underline{i}$th stock price index in period t. There are two reasons for the normalization of Eq. (3). First, similar to taking the natural logarithm when calculating daily returns, dividing $\boldsymbol{x}_{it}$ by the previous day's close price narrows the value range, thus enhancing the stability of the data. Second, the stock price index is the ratio of the data relative to the basement period, and its absolute value size of the stock price index may vary significantly from one stock price index to another. The relative position of quaternary price data, which can reflect intraday gaming dynamics, is more important than the absolute numerical size of the OHLC data (Huang et al. 2022a). Therefore, stock price indices with similar quaternary price location structures should share high similarities. Dividing $\boldsymbol{x}_{it}$ by the previous day's close price eliminates the effect of the absolute value of the stock price index and highlights the importance of the relative position of its quaternary prices (Tao et al. 2017).

Although $\boldsymbol{x}_{it}^{*}$ eliminates the effect of the absolute value of the stock price index, using $\boldsymbol{x}_{it}^{*}$ directly as the basic unit to measure the correlation coefficient is still unreasonable. There are two reasons for this finding. (1) First, the quaternary components of $\boldsymbol{x}_{it}^{*}$ do not differ significantly in value, and the difference between using its quaternary components directly and considering the close price four times is slight. Thus, the economic implications implied by the OHLC data in the relative positional relationship of its quaternary components cannot be adequately examined by $\boldsymbol{x}_{it}^{*}$ (Huang et al. 2022b). (2) Three constraint relationships exist among the quaternary components of $\boldsymbol{x}_{it}^{*}$: 1. $x_{it}^{(l*)} > 0$, 2. $x_{it}^{(l*)} < x_{it}^{(h*)}$, 3. $x_{it}^{(o*)}, x_{it}^{(c*)} \in \left(x_{it}^{(l*)}, x_{it}^{(h*)}\right)$. These constraints limit the range of values of the internal components. Therefore, a method is required that can effectively unconstrain $\boldsymbol{x}_{it}^{*}$ and extract meaningful financial information.

Referring to Huang et al. (2022a), we conducted an unconstrained transformation method on $\boldsymbol{x}_{it}^{*}$ and derived $\boldsymbol{y}_{it}$, which has no more constraints and represents the financial characteristics of the OHLC data well. The transformation formula is as follows:

$$\boldsymbol{y}_{it} = \begin{pmatrix} y_{it}^{(1)} \\ y_{it}^{(2)} \\ y_{it}^{(3)} \\ y_{it}^{(4)} \end{pmatrix} = \begin{pmatrix} \ln x_{it}^{(l*)} \\ \ln\left(x_{it}^{(h*)} - x_{it}^{(l*)}\right) \\ \ln\frac{\lambda_{it}^{(o)}}{1-\lambda_{it}^{(o)}} \\ \ln\frac{\lambda_{it}^{(c)}}{1-\lambda_{it}^{(c)}} \end{pmatrix}, \tag{4}$$

where $\lambda_{it}^{(o)} = \frac{x_{it}^{(o*)} - x_{it}^{(l*)}}{x_{it}^{(h*)} - x_{it}^{(l*)}}$ and $\lambda_{it}^{(c)} = \frac{x_{it}^{(c*)} - x_{it}^{(l*)}}{x_{it}^{(h*)} - x_{it}^{(l*)}}$.

The four components of $\boldsymbol{y}_{it}$ have explicit and fruitful economic implications. The first component, $y_{it}^{(1)}$, is a measure of the absolute size of the stock price index. Given that the difference between $x_{it}^{(l)}$ and $x_{it}^{(c)}$ is not significant, $y_{it}^{(1)} = \ln x_{it}^{(l*)} = \ln\frac{x_{it}^{(l)}}{x_{i(t-1)}^{(c)}}$ is approximately equal to the widely used close-price return, R_{it}. This means that this study extracts three other characteristic indicators from intraday trading prices in addition to the returns considered in other studies. The second component, $y_{it}^{(2)}$ reflects the range of fluctuations in stock price indices. The third and fourth components of $\boldsymbol{y}_{it}$ represent the relative positions of the open and close prices in the stock price index, respectively. A similarity measure between stock markets based on $\boldsymbol{y}_{it}$ instead of $\boldsymbol{x}_{it}$ can examine the original price information and the intraday gaming process between buyers and sellers (Huang et al. 2022a).

For multiple stock markets, the sample set we consider is an $n \times p$ dimensional matrix $\boldsymbol{Y} = \left(\boldsymbol{y}_{ij}\right)_{n\times p}$ containing n time points and p variables, where each element $\boldsymbol{y}_{ij}$ represents the unconstrained stock price index OHLC data. Remark $\boldsymbol{Y}$ as:

$$\boldsymbol{Y} = \begin{pmatrix} \boldsymbol{y}_{11} & \boldsymbol{y}_{12} & \cdots & \boldsymbol{y}_{1p} \\ \boldsymbol{y}_{21} & \boldsymbol{y}_{22} & \cdots & \boldsymbol{y}_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{y}_{n1} & \boldsymbol{y}_{n2} & \cdots & \boldsymbol{y}_{np} \end{pmatrix} = \left(\boldsymbol{Y}_1, \boldsymbol{Y}_2, \ldots, \boldsymbol{Y}_p\right), \tag{5}$$

where $\boldsymbol{Y}_j = \left(\boldsymbol{y}_{1j}, \boldsymbol{y}_{2j}, \ldots, \boldsymbol{y}_{nj}\right)'$ denotes the jth column of matrix $\boldsymbol{Y}$ $\left(j = 1, 2, \ldots, p\right)$, which is composed of n observations $\boldsymbol{y}_{ij} \in \mathbb{R}^4\,(i = 1, 2, \ldots, n)$ corresponding to the stock price index of a country or region. To calculate the correlation coefficient between stock price indices of two countries or regions, the sample mean and covariance are first defined as follows:

(1) For $\boldsymbol{Y}_j \in \mathbb{R}_n^4$, define its sample mean as

$$\overline{\boldsymbol{Y}}_j = \frac{1}{n}\left(\boldsymbol{y}_{1j} + \boldsymbol{y}_{2j} + \cdots + \boldsymbol{y}_{nj}\right) \in \mathbb{R}^4. \tag{6}$$

(2) For any pair of $\boldsymbol{Y}_j, \boldsymbol{Y}_k \in \mathbb{R}_n^4$, define their sample covariance as

$$S_{jk} = \mathrm{Cov}\left(\boldsymbol{Y}_j, \boldsymbol{Y}_k\right) = \frac{1}{n}\sum_{i=1}^{n}\left\langle \boldsymbol{y}_{ij} - \overline{\boldsymbol{Y}}_j, \quad \boldsymbol{y}_{ik} - \overline{\boldsymbol{Y}}_k \right\rangle_{\mathbb{R}^4} \in \mathbb{R}. \tag{7}$$

(3) For $\boldsymbol{Y}_j \in \mathbb{R}_n^4$, define its sample variance as

$$S_j^2 = Var\left(\boldsymbol{Y}_j\right) = \frac{1}{n}\sum_{i=1}^{n}\left\langle \boldsymbol{y}_{ij} - \overline{\boldsymbol{Y}}_j, \quad \boldsymbol{y}_{ij} - \overline{\boldsymbol{Y}}_j \right\rangle_{\mathbb{R}^4} \in \mathbb{R}\ominus. \tag{8}$$

Then, the correlation coefficient of any pair of $\boldsymbol{Y}_j, \boldsymbol{Y}_k \in \mathbb{R}_n^4$ can be deduced by

$$r_{jk} = \frac{S_{jk}}{S_j S_k} \in \mathbb{R}\ominus. \tag{9}$$

In line with the Pearson correlation coefficient, the t test statistic for r_{jk} can be constructed in the context of a large sample (Hollander and Wolfe 1973; Press et al. 1992).

$$t_{r_{jk}} = \frac{r_{jk}}{\sqrt{\frac{1-r_{jk}^2}{4n-2}}} \sim t(4n-2). \tag{10}$$

The corresponding p value of the two-tailed t-test statistic $t_{r_{jk}}$ is given by Eq. (11), where $\Gamma(\cdot)$ is the gamma function.

$$p_{t_{jk}} = 2 * \left(1 - \int_{-\infty}^{t_{r_{jk}}} \frac{\Gamma\left(\frac{4n-1}{2}\right)}{\sqrt{(4n-2)\pi xt}\,\Gamma(2n-1)}\left(1 + \frac{x^2}{4n-2}\right)^{-\frac{4n-1}{2}} dx\right). \tag{11}$$

The null hypothesis (H_0) and alternative hypothesis (H_1) of the t test are given by Eq. (12). When the derived $p_{t_{jk}}$ is greater than 0.05, we consider that the null hypothesis cannot be rejected, and the correlation coefficient r_{jk} between $\boldsymbol{Y}_j$ and $\boldsymbol{Y}_k$ equals zero; that is, there is no linear correlation. Accordingly, no connected edges exist from nodes j to k in a complex network. When the calculated $p_{t_{jk}}$ was less than 0.05, the alternative hypothesis was accepted instead of the null hypothesis. This indicates that r_{jk} is not equal to zero; that is, there is a significant linear correlation between $\boldsymbol{Y}_j$ and $\boldsymbol{Y}_k$. Accordingly, a connected edge exists between nodes j and k in the complex network, indicating stock market co-movement.

$$H_0 : r_{jk} = 0 \quad \text{and} \quad H_1 : r_{jk} \neq 0. \tag{12}$$

Basic indicators of complex network

The world stock market complex network is constructed in the following manner: each country or region is used as a node, and the correlation coefficient between the two stock price indices of the corresponding stock markets is calculated using Eq. (9), and the correlation coefficient that is significant at the 0.05 level is taken as the connection weight between nodes. The basic metrics of the network are as follows:

(1) Number of nodes (N): number of nodes in the network.
(2) Number of edges (E): number of edges in the network.
(3) Average degree (AD): number of edges connected by a node. The directed network is divided into in-degree and out-degree networks, but not into undirected networks. Average degree is the average number of edges connected to a node. In an undirected network,

$$AD = \frac{2 \times E}{N}. \tag{13}$$

(4) Average weighted degree (AWD): the average degree weighted by the weights of the edges. Note the average correlation coefficient as $\overline{r}$ and we have

$$AWD = AD \times \overline{r} = AD \times \frac{\sum_{j \neq k, p_{r_{jk}} < 0.05} r_{jk}}{2 \times E}. \tag{14}$$

(5) Network diameter: the maximum of all shortest paths between two connected nodes.
(6) Network density (ND): Ratio of the actual number of edges to the maximum possible number of edges. The calculation formula is as follows:

$$ND = \frac{E}{N \times (N-1)/2}. \tag{15}$$

(7) Average clustering coefficient: A ratio measurement of whether two different nodes that connect to a common node also have a connection.
(8) Average path length: The shortest path length between two nodes.

Complex network centrality analysis

Centrality is an essential concept in complex network analysis, which describes the degree of importance of individual nodes in a complex network. Existing studies have defined different centrality measures that characterize the potential importance, influence, and prominence of network nodes from different perspectives. The centrality indicators selected for this study are as follows:

(1) Degree centrality ($D(x)$): For a node x, its degree centrality denotes the number of edges it connects to. By denoting the set of edges connected by node x as $e(x)$, we obtain

$$e(x) = \left\{ e_{x1}, e_{x2}, \ldots, e_{xD(x)} \right\}. \tag{16}$$

For a world stock market network, the higher the degree of centrality of a node, the more significantly the stock price indices of other countries are correlated with the stock price index of that country or region.

(2) Weighted degree centrality ($WD(x)$): For node x, the weighted degree centrality is calculated by weighting its connected edges based on their weights. We obtain:

$$WD(x) = \frac{1}{D(x)} \sum_{i=1}^{D(x)} w_{xi}, \tag{17}$$

where w_{xi} is the weight of edge e_{xi} connected to node x. Degree centrality can only measure the number of stock markets in other countries that are significantly correlated with a country or region's stock market but not the strength of positive or negative correlations. The weighted degree centrality can compensate for the insufficient measurement of connection strength. Suppose that the weighted degree centrality of a node is high. In this case, other stock price indices are significantly and positively correlated with the country or region's stock price index and the stock market co-movement phenomenon is more pronounced.

