Hindawi
Complexity
Volume 2023, Article ID 3172181, 17 pages
https://doi.org/10.1155/2023/3172181

Research Article

Connectedness of International Stock Market at Major Public Events: Empirical Study via Dynamic Time Warping-Based Network

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Received 3 July 2022; Revised 31 August 2022; Accepted 6 February 2023; Published 7 March 2023

Academic Editor: Wei Xing Zhou

Several public events have drawn renewed attention to the connectedness of the international stock market since the financial crisis of 2008. We investigate systemic and regional connectedness among stock markets around the world at major public events by constructing correlation networks for 46 markets based on the dynamic time-warping method. We find that (i) geographic regionalization is typically observed in the stock market network, in which France is dominant, (ii) Europe has the greatest and the Middle East and Africa the least within-region connectedness, (iii) the correlation network structure is highly integrated and compact at major public events, and global events influence the international stock market more significantly than regional events do, and (iv) the importance of China reaches its peak during the era of Sino-US trade friction, showing that public events have enormous impacts on the countries involved.

1. Introduction

1.1. Background. Economic integration is a matter of great international concern. Connectedness among financial markets around the world is increasing. This deserves close attention due to the "too connected to fail" risk. Moreover, public events can exacerbate the spread of risk, resulting in financial crises and persistent impacts on national economies. Direct and indirect connectedness among financial markets is accelerating and making them increasingly closely related and interdependent, forming a complex financial network [1–3]. This connectedness is both diversifying financial risks and promoting their spread [4, 5]. Major public events have led to significant changes in the global financial system. Therefore, we focus on the correlation network of the international stock market at major public events.

Recently, the uncertainty of the COVID-19 epidemic has had a negative impact on the global economy. Panic-induced asset sales occurred in the highly leveraged financial market in March 2020. The price of crude oil fell sharply, and the ratings of US shale oil companies were downgraded. In the international stock market, three major US stock indices triggered the first-level circuit breaker mechanism. Over 10 days, the market experienced four circuit breakers and then plummeted in mid-June 2020, which led stock indices around the world to plunge.

Frequent stock market turbulence greatly affects the global economy and financial system. The connectedness among stock markets and the cross-market contagion effect of financial risks at major public events attract much attention from academia and industry. The related research can provide theoretical insights useful for strengthening the connectedness among stock markets, reducing financial risk, and improving investment decisions.

1.2. Literature Review. The international stock market plays an important role in the financial system. One strand of the literature on the connectedness within the international stock market focuses on the transmission between two important countries [6–10], the connectivity among countries participating in international organizations such as the G7 [11–13], and the dependence between the stock market and other markets, such as exchange markets [14, 15], the crude oil market [16–18], markets for other commodities [19–21], and cryptocurrencies [22–24]. Prior works adopt the GARCH family model, the VAR model, and the Copula model to analyze the time-varying correlations between financial markets, and they emphasize the effects of policy factors (e.g., changes in monetary policy or regime) and national economy factors (e.g., financial and trade linkages) on connectedness among stock markets.

Another strand of the literature performs network analyses of the connectedness among stock markets. Network theory, a powerful tool for investigating financial markets, abstracts the financial system into a network with a set of nodes and edges [25]. This method can be used to analyze stock markets comprehensively and reveal the complexity of the system. The minimum spanning tree (MST), planar maximally filtered graph (PMFG), and correlation threshold method (CTM) are commonly used to construct correlation networks. Mantegna [26] first proposed the MST as a way to analyze the similarities among stock prices in the S&P 500 Index, finding significant implications for portfolio optimization. Since then, the network-based method has been widely adopted to examine connectedness among financial markets. Onnela et al. [27] select 116 stocks in the S&P 500 Index and build a dynamic asset tree based on a correlation matrix of stock price fluctuations, finding that changes in tree length over time are related to investment diversification. Lee et al. [28] present a correlation network of South Korea's stock returns based on the MST method and confirm that the volatility of stock returns is positively correlated with the density of the stock market network. Jung et al. [29], Garas and Argyrakis [30], Tabak et al. [31], and Cheong et al. [32] set up a complex network of stock markets in South Korea, Greece, Brazil, Japan, and China, respectively, based on the MST method and investigated its topological structure.

The PMFG was first proposed by Tumminello et al. [33], as part of the continuous advances in complex network theory and is widely employed in various fields. Tumminello et al. [33] utilize the PMFG to establish a network comprising 300 stocks on the New York Stock Exchange and examine the main topological indicators, such as average path length, node betweenness, and degree. Aste et al. [34] create a network comprising 395 US stocks from 1996 to 2009 based on the PMFG method and find that the 2007 US subprime crisis changed the network's structure and that financial sector stocks were no longer its central nodes.