(3) Closeness centrality ($C(x)$): In a network, the closeness centrality of a node is defined as the reciprocal of the sum of the shortest path lengths between that node and all the other connected nodes. Thus, a higher proximity centrality implies that a node is closer to all other nodes, indicating that the node occupies a central position in the network. The proximity centrality of node x was first defined by Bavelas (1950) and is expressed by the following equation:

$$C(x) = \frac{1}{\sum_y d(x, y)}, \tag{18}$$

where $d(x,y)$ denotes the shortest path between the nodes x and the node y connected to it. In practical applications, the normalized form of $C(x)$ is commonly used to represent the average length of the shortest paths, rather than their sum. The normalized form of $C(x)$ is generally obtained by multiplying the previous equation by (N-1). We obtain:

$$\tilde{C}(x) = \frac{N-1}{\sum_y d(x, y)}. \tag{19}$$

The greater the closeness centrality of a node, the more rapid are the changes in the stock market of that country or region that can be transmitted to other stock markets.

(4) Betweenness centrality ($B(x)$): In a fully connected network, the shortest path exists for any pair of nodes s and t. Betweenness centrality is a measure of the complex network centrality based on these shortest paths. The basic idea is to count the ratio of the number of nodes on the shortest paths of the other two nodes to the total number of shortest paths in the network. The first formal definition of intermediary centrality for node x was provided by Freeman (1977).

$$B(x) = \sum_{s \neq x \neq t} \frac{\sigma_{st}(x)}{\sigma_{st}}, \tag{20}$$

where σ_{st} denotes the number of shortest paths between any pair of nodes s and t, and $\sigma_{st}(x)$ denotes the number of nodes x passing through in σ_{st}. In this study, we used the centralized $B(x)$, which was calculated as follows:

$$\tilde{B}(x) = \frac{B(x) - \min}{\max - \min}, \tag{21}$$

where max and min represent the largest and smallest betweenness centralities among all nodes, respectively. A country or region with high betweenness centrality can play an intermediary role in the correlation between the stock price indices of the other two countries and effectively transmit the fluctuations in the two stock markets.

(5) Eigenvector centrality ($E(x)$): Eigenvector centrality assigns more weight to a node's connections with other high-centrality nodes when measuring the importance of a node in a complex network. A high eigenvector score implies that a node is closely connected to many nodes with high eigenvector centrality. For a given complex network G with N nodes and E edges, record $A = \left(a_{x,y}\right)$ as the adjacency matrix, where $a_{x,y} = 1$ if node x is connected to node y, and $a_{x,y} = 0$ otherwise. The eigenvector centrality of node x can be defined as

$$E(x) = \frac{1}{\lambda} \sum_{y \in M(x)} E\left(y\right) = \frac{1}{\lambda} \sum_{y \in G} a_{x,y} E\left(y\right), \tag{22}$$

where $E(x)$ and $E(y)$ represent the eigenvector centralities of nodes x and y, respectively; λ is a constant; $M(x)$ is a set of neighbors of node x. Equation (20) can be rewritten as the eigenvector equation $Ax = \lambda x$. We can derive several different eigenvalues λ based on the eigenvector equation. However, the additional requirement that all entries in the eigenvector should be non-negative indicates that only the most significant eigenvalue outcome can be measured (Lohmann et al. 2010). Power iteration is one of the many eigenvalue algorithms that can be used to determine the principal eigenvector.

Given that multiple information flow mechanisms can coexist in the network (Borgatti 2005), it is difficult to determine which centrality measure to use to judge the importance of stock price indices in the financial market network. Identifying influential nodes in a network is an open problem, because a single centrality measure cannot account for all possible types of interactions between nodes in a network (Chen et al. 2012). Referring to Roy and Sarkar (2013), this study considers centrality indicators together, according to the idea of averaging. Specifically, for each centrality indicator, each stock price index was ranked first in descending order. The sorted stock price indices are then assigned ranks, with the first-ranked stock price index having a rank of one, the second-ranked stock price index having a rank of two, and so on. Stock price indices with the same centrality index were assigned the same ranks, whereas the ranks of the following lower-centrality stock price indices were adjusted according to the number. For example, if two stock price indices are tied for the first centrality, then they will both have a rank of 1, and the third stock price index will have a rank of 3. Given that the mechanism of the different centrality weights is unknown, the final ranking of each stock price index is in ascending order according to the average rank of these five centrality indicators. Therefore, for the centrality indicators, the most important stock price index will have the lowest average rank, and the least important stock price index will have the largest average rank.

Empirical analysis of global stock market complex network

This section first analyzes the overall correlation of global stock markets and divides them global stock market into developed, emerging, and frontier markets for separate discussions. Then, the power-law distribution of the degree centrality of the return-based network and OHLC data-based network is discussed. Finally, an analysis of the complex networks of global stock markets before and after the COVID-19 outbreak is conducted based on basic indicators of complex networks and centrality indicators.

Overall correlation analysis

Figure 4 shows global stock market correlations from 2017 to 2022. The correlation between any two stock markets [calculated using Eq. (9)] are represented by squares. Blue squares indicate positive correlations and red squares indicate negative correlations. Darker blue squares indicate stronger positive correlations, and darker red squares indicate stronger negative correlations.

The overall correlation of the global stock market from 2017 to 2022 exhibits four patterns. First, the blue squares characterize the vast majority of positive correlations, whereas the red squares characterize a few negative correlations and are very light in color. Second, 2020 is the first year of the COVID-19 outbreak. The two stock price indices were positively correlated by 80.21%, which was 16.84%, 9.13%, and 13.27% higher than that in 2017, 2018, and 2019, respectively. This result indicates a significant strengthening of the overall positive correlation in the global stock markets in 2020, which is generally caused by the negative influence of COVID-19 on global stock markets. Third, in 2021, the second year of the COVID-19 outbreak, the number of blue squares decreases significantly lower among the investigated years, indicating a significant decrease in the overall positive correlation of the global stock market. Compared to 2020, the overall positive correlation will decrease by 12.49% by 2021.

The weakening of stock market co-movement in 2021 may be mainly due to the severe polarization of global stock markets. In 2021, the lockdown practices were gradually lifted in various countries, and the economy began to recover. However, owing to differences in the improvement of economic fundamentals in various countries, the traction for stock rebounds was also different. The more a country or region's economy is on an upward trend, the more likely that investment institutions will become bullish in the stock market. Moreover, investment institutions are likely to bear stock markets when a country or region's upward or downward economic trend is weak. Owing to the herding effect, investors amplify the impact of investment institutions on stock market movements. For example, Vietnam, a global hub for processing and manufacturing, received significant foreign investment in 2021 and experienced a rapid rise in its stock price

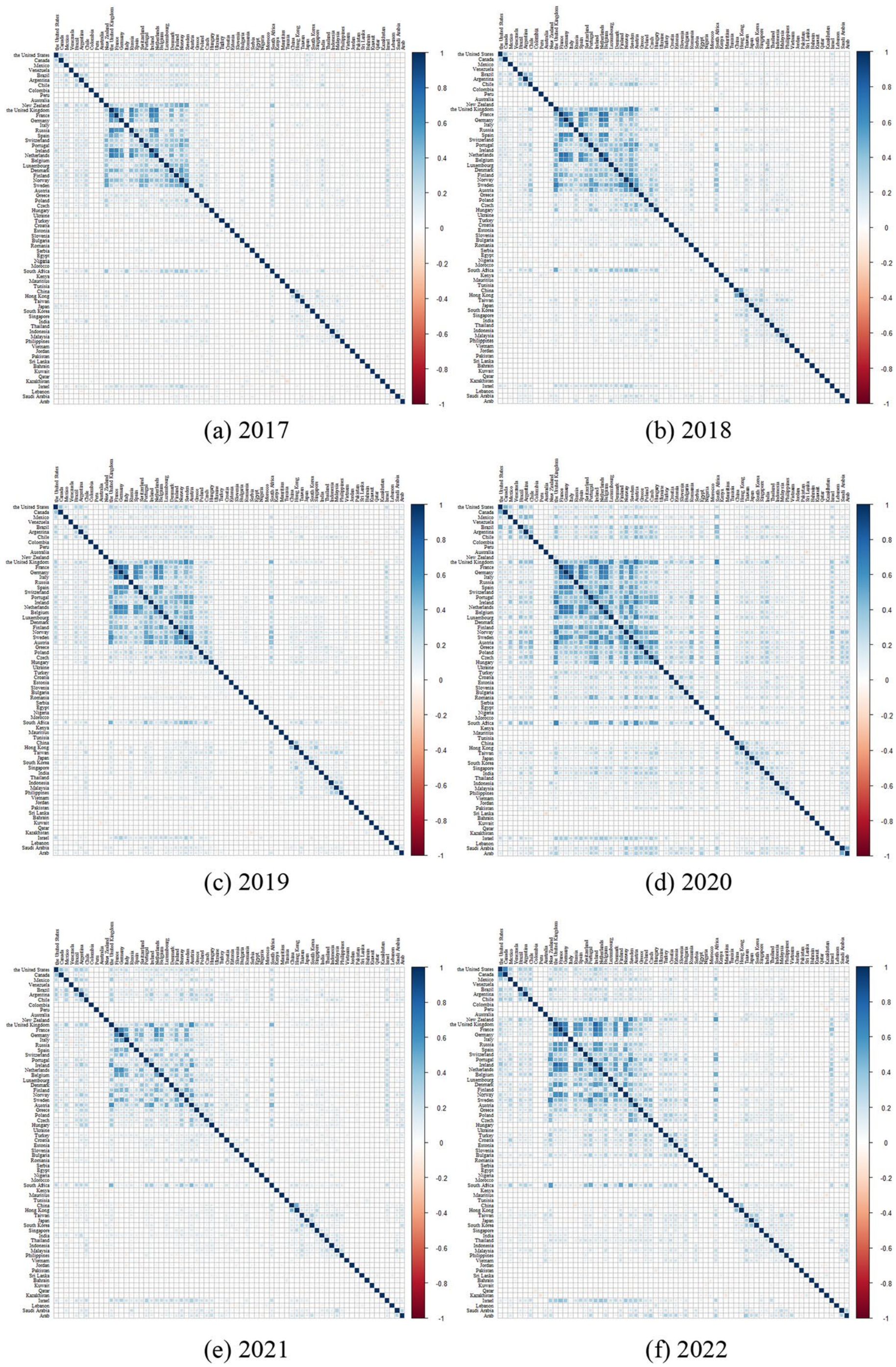


Fig. 4 Overall correlation plots of global stock markets in different years

index by 33.72%; the United States stock market increased by 28.79% due to accommodative monetary policy; Europe experienced substantial economic growth in early 2021 and fell back towards the end of the year due to the impact of the Omicron mutant strain, eventually reaching an increase of around 15%; South Korea and Japan experienced relatively weak economic growth, resulting in an increase of approximately 5.5%

in their stock price indices; China's stock index fell by 6.21% due to the ongoing lockdown, and the Hong Kong stock index fell by 14.83% due to the impact of the mainland. Fourth, the number of blue squares is expected to increase again in 2022 compared with 2021. This indicates an increase in the overall positive correlation of the global stock market by 2022, which is 5.66% higher than that in 2021. This enhanced co-movement is due to the worldwide recovery of economic fundamentals and the strengthening of economic trade.

According to the world-class financial services provider, the FTSE Group, the world stock market can be divided into three market segments. The first category includes developed markets dominated by developed capitalist countries. The second category comprises emerging markets dominated by developing countries in Asia, Africa, and South America. The third category is the frontier market, which mainly comprises countries in Eastern Europe and the Middle East. Table 2 lists countries in these three market segments.