The CTM is used to explore financial market connections and risk contagion by screening nodes and edges of the original network based on a threshold set to meet the researchers' information retention requirements. Boginski et al. [35] investigate the statistical characteristics of the stock network based on the CTM and conclude that the degree distribution has power-law properties. Huang et al. [36] discover that the network of the Chinese stock market is robust but vulnerable to intentional attacks. Xi and An [37] construct a stock correlation network based on financial indicators to detect the cluster characteristics of the community network; they prove that the independence of the community gradually increases as the threshold rises.

Thus, in contrast to the PMFG and CTM, the MST can filter out a large amount of redundant information and reduce interference. Several scholars point out that the MST method can intuitively and comprehensively identify the transmission mechanism of financial market risk [38]. Therefore, we use the MST model to construct a correlation network with which to study the connectedness of the international stock market and the evolution of the network structure at major public events.

The impact of major public events on the connectedness of the international stock market has caught the attention of scholars because such events trigger frequent turbulence in the financial system. For example, Yang et al. [39] build a jump volatility spillover network of Chinese financial institutions using the VAR model and find that network density reaches a peak during China's stock market disaster of 2015. Huang et al. [40] detect the time-varying comovement among individual stocks in both normal and crisis periods based on a directed weighted stock network and a weighted LeaderRank algorithm; their results demonstrate that network density, the average clustering coefficient, and global efficiency can provide an "early warning" of potential future crises. He et al. [41] use a volatility spillover network to detect the correlation structure of stock markets at past crisis events; they confirm that the network shows a clustering effect when the stock market is impacted by major public events. Cheng et al. [42] investigate how the COVID-19 pandemic has affected the connectedness network of stock market volatility in 19 economies around the world using the Diebold-Yilmaz volatility network model, finding that the outbreak of the COVID-19 pandemic strengthened the overall volatility connectedness and that the global connectedness level remained high throughout 2020.

Nevertheless, research studies on the connectedness of financial markets at major public events have several limitations: (i) First, the connectedness between two stock markets is usually calculated through the Pearson correlation function. The Pearson correlation coefficient (PCC) can only measure the linear connectedness between time sequences; this is a problem because the connectedness between financial markets is nonlinear, complex, and dynamic. Moreover, the PCC does not work well for strongly correlated and nonrandom time series [43], and it is not robust and can be misleading if outliers exist [44] because real-world data are high-level heterogeneous [30, 45]. (ii) Moreover, constructing a connectedness measure requires that the calculated time series maintain the same record length and data synchronization. Obtaining uninterrupted and complete data in stock markets is difficult due to the inconsistencies in trading hours and holidays, which lead to variations in record lengths. To solve this problem, traditional data processing methods have been used to fill and delete data, leading to deviations via data repair. (iii) Additionally, the topology properties of complex financial networks are usually analyzed from a static perspective, such as by selecting specific time points of public events, which ignores the continuity of financial crises and omits information on the evolution of the network. (iv) Finally, although scholars are increasingly interested in system-level analyses of complex financial networks, few market-level analyses of systemically important markets have been attempted.

Measures of connectedness among network nodes aim to describe and characterize the correlation between two samples or patterns. Among them, dynamic programming (DP) has good robustness [46, 47]. The DTW model is the most representative DP similarity measure, and it can deal with local displacement in the sequence effectively. This model has three significant advantages. First, it can be used to explore the connectedness among return time series with either equal length or unequal length in the international stock market and is thus suitable for the retractable banner. Second, it has superior robustness to the amplitude change, migration, and noise of time series. Third, it is malleable, in contrast to the traditional Euclidean distance. In addition, it is insensitive to abnormal data and truly reproduces the evolution of the international stock market network at major public events. Thus, we utilize the DTW model to examine connectedness in the international stock market. We focus on major public events that have occurred in recent years in order to help authorities formulate regulatory policies and assist investors in predicting future risk changes and formulating related strategies.

1.3. Main Contributions. Our study on the connectedness of the international stock market at major public events has the following contributions.

(i) First, we combine the DTW model with the MST method to remedy the limitations of existing measures.

(ii) Second, we consider different tree lengths, which shed new light on the analysis of systematically important stock markets. We identify the sensitivity of global markets to public event shocks and confirm that the importance of stock markets changes over time.