Figure 5 and Table 3 present the overall correlation results for the three market segments by year. The overall correlations of different market segments exhibited four

Table 2 FTSE's stock market segmentation

Developed markets		Emerging markets		Frontier markets	
Number	**Country/region**	**Number**	**Country/region**	**Number**	**Country/region**
1	The United States	1	Mexico	1	Croatia
2	Canada	2	Venezuela	2	Estonia
3	Australia	3	Brazil	3	Slovenia
4	New Zealand	4	Argentina	4	Bulgaria
5	The United Kingdom	5	Chile	5	Romania
6	France	6	Colombia	6	Serbia
7	Germany	7	Peru	7	Nigeria
8	Italy	8	Russia	8	Morocco
9	Spain	9	Greece	9	Kenya
10	Switzerland	10	Poland	10	Mauritius
11	Portugal	11	Czech	11	Tunisia
12	Ireland	12	Hungary	12	Vietnam
13	Netherlands	13	Ukraine	13	Jordan
14	Belgium	14	Turkey	14	Sri Lanka
15	Luxembourg	15	Egypt	15	Bahrain
16	Denmark	16	South Africa	16	Kazakhstan
17	Finland	17	China	17	Lebanon
18	Norway	18	Taiwan		
19	Sweden	19	India		
20	Austria	20	Thailand		
21	Hong Kong	21	Indonesia		
22	Japan	22	Malaysia		
23	South Korea	23	Philippines		
24	Singapore	24	Pakistan		
25	Israel	25	Kuwait		
		26	Qatar		
		27	Saudi Arabia		
		28	The United Arab Emirates		

characteristics. (1) The positive correlation in developed markets was significantly higher than that in emerging and frontier markets. From 2017 to 2022, the average positive correlation of developed markets reached 92.00%, compared to 78.22% in emerging markets and 57.23% in frontier markets, which were 17.62% and 60.75% higher, respectively. (2)

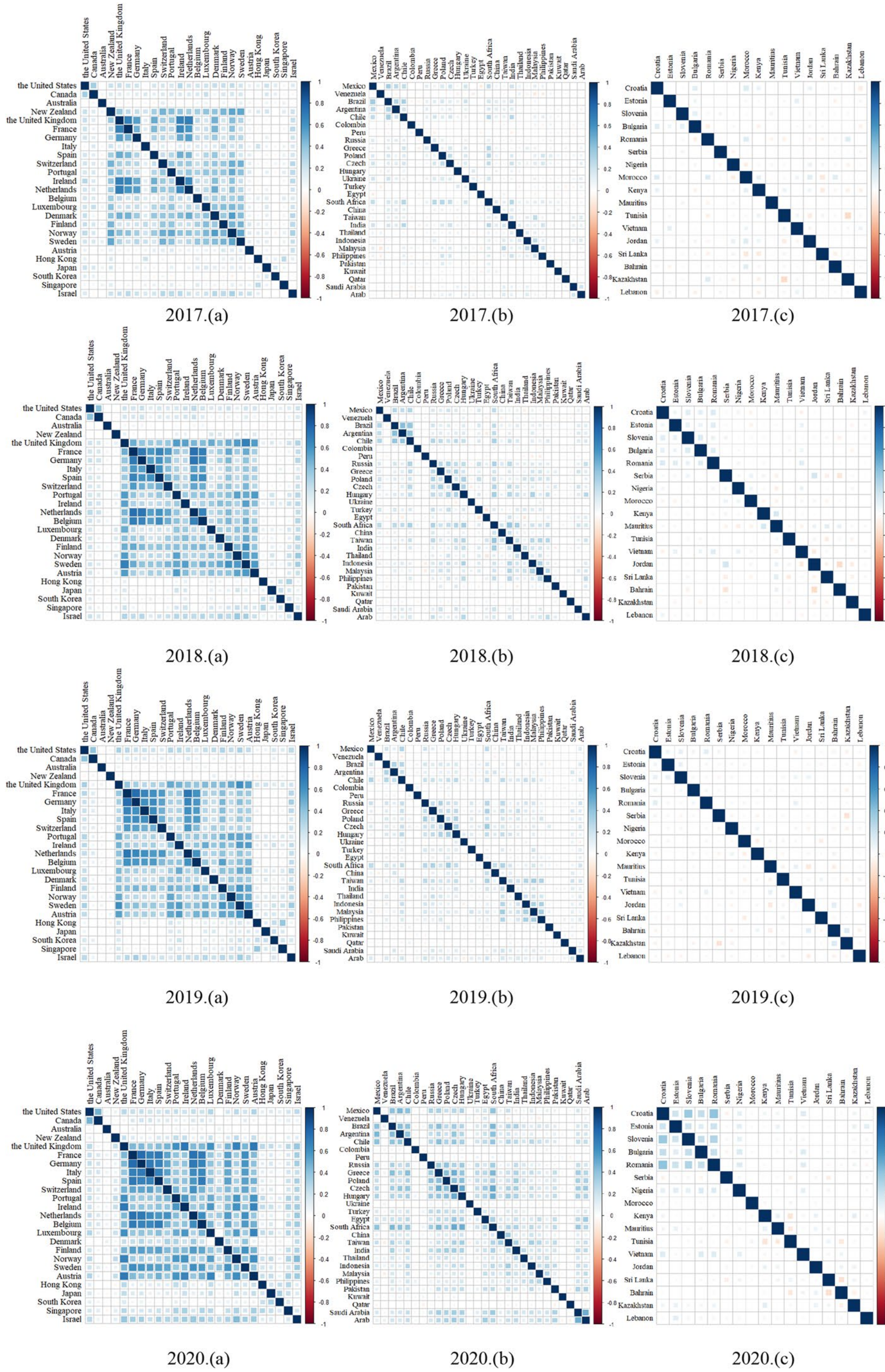


Fig. 5 Correlation coefficient of global stock price index. *Note* The first row is 2017, the second row is 2018, the third row is 2019, the fourth row is 2020, the fifth row is 2021, and the sixth row is 2022; the first column is developed markets, the second column is emerging markets, and the third column is frontier markets

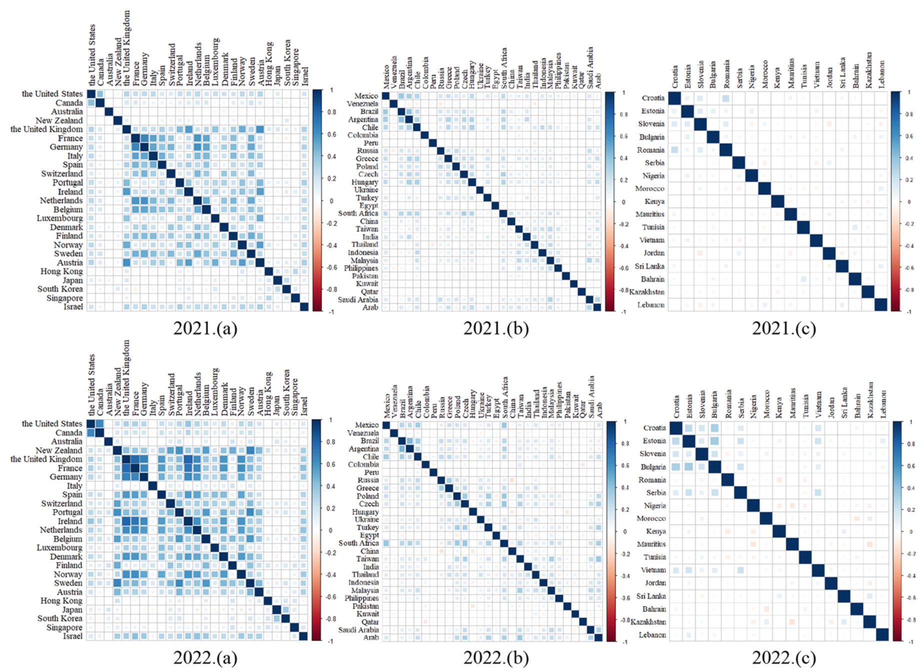


Fig. 5 continued

Table 3 Proportion of positive and negative correlation coefficients for market segments

Year	Market	Positive correlations	Negative correlations
2017	Overall	1658 (68.65%)	757 (31.35%)
	Developed market	273 (91.00%)	27 (9.00%)
	Emerging market	272 (71.96%)	106 (28.04%)
	Frontier market	67 (49.26%)	69 (50.74%)
2018	Overall	1775 (73.50%)	640 (26.50%)
	Developed market	283 (94.33%)	17 (5.67%)
	Emerging market	290 (76.72%)	88 (23.28%)
	Frontier market	78 (57.35%)	58 (42.65%)
2019	Overall	1710 (70.81%)	705 (29.19%)
	Developed market	273 (91.00%)	27 (9.00%)
	Emerging market	297 (78.57%)	81 (21.43%)
	Frontier market	70 (51.47%)	66 (48.53%)
2020	Overall	1937 (80.21%)	478 (19.79%)
	Developed market	295 (98.33%)	5 (1.67%)
	Emerging market	314 (83.07%)	64 (16.93%)
	Frontier market	91 (66.91%)	45 (33.09%)
2021	Overall	1695 (70.19%)	720 (29.81%)
	Developed market	263 (87.67%)	37 (12.33%)
	Emerging market	300 (79.37%)	78 (20.63%)
	Frontier market	80 (58.82%)	56 (41.18%)
2022	Overall	1791 (74.16%)	624 (25.84%)
	Developed market	269 (89.67%)	31 (10.33%)
	Emerging market	301 (79.63%)	77 (20.37%)
	Frontier market	81 (59.56%)	55 (40.44%)

In 2020, when COVID-19 broke out, the positive correlations in the developed, emerging, and frontier markets increased by 8.06%, 5.72%, and 30.00%, respectively, compared to 2019. (3) In 2021, the positive correlation ratios of the developed, emerging, and frontier markets decreased by 10.85%, 4.46%, and 12.09%, respectively, compared to 2020. However, the positive correlation ratios for emerging and frontier markets are still higher in 2021 than in 2017, 2018, and 2019. In contrast, the positive correlation ratios for developed markets in 2021 are lower than those in 2017, 2018, and 2019. (4) The same pattern was witnessed in 2022 as in 2021. The positive correlation ratios for emerging and frontier markets are still higher in 2022 than in 2017, 2018, and 2019. In contrast, the positive correlation ratios for developed markets in 2022 are lower than those in 2017, 2018, and 2019. This result suggests that stock market co-movement in the emerging and frontier markets strengthened after the COVID-19 outbreak. In contrast, stock market co-movement in developed markets strengthened significantly in the first year and weakened significantly in the second and third years. This provides evidence of the diversion of international investments in different developed markets during the post-pandemic period.

Basic indicators of global stock market complex network

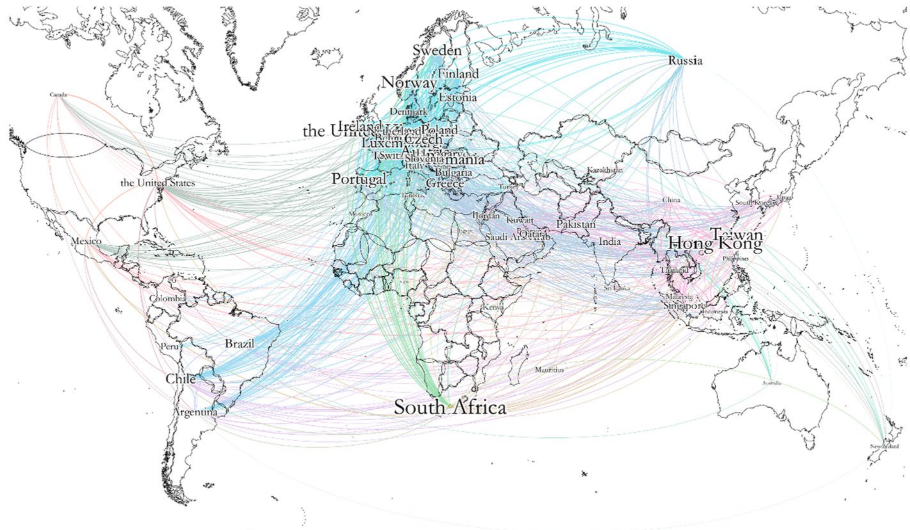
The global stock market complex networks are established by using each country or region as a node and the significant correlations at a significance level of 0.05 as the weights of the edges. Table 4 presents the base indicators of the world stock price index complex network for each year from 2017 to 2022.