(iii) Given the complexity of the international stock market network, we study its topology through time-varying analysis. Furthermore, we identify and observe systemically important stock markets based on influence strength.

(iv) We statically and dynamically explore the connectedness of the international stock market at the system, region, and market levels. We consider global efficiency by investigating the systemic connectivity of the network, and we examine the crossregion, within-region, and total connectedness of several geographical regions in order to assess the systematically important stock markets.

1.4. Article Organization. The rest of this article proceeds as follows: In the next section, we explain the DTW model and the evaluation criteria used for network connectedness. In Section 3, we describe our data and perform a preliminary analysis. In Section 4, we evaluate connectedness on three levels (i.e., system, region, and market). Finally, we conclude the article in Section 5.

2. Methodology

2.1. Dynamic Time Warping. We use the dynamic time warping (DTW) model to study a return time series with equal and unequal lengths in the international stock market while dealing with the local displacement, which overcomes the synchronous constraint of the PCC [48]. This model is widely employed in speech recognition and other pattern recognition tasks, such as sign language recognition, gesture recognition, online signature matching, data mining, time series clustering, handwriting, and computer vision. However, few scholars have applied it to finance research [49–51].

After constructing a distance matrix, we utilize dynamic programming to seek the optimal curved path with the smallest cumulative distance to measure the connectedness among stock markets. Supposing that two stock indices' normalized log-returns, R_i and R_j, have the lengths of M and N, respectively, where $R_i = \{R_i(1), R_i(2), \ldots, R_i(m), \ldots, R_i(M)\}$ and $R_j = \{R_j(1), R_j(2), \ldots, R_j(n), \ldots, R_j(N)\}$, we define the local cost matrix C_{ij} for the alignment of two sequences R_i and R_j as follows:

$$C_{ij} = \begin{bmatrix} d\left(R_i(1), R_j(1)\right) & d\left(R_i(1), R_j(2)\right) & \cdots & d\left(R_i(1), R_j(N)\right) \\ d\left(R_i(2), R_j(1)\right) & d\left(R_i(2), R_j(2)\right) & \cdots & d\left(R_i(2), R_j(N)\right) \\ \vdots & \vdots & \ddots & \vdots \\ d\left(R_i(M), R_j(1)\right) & d\left(R_i(M), R_j(2)\right) & \cdots & d\left(R_i(M), R_j(N)\right) \end{bmatrix}, \tag{1}$$

where the (mth, nth) element of the matrix denotes the square distance $d(R_i(m), R_j(n))$ between the two points $R_i(m)$ and $R_j(n)$; thus, $d(R_i(m), R_j(n) = (R_i(m) - R_j(n)^2$.

The warping path is a sequence $p = \{p_1, p_2, \ldots, p_k, \ldots, p_{k+1}\}$ that satisfies the following criteria [52]:

(i) Boundedness: $\max(M, N) \leq K \leq M + N + 1$

(ii) Boundary condition: $p_1 = (1, 1)$ and $p_k = (M, N)$; they are used to indicate the start and end of a curved path

(iii) Monotonicity condition: $m - m' \geq 0$ and $n - n' \geq 0$

(iv) Continuity: assuming that two adjacent elements $p_{k+1} = (m, n)$ and $p_k = (m', n')$ are on a curved path, there must be $m - m' \le 1$ and $n - n' \le 1$; that is, the adjacent elements in the warping path are also adjacent in a local cost matrix

The total cost c_{ij}^{p} of a warping path p between R_i and R_j with respect to the local cost matrix C_{ij} (all pairwise distances) is defined as follows [52]:

$$c_{ij}^{p} = \sum_{k=1}^{K} C_{ij}(m_k, n_k), \tag{2}$$

where $C_{ij}(m_k, n_k)$ is the element of the m_kth row and the n_kth column of the local cost matrix C_{ij}.

There are exponentially warping paths that meet the aforementioned conditions, and the connectedness measure D_{ij} between R_i and R_j is the length of optimal warping path p^* that minimizes the warping cost. It is defined as follows:

$$D_{ij} = \frac{1}{K} c_{ij}^{p*}, \tag{3}$$

such that $p* = \{p_1^*, p_2^*, \ldots, p_k^*, \ldots, p_K^*\} = \text{argmin}(c_{ij}^{p}, p \in P^{M\times N})$, where $P^{M\times N}$ is the set of all possible warping paths, and K in the denominator is employed to address the disadvantage that warping paths may have different lengths. If two stock indices, i and j, are entirely similar, then $D_{ij} = 0$; if the two stock indices are completely dissimilar, then $D_{ij} = 1$. Consequently, $0 \le D_{ij} \le 1$.