According to Table 4 and Fig. 6, the following conclusions can be found.

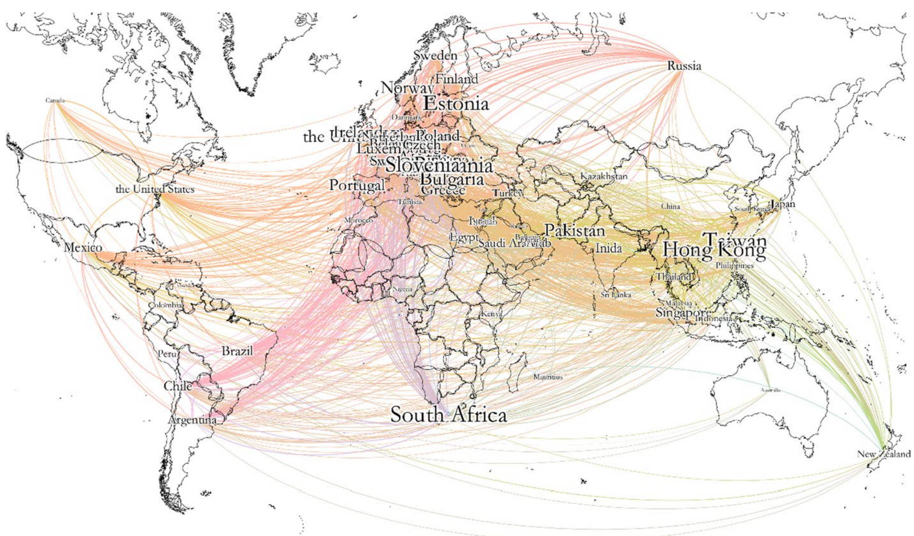
(1) The global stock market network was relatively stable from 2017 to 2019 before the COVID-19 outbreak. Stock market co-movement was weakest in 2017 and strongest in 2018. For these 3 years, each region's stock price index is significantly correlated with the stock price indices of 25.143, 30.171, and 27.171 in other regions. The average weighted degrees are positive, indicating that the stock price indices of each country or region are mostly positively correlated, with an average correlation coefficient of around 0.14–0.17. The average path lengths are below 2, indicating a "small world" phenomenon in the global stock market network, which was also verified in the works of Tse et al. (2010), Li and Pi (2018), and Yang and Hou (2022).

Table 4 Basic indicators of the world stock market complex network during 2017–2022

Indicator	2017	2018	2019	2020	2021	2022
Number of nodes	70	70	70	70	70	70
Number of edges	880	1056	951	1364	920	1123
Average degree	25.143	30.171	27.171	38.971	26.286	32.086
Average weighted degree	3.675	5.112	4.540	8.422	4.159	6.036
Average correlation coefficient	0.146	0.169	0.167	0.216	0.158	0.188
Network diameter	4	3	4	4	4	3
Network density	0.364	0.437	0.394	0.565	0.381	0.465
Average clustering coefficient	0.552	0.628	0.604	0.759	0.605	0.675
Average path length	1.683	1.589	1.661	1.469	1.717	1.556



(a) Global stock market complex network of 2019



(b) Global stock market complex network of 2020

Fig. 6 A comparison of the global stock market complex network between 2019 and 2020

(2) In 2020, when the COVID-19 outbreak began, the global stock market co-movement became more pronounced. Compared to 2017, 2018, and 2019, there were significantly more stock markets with significant correlations in 2020, with a significant increase in the average degree, average weighted degree, network density, and average cluster coefficient, and a decrease in the average path length. Compared with 2019, the average degree, average weighted degree, average correlation coefficient, network density, and average clustering coefficient of the global stock market network in 2020 increased by 43.43%, 85.51%, 29.34%, 43.40%, and 25.66%, respectively. The year 2020 also witnessed an 11.56% decrease in the average path length compared with 2019. Figure 6 illustrates a comparison of the global stock market complex networks for 2019 and 2020. The size of the nodes in Fig. 6 is proportional

to the degree of centrality, and the degree of centrality of each node in 2020 was significantly larger than in 2019. This phenomenon indicates a general downward trend of stock price indices in most countries under COVID-19, making stock market co-movement significantly more robust in 2021 than in 2020. These results are consistent with those reported by Aslam et al. (2020), Ashraf (2020), Gupta et al. (2020), Jackson (2021) and Samitas et al. (2022).

(3) The 2021 global stock price index complex network exhibits more inconsistent characteristics, and only 920 pairs of stock markets are significantly correlated. Compared to 2020, the average degree decreased by 32.55%, average weighted degree decreased by 50.62%, average correlation coefficient decreased by 26.85%, network density decreased by 32.57%, average clustering coefficient decreased by 20.29%, and average path length increased by 16.88%. This finding illustrates the different ups and downs in stock price indices worldwide in 2021, and the weakening of stock market co-movement. For countries where the epidemic was under control and the lockdown was lifted, industrial production gradually recovered, consumer confidence increased, and stock price indices showed an upward trend. Their stock price indices tended to decline in countries where the epidemic persisted or where the lockdown persisted.

(4) The year 2022 witnessed a strengthening of global stock market co-movement. The closeness of the global stock market network in 2022 is second only to that in 2020 during the entire observation period. Compared to 2021, the average degree, average weighted degree, average correlation coefficient, network density, and average clustering coefficient increased by 22.06%, 45.13%, 18.99%, 22.05%, and 11.57%, respectively, whereas the network diameter and average path length decreased by 25.00% and 9.38%, respectively. Due to the milder disease caused by the Omicron strain and the successful promotion of vaccines and potent drugs, the epidemic's impact on economic production activities has decreased (Antonini et al. 2022; Deb et al. 2022b). The year 2022 saw a consistent improvement in economic fundamentals across countries and more frequent import and export trade, strengthening economic ties between countries. Therefore, stock market co-movement is enhanced by 2022.

Power-law distribution of degree centrality

Aiello et al. (2001) argued that the degree centricity distributions of complex networks in the Internet, telecommunications, finance, biology, sociology, and other fields follow a power law model. Boginski et al. (2006) measured the similarity of listed stock returns in the financial sector in the United States from 1998 to 2002. They found that in the threshold network, the degree centricity showed a precise power-law distribution. Tse et al. (2010) constructed a complex network based on the close prices of all U.S. stocks from July 2005 to August 2007 and from June 2007 to May 2009. The results show that the stock market network's degree distribution is scale-free and follows a power-law distribution. According to this pattern, the degree centrality distribution of the global stock market complex network constructed using an appropriate network construction method should be characterized by a power-law distribution.

The testing and characterization of power-law distributions are complicated because of fluctuations in the long-tail component and an uncertain range of applicability values. Therefore, the commonly used ordinary least squares method may perform poorly, leading to biased estimations and misleading conclusions. Clauset et al. (2009) proposed a framework for identifying and measuring power-law distributions. The model is based on the Kolmogorov–Smirnov statistic, which combines the maximum likelihood estimation method. They argued that random variables may obey power-law distributions in ranges larger than $X_{\min}$ instead of the full value range. Compared to the BIC, Kuiper, and Anderson–Darling statistics (D'Agostino and Stephens 1986), Clauset et al. (2009) proved that the Kolmogorov–Smirnov statistic is a better goodness-of-fit test method for determining $X_{\min}$. As the degree centricity distribution in this study did not have heavy tails, $X_{\min} = 1$ was set to ensure the integrity of the data. The bootstrapping method based on the Kolmogorov–Smirnov statistic proposed by Clauset et al. (2009) is used to measure the extent to which the degree centricity distribution of the network obeys a power-law distribution.

For the return-based and OHLC data-based networks, the degree of centrality and corresponding number of nodes are summarized for the years from 2017 to 2022. Power-law distributions were fitted to the degree centrality of the two network types using the maximum-likelihood estimation method. The results are shown in Fig. 7. The estimation yielded a goodness-of-fit of 0.5369 for the return-based network and 0.5939 for the OHLC data-based network. The 500 bootstrapping of Kolmogorov–Smirnov statistics shows that the degree centricity of the return-based network has a 10.4% probability of obeying a power law distribution. In contrast, the probability of the OHLC data-based network was 78.6%. These results show that the proposed OHLC data-based network outperforms the traditional return-based network in terms of the scale-free power-law distribution properties of the global stock market network.

Centrality analysis of the global stock market complex network

This section examines the five centrality indicators: degree, weighted degree, closeness, betweenness, and eigenvalue centrality. Table 5 summarizes the average rankings of the five degree centrality indicators for the different market segments and continents for each year from 2017 to 2022. Table 6 presents detailed results for each sample country or region. The individual rankings of the five centrality indicators are

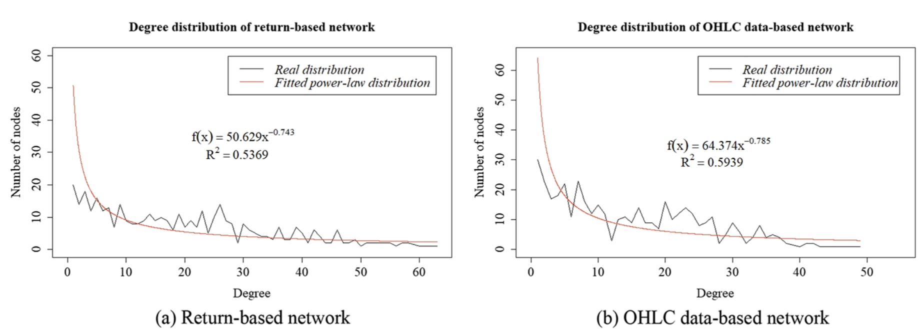


Fig. 7 Power-law distribution of return-based and OHLC data-based networks

Table 5 Average rankings of centrality in 2017 to 2022 by market segments and continent

Segments	2017	2018	2019	2020	2021	2022	Before	After	Average
Developed markets	22.58	24.66	23.10	26.84	24.22	26.65	23.45	25.90	24.68
Emerging markets	35.11	34.86	33.34	33.37	34.00	34.40	34.44	33.92	34.18
Frontier markets	53.62	51.49	56.19	49.47	50.73	51.47	53.77	50.56	52.16
Europe	25.92	26.05	26.52	25.37	25.10	25.80	26.16	25.42	25.79
South America	31.00	39.12	29.32	33.00	32.20	32.88	33.15	32.69	32.92
North America	30.95	34.85	38.70	32.10	35.00	39.60	34.83	35.57	35.20
Oceania	30.10	48.40	44.40	47.10	42.10	28.30	40.97	39.17	40.07
Asia	43.94	42.10	40.92	42.87	41.85	42.70	42.32	42.47	42.40
Africa	51.17	44.63	52.26	48.14	49.17	51.09	49.35	49.47	49.41

given in Table 8, 9, 10, 11 and 12 in the Appendix. Fruitful findings were derived from the figures in Tables 5 and 6. (1) In terms of market segmentation, developed markets occupied an overwhelmingly dominant position in the world stock market network, with an average centrality ranking of 24.68 for the 25 developed markets' stock price indices from 2017 to 2022. Emerging markets were in second place, with an average centrality ranking of 34.18, for its 28 stock price indices. Frontier markets had the lowest importance, with an average centrality ranking of only 52.16 for the 17 stock price indices included. Liu and Tse (2012) and Aslam et al. (2020) similarly find that developed markets have more robust connectivity properties than other markets in the global stock market. (2) Regarding continents, Europe occupies the most critical position in the world stock market network. The average centrality ranking of the stock price indices in the European region from 2017 to 2022 is 25.79, followed by South America (average ranking of 32.92), North America (average ranking of 35.20), Oceania (average ranking of 40.07), Asia (average ranking 42.40), and Africa (average ranking 49.41). Roy and Sarkar (2013), Qiao et al. (2015), Wen et al. (2019), and Samitas et al. (2022) also find European countries dominate the global stock market network. They explained that the European countries' shared commercial trade and common currency meant that their links were intensely weighted. (3) Developed markets were centered on Austria (average ranking 9.3), Portugal (average ranking 9.7), the United Kingdom (average ranking 12.0), Ireland (average ranking 13.1), Sweden (average ranking 13.4), and Norway (average ranking 10.30); emerging markets were centered on South Africa (average ranking 9.7), the Czech Republic (average ranking 14.6), Poland (average ranking 15.9), Chile (average ranking 14.9), Brazil (average ranking 18.4), Mexico (average ranking 18.6), and Argentina (average ranking 20.3); and frontier markets were centered in Croatia (average ranking 37.8) and Romania (average ranking 38.1). Several other studies have reported similar findings. Examples include Aslam et al. (2020), who revealed the importance of Poland and the Czech Republic in the stock market network before and after the COVID-19 epidemic using a minimum spanning tree (MST); Memon and Yao (2021), who identified Austria and Sweden as super-hub nodes in Europe during the first wave of the COVID-19 epidemic based on MST; and Samitas et al. (2022), who found that South Africa and Sweden had high centrality in global stock markets from 2018 to 2020 based on dependency dynamics and network analysis.

Table 6 Each country or region's average ranking of centrality indicators in 2017–2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	Austria	19.8	4.2	3.8	9.4	2.8	16.0	9.3	Europe	Developed
2	South Africa	3.6	2.2	7.0	17.0	22.0	6.6	9.7	Africa	Emerging
3	Portugal	28.6	5.4	4.0	12.2	10.4	5.2	11.0	Europe	Developed
4	The United Kingdom	18.6	2.4	2.4	14.4	2.6	31.4	12.0	Europe	Developed
5	Ireland	12.2	6.6	10.0	4.0	15.2	30.4	13.1	Europe	Developed
6	Sweden	5.0	13.4	1.0	32.0	14.8	14.0	13.4	Europe	Developed
7	Norway	8.4	11.8	4.6	21.6	3.2	31.2	13.5	Europe	Developed
8	Finland	8.2	21.8	11.0	24.8	16.2	5.4	14.6	Europe	Developed
8	Czech	15.2	12.2	8.2	26.4	13.8	11.8	14.6	Europe	Emerging
10	Chile	4.6	16.8	8.0	26.4	16.6	17.2	14.9	South America	Emerging
11	Poland	9.4	25.2	16.8	9.2	28.8	6.2	15.9	Europe	Emerging
12	Brazil	16.4	22.8	13.2	17.0	26.0	14.8	18.4	South America	Emerging
13	Mexico	7.8	22.6	28.8	18.4	11.6	22.4	18.6	North America	Emerging
13	Belgium	12.2	35.2	21.4	25.4	12.6	5.0	18.6	Europe	Developed
15	Luxembourg	19.2	16.0	13.6	8.2	14.6	43.4	19.2	Europe	Developed
16	Argentina	22.2	25.8	21.2	15.2	14.6	22.6	20.3	South America	Emerging
17	Denmark	15.8	5.8	12.2	39.0	30.6	22.6	21.0	Europe	Developed
18	Switzerland	14.6	27.8	35.4	19.6	25.6	3.8	21.1	Europe	Developed
19	Greece	26.4	20.8	25.2	9.2	14.8	32.0	21.4	Europe	Emerging
20	Russia	23.8	10.0	19.2	31.4	19.0	37.2	23.4	Europe	Emerging
21	India	10.0	27.0	26.4	30.6	17.2	30.6	23.6	Asia	Emerging
22	Israel	19.0	20.2	27.4	37.8	19.4	23.8	24.6	Asia	Developed
23	The United States	23.4	17.4	25.8	28.2	31.2	26.8	25.5	North America	Developed
24	France	25.8	17.4	26.8	28.2	28.6	26.8	25.6	Europe	Developed
25	Singapore	36.4	21.8	37.8	15.6	29.6	17.8	26.5	Asia	Developed
26	Hungary	46.8	12.2	20.2	10.0	8.0	63.6	26.8	Europe	Emerging

Table 6 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
27	The United Arab Emirates	48.6	24.0	23.0	18.6	27.0	27.0	28.0	Asia	Emerging
28	Taiwan	33.6	25.8	25.0	19.6	24.8	40.2	28.2	Asia	Emerging
29	Italy	11.6	37.8	32.4	19.4	21.4	48.6	28.5	Europe	Developed
30	Netherlands	31.4	31.6	21.0	26.4	30.2	31.4	28.7	Europe	Developed
31	Spain	14.2	37.0	27.6	28.8	37.0	31.2	29.3	Europe	Developed
32	Germany	29.6	31.4	28.2	31.4	29.6	27.4	29.6	Europe	Developed
33	New Zealand	12.6	36.6	41.0	49.0	40.0	5.8	30.8	Oceania	Developed
34	Thailand	39.2	28.6	30.4	40.0	36.2	15.6	31.7	Asia	Emerging
35	Japan	35.8	33.2	48.4	28.0	27.6	30.0	33.8	Asia	Developed
36	Hong Kong	34.4	35.8	18.6	33.8	40.4	42.6	34.3	Asia	Developed
37	Malaysia	33.4	24.4	32.0	52.8	41.4	22.4	34.4	Asia	Emerging
38	Saudi Arabia	48.6	45.2	24.4	27.8	31.6	43.0	36.8	Asia	Emerging
39	Canada	30.6	38.2	36.0	36.4	37.2	48.2	37.8	North America	Developed
39	Croatia	43.0	45.6	57.2	28.6	39.0	13.4	37.8	Europe	Frontier
41	Romania	49.0	26.8	38.4	26.0	26.2	62.4	38.1	Europe	Frontier
42	Turkey	58.2	35.0	48.2	33.2	30.8	26.2	38.6	Europe	Emerging
43	Estonia	53.6	55.6	47.0	25.4	42.0	11.2	39.1	Europe	Frontier
44	Bulgaria	33.0	42.0	53.6	43.4	53.0	13.4	39.7	Europe	Frontier
45	Indonesia	44.8	28.8	42.8	46.4	41.0	42.2	41.0	Asia	Emerging
46	Slovenia	46.8	41.8	52.8	28.8	39.2	37.2	41.1	Europe	Frontier
47	Philippines	30.0	41.0	42.0	39.4	44.4	52.4	41.5	Asia	Emerging
48	China	37.8	37.6	43.0	52.2	37.2	46.6	42.4	Asia	Emerging
49	South Korea	49.6	47.4	39.4	52.2	40.4	42.6	45.3	Asia	Developed
50	Vietnam	49.2	44.6	34.6	48.2	55.4	48.2	46.7	Asia	Frontier
51	Ukraine	26.6	63.2	61.8	51.8	61.8	21.0	47.7	Europe	Emerging
52	Australia	47.6	60.2	47.8	45.2	44.2	50.8	49.3	Oceania	Developed

Table 6 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
53	Pakistan	49.8	53.2	47.4	45.0	47.8	53.2	49.4	Asia	Emerging
54	Egypt	64.6	53.2	55.4	24.0	48.4	60.4	51.0	Africa	Emerging
55	Peru	59.6	67.6	54.4	47.8	46.6	47.4	53.9	South America	Emerging
56	Nigeria	63.6	47.0	58.8	51.0	49.0	55.6	54.2	Africa	Frontier
57	Serbia	44.6	59.4	65.0	67.6	56.0	38.8	55.2	Europe	Frontier
58	Qatar	55.6	65.6	45.2	56.4	61.8	51.6	56.0	Asia	Emerging
59	Kenya	59.6	56.4	52.2	59.0	49.8	61.8	56.5	Africa	Frontier
60	Sri Lanka	63.4	54.0	63.0	51.2	49.0	59.4	56.7	Asia	Frontier
61	Morocco	44.6	49.2	68.0	67.6	53.8	58.0	56.9	Africa	Frontier
62	Colombia	52.2	62.6	49.8	58.6	57.2	62.4	57.1	South America	Emerging
63	Lebanon	53.0	61.4	65.6	52.0	56.0	55.0	57.2	Asia	Frontier
64	Jordan	66.6	54.0	55.0	61.8	52.0	55.4	57.5	Asia	Frontier
65	Tunisia	54.4	53.0	60.4	55.8	59.0	67.4	58.3	Africa	Frontier
66	Kuwait	52.4	61.4	50.2	64.6	61.6	63.0	58.9	Asia	Emerging
67	Venezuela	62.0	61.2	64.2	45.4	60.0	61.0	59.0	North America	Emerging
68	Mauritius	67.8	51.4	64.0	62.6	62.2	47.8	59.3	Africa	Frontier
69	Bahrain	62.0	67.2	60.2	57.6	59.0	55.0	60.2	Asia	Frontier
70	Kazakhstan	57.4	66.0	59.4	54.4	61.8	64.4	60.6	Asia	Frontier

Table 7 shows the significant changes in the centrality rankings of the world stock market network in 2020, 2021, and 2022 after the COVID-19 outbreak. In this study, a country or region is considered significantly less or more critical if its stock price index has increased or decreased by at least ten places compared to the previous year's centrality ranking. The centrality ranking in this study was calculated based on the average degree centrality, weighted degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. These five centrality indicators provide a comprehensive measure of the importance of a stock price index in a global stock market network from various perspectives (Roy and Sarkar 2013). When the centrality ranking of a stock price index decreases or increases significantly, it means that

Table 7 Stock price indices with significant changes in centrality ranking

Country/region	2020	2021	2022	Country/region	2020	2021	2022
Ireland	–	Down	Down	Bahrain	–	–	–
Chile	Down	–	–	Colombia	–	–	–
Denmark	Down	–	–	the United States	–	–	–
Hong Kong	Down	–	–	Tunisia	–	–	–
Kuwait	Down	–	–	Portugal	–	–	–
Vietnam	Down	–	–	Spain	–	–	–
Norway	Down	Up	Down	Indonesia	–	–	–
Russia	Down	Up	Down	Poland	–	Down	Up
the United Kingdom	Down	Up	Down	India	–	Up	Down
Luxembourg	–	–	Down	Venezuela	Up	Down	–
Kenya	–	–	Down	Slovenia	Up	Down	–
Austria	–	–	Down	Romania	Up	–	Down
Canada	–	–	Down	Sri Lanka	Up	–	Down
Saudi Arabia	–	–	Down	Greece	Up	–	Down
Taiwan	–	–	Down	Hungary	Up	–	Down
Egypt	Up	Down	Down	Italy	Up	–	Down
Czech	Down	Up	–	Mexico	Up	–	Down
Israel	Down	Up	–	Malaysia	Down	Up	Up
South Korea	Down	Up	–	Croatia	Up	Down	Up
Sweden	Down	Up	–	Estonia	Up	Down	Up
Finland	Down	–	Up	Singapore	Up	Down	Up
Qatar	Down	–	Up	Ukraine	Up	Down	Up
South Africa	Down	–	Up	Japan	Up	–	–
the United Arab Emirates	–	–	–	Lebanon	Up	–	–
France	–	–	–	Belgium	–	Up	–
Germany	–	–	–	China	–	Up	–
Jordan	–	–	–	Brazil	–	–	Up
Kazakhstan	–	–	–	Mauritius	–	–	Up
Netherlands	–	–	–	New Zealand	–	–	Up
Nigeria	–	–	–	Thailand	–	–	Up
Pakistan	–	–	–	Morocco	–	Up	–
Peru	–	–	–	Turkey	Up	–	–
Philippines	–	–	–	Bulgaria	Up	–	Up
Argentina	–	–	–	Switzerland	Up	–	Up
Australia	–	–	–	Serbia	–	Up	Up

there are more or less other stock price indices with which it has a significant correlation, the strength of the correlation is greater or smaller, changes in that stock market are transmitted to other stock markets faster or slower, the efficiency of transmitting fluctuations between two other stock markets is higher or lower, and the connection to other important stock price indices is tighter or looser (Moghadam et al. 2019).