We obtain the similarity matrix (i.e., connectedness matrix) by calculating the connectedness D_{ij} between any two stock markets. Then, the adjacency matrix can be counted based on the similarity matrix.

Finally, the adjacency matrix is converted into the international stock market network by the MST method. Following graph theory, we construct the MST that is a tree structure, by connecting N nodes with $N - 1$ edges. Each stock market corresponds to a node, and the connectedness between two stock markets corresponds to an edge in the network. It is required that the sum of the weights of all edges in the tree be the smallest and that the edges do not form a loop. Thus, MST is utilized to select $N - 1$ edges with the strongest connectedness (i.e., the smallest distance) for each stock market to form a network. Therefore, MST has superior robustness and is the preferred network analysis tool for many scholars.

2.2. Evaluation Criteria for Network Connectedness. We employ specific evaluation criteria for network connectedness to examine the topology of the international stock market.

We first introduce normalized tree length (NTL). Based on the $N \times N$ similarity matrix D, the NTL measure is used to explore the properties of the MST of the international stock market, which is defined as follows [27, 43]:

$$NTL = \frac{1}{N-1} \sum_{D_{ij}\in\Theta} D_{ij}. \tag{4}$$

Similarly, we explore connectedness and information exchange efficiency in the international stock market network using global efficiency (GE), which comprehensively considers the connection efficiency of node pairs. The GE measure is generally defined as follows:

$$GE = \frac{1}{N(N-1)} \sum_{i\neq j\&i,j=1}^{N} \frac{1}{d(i,j)}, \tag{5}$$

where $d(i,j)$ denotes the shortest path length from node i to j and $d(i,j) = +\infty$ if there is no path from i to j in the network.

Regional and sectoral aggregation is widely investigated in [9, 53–58]. Following the region-level connectivity measure proposed by Wang et al. [59], we apply regional distance (RD) and regional connectedness (RC) from one region m to another region n (including itself), which are defined as follows:

$$RD_{m\Leftrightarrow n} = \frac{1}{N_m N_n} \sum_{i=1}^{N_n} \sum_{j=1}^{N_m} D_{ij}, \tag{6}$$

$$RC_{m\Leftrightarrow n} = 1 - RD_{m\Leftrightarrow n}, \tag{7}$$

where N_m and N_n are the number of stock markets in regions m and n, respectively. When $m = n$, $N_n = N_m - 1$, and $i \neq j$.

In equation (6), we standardize the distance between two regions by utilizing their respective numbers of stock markets to eliminate the sample size bias because four regions have different numbers in our sample.

In the network, letting Γ_i be the set of nodes connected to node (i.e., stock market index) i, we define the influence strength (IS) of node i as follows:

$$IS_i = \sum_{j\in\Gamma_i} \rho_{ij}, \tag{8}$$

where ρ_{ij} is the correlation coefficient between node i and j, and the conversion formula between ρ_{ij} and D_{ij} is as follows:

$$\rho_{ij} = 1 - D_{ij}^2. \tag{9}$$

If two stock indices, i and j, are entirely similar, then $\rho_{ij} = 1$; if the two stock indices are completely dissimilar, then $\rho_{ij} = 0$. Consequently, $0 \le \rho_{ij} \le 1$.

Therefore, the value of IS depends on two factors: the number of edges connecting the node and the value of the correlation coefficient.

3. Data Description and Preliminary Analysis

3.1. Sample Selection. We select the daily closing prices of 46 important stock market indices from January 23, 2003, to July 16, 2021, provided by the *Wind* database. Our sample comprehensively reflects quotations on the international stock market. Complete data for all 50 stock markets is not available. Hence, the sample includes 46 of the top 50 markets ranked by their average daily trading volumes, which are geographically widespread and account for 90% of international stock market capitalization.

These 46 important stock markets are in four regions: Europe, the Middle East and Africa, America, and the Asia-Pacific region. The location and descriptive statistics of each stock market are shown in tables 1 and 2 (in the Appendix). The average returns of the stock markets were all positive during the sample period, implying that they offer generally good investment value. Additionally, the skewness and kurtosis values show that the return series of the stock markets have a sharp peak and thick tail, reflecting a non-normality of the unconditional distribution of the return time series.