Several patterns were derived from the results presented in Table 7. First, the stock price indices for Norway, Russia, the United Kingdom, and Egypt witnessed significant centrality ranking changes for three consecutive years in 2020, 2021, and 2022. This indicates that the financial markets in these countries are more volatile and that attention should be paid to strengthening financial risk prevention during the epidemic. A typical example is the United Kingdom, which adopted a herd immunization policy at the beginning of the COVID-19 outbreak in 2020, resulting in a large population being infected (Burckhardt et al. 2022). The widespread infection caused a tight labor market and an economic downturn, corresponding to a decline in the importance of its stock price index in 2020. As vaccine promotion and herd immunity were achieved, the United Kingdom economy gradually recovered in 2021 and experienced an increase in the importance of its stock price index in 2021. In 2022, the United Kingdom's economy was hit by an Omicron strain, with a record number of infections. Repeated epidemic outbreaks led to a lack of investor confidence and a renewed decline in the importance of the stock price index in 2021. Second, for countries that experienced only a drop in the stock price index centrality ranking, attention should be paid to encouraging production and economic recovery during the epidemic. For example, Ireland is the only country or region that has seen two drops in its centrality rankings in 2021 and 2022, respectively. In the general context of an epidemic, Ireland should pay particular attention to encouraging people to work, vigorously reviving production, and stabilizing economic levels to attract investment. Third, the centrality rankings of many established capitalist countries such as France, Germany, the Netherlands, Australia, the United States, Portugal, and Spain did not change significantly between 2020 and 2022. This result indicates that the stock markets of these countries were more resilient to financial volatility in an epidemic environment than those with significant centrality ranking changes. Fourth, Bulgaria, Switzerland, and Serbia experience two increases in their stock price index rankings from 2020 to 2022. International investors can focus on these markets for effective asset allocation.

Conclusions

This study investigates global stock market co-movements during the COVID-19 pandemic. This study has important implications for determining the impact of the COVID-19 outbreak on the topology of the global stock market network, government policies and regulations in financial markets, portfolio adjustments, and risk management by individual and institutional investors (Tang et al. 2018; Aslam et al. 2020). A novel complex network construction method is proposed based on OHLC data and hypothesis testing for edge selection. The degree distribution of the OHLC data-based network exhibited better power-law distribution properties than those of the return-based network, implying a more rational construction of the complex network. The topologies of the global stock market complex networks constructed using 70 important global stock price indices before (2017–2019) and after (2020–2022) the COVID-19 outbreak were examined using a fruitful dataset. Several important conclusions are drawn.

First, significant stock market co-movements occurred before and after the COVID-19 pandemic. This positive correlation is significantly higher in developed markets than in emerging or frontier markets. The positive correlation ratios between the two stock price indices in the global stock market complex network reached 68.65% in 2017, 73.50% in 2018, 70.81% in 2019, 80.21% in 2020, 70.19% in 2021 and 74.16% in 2022. In addition, the developed markets' average positive correlation ratio from 2017 to 2022 is 92.00%, 17.62%, and 60.75% higher than those of the emerging and frontier markets, respectively.

Second, stock market co-movement in emerging and frontier markets strengthened from 2020 to 2022, following the outbreak of the COVID-19 pandemic. In contrast, the stock market co-movement of developed markets strengthened in 2020 but weakened in 2021 and 2022. The results provide evidence of the diversion of international investments in different developed markets during the post-pandemic period.

Third, in the wake of the COVID-19 outbreak, the global stock market network became very dense in 2020, relatively sparse in 2021, and returned to a dense state by 2022. Compared with 2019, the average degree of the 2020 global stock market complex network increased by 43.43%. The year 2021 witnessed inconsistent characteristics in the complex network of the world stock market. Compared to 2020, the 2021 global stock market complex network shows a 32.55% decrease in the average degree. In 2022, the closeness of the global stock market network is second only to that of 2020 during the entire investigation period from 2017 to 2022. Compared to 2021, the average degree of the 2022 global stock market complex network increases by 22.06%.

Fourth, the stock price indices of developed markets and European countries occupy a dominant position in the world's stock market complex network. The rankings based on the five centrality indicators indicated an average ranking of 24.68 for developed markets, 34.18 for emerging, and 52.16 for frontier markets 2017 to 2022. The centers of developed markets are recognized as Austria, Portugal, the United Kingdom, Ireland, Sweden, and Norway; the centers of emerging markets are South Africa, the Czech Republic, Poland, Chile, Brazil, Mexico, and Argentina; and the centers of frontier markets are Croatia and Romania. The European region occupies the most crucial position in the world's stock market network, with an average centrality ranking of 25.79 from 2017 to 2022, followed by South America (32.92), North America (35.20), Oceania (40.07), Asia (42.40), and Africa (49.41).

Fifth, the centrality rankings of different countries showed different dynamics during the pandemic period. The stock price indices for Norway, Russia, the United Kingdom, and Egypt witnessed significant changes over three consecutive years from 2020 to 2022. Ireland was the only country or region with two drops in rankings in 2021 and 2022, respectively. The centrality rankings of established capitalist countries, such as France, Germany, the Netherlands, Australia, the United States, Portugal, and Spain, did not change significantly from 2020 to 2022. Countries such as Bulgaria, Switzerland, and Serbia only experienced an increase in their stock price index rankings from 2020 to 2022.

Based on the estimation results of the OHLC data-based complex network, an array of concrete recommendations is provided. First, developed markets enjoy better stock market co-movement characteristics than do emerging and frontier markets. This indicates that the economic fundamentals of developed countries are interconnected with those of other countries. As a result, developed market stock price indices have more stable real economic support and are suitable for long-term investors. Establishing capitalist countries with high financial risk resilience during an epidemic is a good choice. Second, the frontier and emerging markets are uncertain because of their weaker overall interconnectedness with global stock markets. More uncertainty indicates more significant rates of return and risk. Short-term investors seeking substantial profits can focus on frontier and emerging markets. Bulgaria and Serbia, which have consistently increased in terms of centrality in the global stock market network, can be considered. Third, as the COVID-19 pandemic progressed, the economic trends in each country or region varied depending on epidemic prevention and economic recovery. Greater volatility and uncertainty in the global equity markets are double-edged swords for investors. Investors should divest appropriately to control risk when an epidemic and production recovery are uncertain.

Moreover, additional investments can lead to substantial profits when epidemics and production recovery are inevitable. Fourth, for international investors, risk can be reduced by reducing their exposure to countries with strong economic correlations. One potential investment strategy is to choose several countries and regions with different co-movement patterns for diversification. Pairs trading strategies designed based on the movement of correlated stock price indices can also be considered (Elliott et al. 2005; Gatev et al. 2006; Mudchanatongsuk et al. 2008). Fifth, Norway, Russia, the United Kingdom, and Egypt continue to witness significant changes in their centrality rankings in 2020, 2021, and 2022, respectively. These countries should improve their public healthcare protection systems and enhance their epidemic risk resilience, thereby improving their financial risk-prevention capabilities and protecting their macroeconomic security. Finally, high-welfare countries, led by Ireland, must encourage the workforce and make solid efforts to restore production and stabilize economic levels.

The primary limitation of this study is the relatively macroscopic nature of the participants. Considering that most investors choose portfolios that tend to be on the same stock market, future studies could employ the proposed complex network construction approach to conduct an in-depth investigation of various stocks in a particular stock market. Thus, the network topology may be utilized to optimize portfolios and provide investors with practical trading strategies (Boginski et al. 2014; Tang et al. 2018).

Appendix

See Tables 8, 9, 10, 11 and 12.

Table 8 Degree centrality ranking in 2017 to 2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	South Africa	1	1	5	2	8	3	3.33	Developed	Africa
2	Portugal	26	3	4	4	5	4	7.67	Emerging	Europe
3	Austria	18	3	5	4	3	18	8.50	Developed	Europe
4	Czech	8	11	5	18	5	11	9.67	Emerging	Europe
5	Chile	1	11	5	24	9	13	10.50	Emerging	South America
6	Norway	7	9	2	12	1	34	10.83	Developed	Europe
7	Poland	6	17	15	1	26	3	11.33	Emerging	Europe
8	Ireland	13	3	10	2	12	31	11.83	Developed	Europe
9	The United Kingdom	20	1	2	12	1	37	12.17	Developed	Europe
10	Sweden	3	9	1	33	17	12	12.50	Developed	Europe
11	Finland	7	17	13	31	9	1	13.00	Developed	Europe
12	Brazil	14	17	13	12	22	10	14.67	Emerging	South America
13	Mexico	4	17	25	24	4	17	15.17	Emerging	North America
14	Greece	24	14	15	4	9	27	15.50	Emerging	Europe
15	Luxembourg	18	11	10	4	14	42	16.50	Developed	Europe
16	Argentina	20	24	15	18	12	18	17.83	Emerging	South America
17	India	4	26	24	18	14	24	18.33	Emerging	Asia
18	Belgium	12	36	21	24	17	4	19.00	Developed	Europe
19	Denmark	13	3	9	49	26	25	20.83	Developed	Europe
20	Russia	26	7	12	31	16	35	21.17	Emerging	Europe
21	Switzerland	13	28	34	18	35	1	21.50	Developed	Europe
22	The United States	20	15	19	35	24	23	22.67	Developed	North America
23	Hungary	46	7	15	4	5	64	23.50	Emerging	Europe
24	Israel	20	15	25	35	19	29	23.83	Developed	Asia
25	Taiwan	38	21	21	10	19	38	24.50	Emerging	Asia
26	The United Arab Emirates	43	26	21	12	22	27	25.17	Emerging	Asia

Table 8 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
26	Singapore	38	21	30	4	43	15	25.17	Developed	Asia
28	France	24	24	30	35	26	26	27.50	Developed	Europe
29	Italy	7	38	30	24	24	51	29.00	Developed	Europe
30	Germany	26	35	25	35	26	30	29.50	Developed	Europe
31	Netherlands	30	33	25	35	30	32	30.83	Developed	Europe
32	Spain	13	36	30	40	33	34	31.00	Developed	Europe
33	Japan	32	33	42	24	30	27	31.33	Developed	Asia
34	New Zealand	7	42	50	42	48	7	32.67	Developed	Oceania
35	Thailand	40	30	36	33	47	11	32.83	Emerging	Asia
36	Hong Kong	33	40	19	24	37	46	33.17	Developed	Asia
37	Romania	52	23	36	10	19	64	34.00	Frontier	Europe
38	Malaysia	34	28	34	49	41	22	34.67	Emerging	Asia
39	Croatia	52	46	55	18	30	9	35.00	Frontier	Europe
40	Estonia	55	53	46	18	43	3	36.33	Frontier	Europe
41	Saudi Arabia	46	44	25	24	40	42	36.83	Emerging	Asia
41	Turkey	59	30	42	40	33	17	36.83	Emerging	Europe
43	Bulgaria	34	46	48	42	51	9	38.33	Frontier	Europe
44	Slovenia	46	49	48	12	35	41	38.50	Frontier	Europe
45	Indonesia	41	30	45	45	39	43	40.50	Emerging	Asia
45	Canada	26	42	41	53	41	44	41.17	Developed	North America
47	China	34	40	39	48	37	50	41.33	Emerging	Asia
48	Philippines	34	38	42	44	43	48	41.50	Emerging	Asia
49	South Korea	43	46	36	52	43	36	42.67	Developed	Asia
50	Vietnam	46	44	40	47	54	44	45.83	Frontier	Asia
51	Egypt	66	51	50	12	56	56	48.50	Emerging	Africa
52	Pakistan	47	52	47	46	49	52	48.83	Emerging	Asia

Table 8 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
53	Ukraine	30	65	61	54	66	20	49.33	Emerging	Europe
54	Australia	43	62	53	58	54	48	53.00	Developed	Oceania
55	Serbia	42	60	67	69	59	39	56.00	Frontier	Europe
56	Nigeria	68	50	61	49	50	59	56.17	Frontier	Africa
57	Venezuela	57	59	58	55	56	60	57.50	Emerging	North America
58	Peru	63	69	53	56	51	55	57.83	Emerging	South America
59	Lebanon	51	62	67	58	60	53	58.50	Frontier	Asia
59	Morocco	52	53	70	67	51	63	59.33	Frontier	Africa
61	Colombia	55	65	55	60	60	62	59.50	Emerging	South America
62	Jordan	69	56	58	63	56	61	60.50	Frontier	Asia
63	Qatar	58	69	50	63	70	58	61.33	Emerging	Asia
64	Kenya	63	60	60	63	60	63	61.50	Frontier	Africa
65	Bahrain	66	67	61	60	60	57	61.83	Frontier	Asia
65	Tunisia	58	55	64	60	65	69	61.83	Frontier	Africa
67	Mauritius	70	56	64	67	66	54	62.83	Frontier	Africa
68	Kazakhstan	58	67	64	56	66	68	63.17	Frontier	Asia
69	Kuwait	58	62	55	70	66	69	63.33	Emerging	Asia
69	Sri Lanka	63	58	69	63	60	67	63.33	Frontier	Asia

Table 9 Weighted degree centrality ranking in 2017–2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	The United Kingdom	6	1	2	1	1	8	3.17	Developed	Europe
2	Portugal	9	4	4	5	7	3	5.33	Emerging	Europe
3	Sweden	3	2	1	17	9	2	5.67	Developed	Europe
4	Norway	2	5	5	3	3	18	6.00	Developed	Europe
5	Ireland	11	7	7	4	4	7	6.67	Developed	Europe
6	South Africa	10	6	9	6	5	5	6.83	Developed	Africa
7	Finland	5	8	6	13	6	12	8.33	Developed	Europe
8	Austria	29	3	3	2	2	13	8.67	Developed	Europe
9	Belgium	16	13	8	12	8	4	10.17	Developed	Europe
10	France	13	10	11	15	17	6	12.00	Developed	Europe
11	Netherlands	8	15	12	19	18	11	13.83	Developed	Europe
12	Germany	17	21	13	14	13	15	15.50	Developed	Europe
12	Luxembourg	12	11	10	7	16	37	15.50	Developed	Europe
14	Switzerland	7	18	18	16	28	9	16.00	Developed	Europe
15	Czech	23	19	14	8	19	16	16.50	Emerging	Europe
16	Chile	15	12	19	20	14	24	17.33	Emerging	South America
17	Denmark	4	9	15	46	25	10	18.17	Developed	Europe
18	Poland	20	26	21	11	27	14	19.83	Emerging	Europe
19	Russia	14	16	22	24	26	20	20.33	Emerging	Europe
19	Greece	27	24	25	9	11	26	20.33	Emerging	Europe
21	Spain	19	20	17	22	24	21	20.50	Developed	Europe
22	Israel	22	17	26	29	15	25	22.33	Developed	Asia
23	Brazil	18	25	23	23	23	23	22.50	Emerging	South America
24	The United States	26	27	20	36	21	22	25.33	Developed	North America
25	Italy	25	22	16	21	20	50	25.67	Developed	Europe

Table 9 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
26	Argentina	28	29	28	32	10	33	26.67	Emerging	South America
26	Mexico	21	32	31	27	22	27	26.67	Emerging	North America
28	Hungary	48	14	24	10	12	64	28.67	Emerging	Europe
29	Taiwan	35	23	27	31	30	32	29.67	Emerging	Asia
30	New Zealand	1	44	51	43	48	1	31.33	Developed	Oceania
31	India	24	31	37	26	31	42	31.83	Emerging	Asia
32	The United Arab Emirates	40	35	32	28	29	31	32.50	Emerging	Asia
33	Singapore	34	28	30	25	44	40	33.50	Developed	Asia
34	Malaysia	36	33	34	47	36	34	36.67	Emerging	Asia
35	Saudi Arabia	45	37	33	30	35	41	36.83	Emerging	Asia
35	Hong Kong	33	38	29	40	34	47	36.83	Developed	Asia
37	Turkey	53	34	43	37	37	28	38.67	Emerging	Europe
38	Japan	32	40	41	38	39	43	38.83	Developed	Asia
39	Croatia	49	47	54	35	33	19	39.50	Frontier	Europe
40	Bulgaria	37	46	49	42	50	17	40.17	Frontier	Europe
41	Thailand	41	45	40	44	46	30	41.00	Emerging	Asia
42	Indonesia	46	36	42	39	38	48	41.50	Emerging	Asia
43	Canada	30	43	45	53	42	38	41.83	Developed	North America
44	Romania	64	30	38	18	32	70	42.00	Frontier	Europe
45	China	39	41	36	49	40	51	42.67	Emerging	Asia
45	South Korea	51	42	35	50	43	36	42.83	Developed	Asia
47	Philippines	38	39	44	48	47	49	44.17	Emerging	Asia
48	Estonia	65	51	46	41	45	29	46.17	Frontier	Europe
49	Pakistan	44	50	47	45	53	52	48.50	Emerging	Asia
50	Slovenia	59	49	69	33	41	45	49.33	Frontier	Europe
50	Vietnam	52	48	39	51	60	46	49.33	Frontier	Asia

Table 9 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
52	Ukraine	31	64	56	54	63	35	50.50	Emerging	Europe
53	Serbia	42	62	58	67	56	39	54.00	Frontier	Europe
54	Australia	43	60	55	59	66	44	54.50	Developed	Oceania
55	Egypt	66	65	48	34	49	66	54.67	Emerging	Africa
56	Peru	63	63	50	58	52	57	57.17	Emerging	South America
56	Nigeria	60	52	53	52	61	65	57.17	Frontier	Africa
58	Qatar	58	59	59	66	55	55	58.67	Emerging	Asia
59	Colombia	57	57	52	63	59	68	59.33	Emerging	South America
59	Lebanon	70	54	60	57	62	53	59.33	Frontier	Asia
61	Tunisia	67	53	57	68	54	60	59.83	Frontier	Africa
62	Kuwait	50	67	61	64	57	61	60.00	Emerging	Asia
63	Kenya	54	55	68	61	67	63	61.33	Frontier	Africa
64	Mauritius	62	61	65	62	65	54	61.50	Frontier	Africa
65	Kazakhstan	61	66	63	55	58	67	61.67	Frontier	Asia
65	Sri Lanka	68	58	64	70	51	59	61.67	Frontier	Asia
67	Jordan	55	69	62	60	69	56	61.83	Frontier	Asia
68	Bahrain	56	68	66	65	64	58	62.83	Frontier	Asia
69	Morocco	47	70	67	69	68	62	63.83	Frontier	Africa
70	Venezuela	69	56	70	56	70	69	65.00	Emerging	North America

Table 10 Closeness centrality ranking in 2017 to 2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	South Africa	1	1	5	3	8	4	3.67	Developed	Africa
2	Portugal	25	3	2	4	6	2	7.00	Emerging	Europe
3	Austria	15	3	5	4	2	18	7.83	Developed	Europe
4	Czech	8	11	7	18	6	15	10.83	Emerging	Europe
5	Chile	1	13	7	24	9	12	11.00	Emerging	South America
6	Ireland	12	3	10	1	12	30	11.33	Developed	Europe
7	Norway	8	9	3	12	2	35	11.50	Developed	Europe
7	The United Kingdom	21	1	2	12	1	32	11.50	Developed	Europe
9	Sweden	3	9	1	33	18	8	12.00	Developed	Europe
10	Poland	5	17	15	1	31	4	12.17	Emerging	Europe
11	Finland	8	17	15	31	9	6	14.33	Developed	Europe
12	Mexico	5	17	25	24	4	17	15.33	Emerging	North America
13	Greece	25	13	18	4	9	27	16.00	Emerging	Europe
14	Brazil	18	20	13	12	21	13	16.17	Emerging	South America
15	Luxembourg	18	11	10	4	12	46	16.83	Developed	Europe
16	Argentina	21	23	13	18	12	18	17.50	Emerging	South America
17	India	4	27	21	18	15	25	18.33	Emerging	Asia
18	Belgium	12	36	23	24	15	2	18.67	Developed	Europe
19	Russia	23	7	12	31	15	36	20.67	Emerging	Europe
20	Denmark	15	3	9	49	25	24	20.83	Developed	Europe
21	Switzerland	15	27	35	18	36	1	22.00	Developed	Europe
22	The United States	23	15	18	35	25	20	22.67	Developed	North America
23	Taiwan	37	20	21	4	18	38	23.00	Emerging	Asia
24	Hungary	47	7	18	4	4	66	24.33	Emerging	Europe
25	Israel	18	15	28	39	20	27	24.50	Developed	Asia
26	Singapore	37	20	33	4	43	14	25.17	Developed	Asia
26	France	25	23	27	35	25	26	26.83	Developed	Europe

Table 10 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
28	The United Arab Emirates	51	26	23	12	21	29	27.00	Emerging	Asia
29	Italy	7	38	27	24	21	51	28.00	Developed	Europe
30	Spain	12	36	25	39	33	35	30.00	Developed	Europe
31	Germany	25	35	27	35	28	32	30.33	Developed	Europe
32	Netherlands	31	34	27	35	28	31	31.00	Developed	Europe
32	Japan	32	32	43	24	28	27	31.00	Developed	Asia
34	Hong Kong	33	38	15	24	36	42	31.33	Developed	Asia
35	New Zealand	8	41	51	42	47	2	31.83	Developed	Oceania
36	Thailand	40	30	35	33	47	10	32.50	Emerging	Asia
37	Romania	43	23	37	11	21	62	32.83	Frontier	Europe
38	Croatia	47	45	57	18	31	9	34.50	Frontier	Europe
39	Malaysia	37	27	33	49	41	23	35.00	Emerging	Asia
40	Estonia	47	54	46	18	46	7	36.33	Frontier	Europe
41	Saudi Arabia	47	45	29	24	40	42	37.83	Emerging	Asia
41	Slovenia	46	48	48	12	33	40	37.83	Frontier	Europe
43	Turkey	66	30	45	39	33	20	38.83	Emerging	Europe
44	Bulgaria	33	48	49	42	54	9	39.17	Frontier	Europe
45	Indonesia	41	32	44	45	39	44	40.83	Emerging	Asia
45	Philippines	35	38	41	44	44	49	41.83	Emerging	Asia
47	Canada	26	43	41	53	42	47	42.00	Developed	North America
47	China	35	41	40	48	38	50	42.00	Emerging	Asia
49	South Korea	54	45	37	52	44	41	45.50	Developed	Asia
50	Vietnam	43	43	39	47	57	45	45.67	Frontier	Asia
51	Egypt	66	51	51	12	56	58	49.00	Emerging	Africa
51	Ukraine	30	63	64	54	64	19	49.00	Emerging	Europe
53	Pakistan	51	51	46	46	49	54	49.50	Emerging	Asia

Table 10 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
54	Australia	43	60	55	56	52	48	52.33	Developed	Oceania
55	Nigeria	65	50	61	49	50	59	55.67	Frontier	Africa
56	Serbia	42	59	67	69	62	39	56.33	Frontier	Europe
57	Peru	56	70	53	56	53	53	56.83	Emerging	South America
58	Lebanon	51	64	63	59	57	55	58.17	Frontier	Asia
59	Morocco	56	53	70	68	51	58	59.33	Frontier	Africa
59	Colombia	54	64	55	60	59	70	60.33	Emerging	South America
61	Venezuela	64	66	58	55	59	61	60.50	Emerging	North America
62	Jordan	70	55	60	67	55	57	60.67	Frontier	Asia
63	Qatar	62	67	50	64	70	56	61.50	Emerging	Asia
64	Sri Lanka	61	58	65	61	63	63	61.83	Frontier	Asia
65	Kazakhstan	56	67	61	58	68	64	62.33	Frontier	Asia
65	Kenya	68	60	59	61	61	65	62.33	Frontier	Africa
67	Kuwait	56	62	54	70	66	68	62.67	Emerging	Asia
67	Tunisia	57	57	65	64	64	69	62.67	Frontier	Africa
69	Mauritius	69	56	68	64	69	52	63.00	Frontier	Africa
70	Bahrain	62	67	69	61	66	65	65.00	Frontier	Asia

Table 11 Betweenness centrality ranking in 2017–2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	Austria	17	4	3	24	3	9	10.00	Developed	Europe
2	South Africa	3	1	10	14	40	18	14.33	Developed	Africa
3	Mexico	4	27	32	16	1	36	19.33	Emerging	North America
4	The United Kingdom	23	8	4	41	4	44	20.67	Developed	Europe
5	Argentina	24	28	31	6	14	24	21.17	Emerging	South America
6	Thailand	35	5	9	45	18	16	21.33	Emerging	Asia
7	Czech	29	6	7	55	29	4	21.67	Emerging	Europe
8	Norway	18	26	8	47	2	35	22.67	Developed	Europe
9	Finland	12	52	11	22	35	7	23.17	Developed	Europe
10	Poland	10	49	19	5	58	2	23.83	Emerging	Europe
11	Ireland	8	17	14	2	45	58	24.00	Developed	Europe
11	Singapore	37	18	58	15	13	3	24.00	Developed	Asia
13	Denmark	36	9	17	30	32	25	24.83	Developed	Europe
14	Portugal	61	10	6	28	33	12	25.00	Emerging	Europe
15	The United Arab Emirates	64	3	18	9	44	13	25.17	Emerging	Asia
15	Switzerland	25	39	54	27	5	1	25.17	Developed	Europe
17	Belgium	7	57	35	36	7	11	25.50	Developed	Europe
18	Brazil	20	33	5	31	53	14	26.00	Emerging	South America
19	Sweden	14	41	1	54	9	39	26.33	Developed	Europe
20	Chile	5	37	2	59	36	21	26.67	Emerging	South America
21	India	2	23	24	55	20	38	27.00	Emerging	Asia
22	Taiwan	19	44	33	3	8	56	27.17	Emerging	Asia
23	Israel	16	38	30	49	25	8	27.67	Developed	Asia
24	Luxembourg	33	35	25	10	19	46	28.00	Developed	Europe
24	Malaysia	22	2	26	64	48	6	28.00	Emerging	Asia
26	Hong Kong	40	19	15	23	46	33	29.33	Developed	Asia

Table 11 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
26	New Zealand	43	13	12	67	26	17	29.67	Developed	Oceania
28	Hungary	45	29	27	7	6	65	29.83	Emerging	Europe
29	Canada	41	21	16	19	17	68	30.33	Developed	North America
30	Japan	51	24	66	11	11	22	30.83	Developed	Asia
31	Italy	9	53	55	20	16	40	32.17	Developed	Europe
32	Croatia	15	43	61	4	52	20	32.50	Frontier	Europe
33	Slovenia	34	14	45	46	38	19	32.67	Frontier	Europe
34	Romania	32	34	42	34	10	53	34.17	Frontier	Europe
35	Estonia	48	67	51	8	27	5	34.33	Frontier	Europe
36	Russia	28	11	34	53	24	63	35.50	Emerging	Europe
37	Sri Lanka	63	36	52	1	22	41	35.83	Frontier	Asia
38	Spain	1	58	37	33	60	28	36.17	Developed	Europe
38	Greece	27	40	44	12	37	57	36.17	Emerging	Europe
40	Saudi Arabia	54	60	13	21	23	47	36.33	Emerging	Asia
41	The United States	21	12	47	32	57	50	36.50	Developed	North America
42	France	42	7	39	44	42	51	37.50	Developed	Europe
43	Kenya	44	46	21	51	12	52	37.67	Frontier	Africa
44	Philippines	6	51	41	17	49	67	38.50	Emerging	Asia
45	Peru	52	68	60	13	28	15	39.33	Emerging	South America
45	Bulgaria	26	22	67	39	61	26	40.17	Frontier	Europe
47	Indonesia	53	15	40	65	51	29	42.17	Emerging	Asia
48	Australia	65	56	28	18	21	66	42.33	Developed	Oceania
49	Morocco	13	16	63	69	50	45	42.67	Frontier	Africa
49	China	47	25	56	62	34	32	42.67	Emerging	Asia
51	Turkey	57	55	62	26	15	48	43.83	Emerging	Europe
51	Jordan	69	32	38	50	31	43	43.83	Frontier	Asia

Table 11 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
53	Germany	56	30	46	58	47	27	44.00	Developed	Europe
53	Netherlands	67	47	23	29	43	55	44.00	Developed	Europe
55	Qatar	39	66	22	42	65	31	44.17	Emerging	Asia
56	Colombia	30	62	36	43	59	42	45.33	Emerging	South America
57	Tunisia	31	45	53	25	63	70	47.83	Frontier	Africa
57	Ukraine	11	65	64	68	69	10	47.83	Emerging	Europe
59	Mauritius	70	20	57	57	62	23	48.17	Frontier	Africa
59	Nigeria	58	31	59	66	41	34	48.17	Frontier	Africa
61	Bahrain	60	64	43	38	56	30	48.50	Frontier	Asia
62	Vietnam	59	42	20	48	66	64	49.83	Frontier	Asia
63	Pakistan	66	63	50	35	39	54	51.17	Emerging	Asia
64	South Korea	50	59	49	61	30	61	51.67	Developed	Asia
64	Kuwait	38	54	29	70	70	49	51.67	Emerging	Asia
65	Kazakhstan	49	61	48	37	68	59	53.67	Frontier	Asia
67	Serbia	55	50	65	63	54	37	54.00	Frontier	Europe
68	Egypt	68	48	70	40	64	69	59.83	Emerging	Africa
69	Lebanon	46	70	69	60	55	62	60.33	Frontier	Asia
70	Venezuela	62	69	68	52	67	60	63.00	Emerging	North America

Table 12 Eigenvector centrality ranking in 2017 to 2022

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
1	Chile	1	11	7	5	15	16	9.17	Emerging	South America
2	Portugal	22	7	4	20	1	5	9.83	Emerging	Europe
3	Sweden	2	6	1	23	21	9	10.33	Developed	Europe
4	Ireland	17	3	9	11	3	26	11.50	Developed	Europe
5	Austria	20	8	3	13	4	22	11.67	Developed	Europe
6	The United Kingdom	23	1	2	6	6	36	12.33	Developed	Europe
7	Brazil	12	19	12	7	11	14	12.50	Emerging	South America
7	Poland	6	17	14	28	2	8	12.50	Emerging	Europe
9	Finland	9	15	10	27	22	1	14.00	Developed	Europe
10	Czech	8	14	8	33	10	13	14.33	Emerging	Europe
11	Norway	7	10	5	34	8	34	16.33	Developed	Europe
12	Mexico	5	20	31	1	27	15	16.50	Emerging	North America
13	Argentina	18	25	19	2	25	20	18.17	Emerging	South America
14	Luxembourg	15	12	13	16	12	46	19.00	Developed	Europe
14	Greece	29	13	24	17	8	23	19.00	Emerging	Europe
16	Russia	28	9	16	18	14	32	19.50	Emerging	Europe
17	Belgium	14	34	20	31	16	4	19.83	Developed	Europe
18	The United States	27	18	25	3	29	19	20.17	Developed	North America
19	Denmark	11	5	11	21	45	29	20.33	Developed	Europe
20	South Africa	3	2	6	60	49	3	20.50	Developed	Africa
21	Switzerland	13	27	36	19	24	7	21.00	Developed	Europe
22	India	16	28	26	36	6	24	22.67	Emerging	Asia
23	Netherlands	21	29	18	14	32	28	23.67	Developed	Europe
24	France	25	23	27	12	33	25	24.17	Developed	Europe
25	Singapore	36	22	38	30	5	17	24.67	Developed	Asia
25	Israel	19	16	28	37	18	30	24.67	Developed	Asia

Table 12 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
26	Hungary	48	4	17	25	13	59	27.67	Emerging	Europe
28	Italy	10	38	34	8	26	51	27.83	Developed	Europe
29	Germany	24	36	30	15	34	33	28.67	Developed	Europe
29	New Zealand	4	43	41	51	31	2	28.67	Developed	Oceania
31	Spain	26	35	29	10	35	38	28.83	Developed	Europe
32	The United Arab Emirates	45	30	21	32	19	35	30.33	Emerging	Asia
33	Thailand	40	33	32	45	23	11	30.67	Emerging	Asia
34	Canada	30	42	37	4	44	44	33.50	Developed	North America
35	Turkey	56	26	49	24	36	18	34.83	Emerging	Europe
36	Saudi Arabia	51	40	22	40	20	43	36.00	Emerging	Asia
37	Taiwan	39	21	23	50	49	37	36.50	Emerging	Asia
38	Japan	32	37	50	43	30	31	37.17	Developed	Asia
39	Malaysia	38	32	33	55	41	27	37.67	Emerging	Asia
40	Indonesia	43	31	43	38	38	47	40.00	Emerging	Asia
41	Hong Kong	33	44	15	58	49	45	40.67	Developed	Asia
42	Bulgaria	35	48	55	52	49	6	40.83	Frontier	Europe
43	Philippines	37	39	42	44	39	49	41.67	Emerging	Asia
44	Ukraine	31	59	64	29	47	21	41.83	Emerging	Europe
45	Estonia	53	53	46	42	49	12	42.50	Frontier	Europe
45	Vietnam	46	46	35	48	40	42	42.83	Frontier	Asia
47	Egypt	57	51	58	22	17	53	43.00	Emerging	Africa
48	China	34	41	44	54	37	50	43.33	Emerging	Asia
49	South Korea	50	45	40	46	42	39	43.67	Developed	Asia
50	Australia	44	63	48	35	28	48	44.33	Developed	Oceania
51	Slovenia	49	49	54	41	49	41	47.17	Frontier	Europe
52	Croatia	52	47	59	68	49	10	47.50	Frontier	Europe

Table 12 (continued)

Rank	Country/region	2017	2018	2019	2020	2021	2022	Average	Continent	Segment
53	Romania	54	24	39	57	49	63	47.67	Frontier	Europe
54	Venezuela	58	56	67	9	48	55	48.83	Emerging	North America
55	Pakistan	41	50	47	53	49	54	49.00	Emerging	Asia
56	Lebanon	47	57	69	26	46	52	49.50	Frontier	Asia
57	Nigeria	67	52	60	39	43	61	53.67	Frontier	Africa
58	Qatar	61	67	45	47	49	58	54.50	Emerging	Asia
59	Serbia	42	66	68	70	49	40	55.83	Frontier	Europe
59	Kuwait	60	62	52	49	49	68	56.67	Emerging	Asia
61	Peru	64	68	56	56	49	57	58.33	Emerging	South America
62	Morocco	55	54	70	65	49	62	59.17	Frontier	Africa
63	Kenya	69	61	53	59	49	66	59.50	Frontier	Africa
63	Tunisia	59	55	63	62	49	69	59.50	Frontier	Africa
65	Jordan	70	58	57	69	49	60	60.50	Frontier	Asia
65	Sri Lanka	62	60	65	61	49	67	60.67	Frontier	Asia
67	Mauritius	68	64	66	63	49	56	61.00	Frontier	Africa
68	Colombia	65	65	51	67	49	70	61.17	Emerging	South America
69	Kazakhstan	63	69	61	66	49	64	62.00	Frontier	Asia
70	Bahrain	66	70	62	64	49	65	62.67	Frontier	Asia

Abbreviations

COVID-19	Coronavirus Disease 2019
OHLC	Open-high-low-close
N	Number of nodes
E	Number of edges
AD	Average degree
AWD	Average weighted degree
ND	Network density
D(*x*)	Degree centrality
WD(*x*)	Weighted degree centrality
C(*x*)	Closeness centrality
B(*x*)	Betweenness centrality
E(*x*)	Eigenvector centrality

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Declaration

Competing interests
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