3.2. Data Description. Figure 1 shows the average annual return and the average daily return of the stock market indices from 2003 to 2021. We find that the average annual return changes greatly at public events and drops significantly during the 2008 subprime mortgage crisis (with the lowest value being −0.29%), the 2010-2011 European sovereign debt crisis, the 2013–2015 Fed rate hike and international crude oil plunge, the 2018–2021 period of Sino-US trade friction, and the COVID-19 pandemic. A rebound occurs during a time of financial stability.

There is a close correlation between the average daily return fluctuation and the major public events. The fluctuations, ranging from large to small, correspond to the following events: the US subprime crisis, the COVID-19 pandemic, the Fed rate hike, the Chinese A-share "stock disaster," and the European debt crisis.

Figure 1 also shows that the sample period is split into five periods according to the major public events. In each period, the average annual return declines and rises along with the beginning and ending of the events, and the fluctuations in the average daily return grow from small to large and then decline back to small.

3.3. Subdivision Basis of Sample Period. We examine the impact of public events on the international stock market by dividing the sample period into five subperiods, as described below.

(i) In the first half of 2003, the People's Bank of China, the State Administration of Foreign Exchange, and the relevant financial departments issued a series of policies and regulations on foreign exchange management and overseas investment to adapt to the requirements of the World Trade Organization. As an emerging market economy, China began to integrate into the world financial system. We denote the period before the US subprime crisis (January 2003–June 2007) as Period I.

(ii) Several scholars consider that the US subprime crisis started in June 2007 and ended in June 2009 [43]. We thus denote the period from June 2007 to June 2009 (during the US subprime crisis) as Period II.

(iii) After that crisis, the international financial market entered a recovery phase, and the European debt crisis began, starting in Greece. Larger countries such as France and Germany were affected later. The sovereign rating of France declined from the AAA level in early 2012. Afterward, Ireland became the first Euro Zone country to officially withdraw from the rescue measures on December 15, 2013, meaning that the European debt crisis was greatly eased and temporarily came to an end. We denote the period spanning the global financial crisis recovery and the European debt crisis (June 2009–December 2013) as Period III.

(iv) In the next subperiod, from 2013 to 2018, a series of Black Swan events occurred that had adverse effects

Table 1: Stock market indices and their corresponding regions.

Country	Stock market index	Region
Chile	IPSA	America
Argentina	Merval	America
Ireland	ISEQ	Europe
Austria	ATX	Europe
Australia	AORD	Asia-Pacific
Belgium	BFX	Europe
Denmark	OMX20	Europe
Germany	DAX	Europe
Russia	RTS	Europe
France	CAC40	Europe
Philippines	PSI	Asia-Pacific
Finland	OMX helsinki	Europe
United Kingdom	FTSE 100	Europe
Singapore	STI	Asia-Pacific
South Korea	KS11	Asia-Pacific
Netherlands	AEX	Europe
Canada	GSPTSE	America
Czech	PX	Europe
Luxembourg	LUXX	Europe
Malaysia	KLSE	Asia-Pacific
United States	S&P500	America
Mexico	MXX	America
Norway	OSE	Europe
Portugal	PSI	Europe
Japan	NIKKEI 225	Asia-Pacific
Sweden	OMXSP	Europe
Switzerland	SSMI	Europe
China	SSE	Asia-Pacific
Thailand	SET INDEX	Asia-Pacific
Spain	SMSI	Europe
Greece	ASE	Europe
Hungary	BUX	Europe
Israel	TA100	Middle East and Africa
Italy	FTSEMI	Europe
Indonesia	JKSE	Asia-Pacific
Poland	WIG	Europe
Vietnam	VNINDEX	Asia-Pacific
Iceland	ICEXI	Europe
New Zealand	NZ50	Asia-Pacific
India	SENSEX	Asia-Pacific
Brazil	IBOVESPA	America
Venezuela	IBC	America
Turkey	XU100	Middle East and Africa
Egypt	CASE30	Middle East and Africa
Nigeria	NGSEINDX	Middle East and Africa
Lebanon	BLOM	Middle East and Africa

Table 2: Descriptive statistics of each stock market index.

	Mean	Std. dev	Maximum	Minimum	Skewness	Kurtosis
Chile	0.000414713	0.010738	0.151686	−0.15297	36.52445	−0.47002
Argentina	0.001065713	0.02271	0.139005	−0.47692	58.1052	−2.86732
Ireland	0.000133197	0.013661	0.097331	−0.10416	9.483857	−0.43244
Austria	0.00025793	0.015116	0.12021	−0.1482	11.43452	−0.47025
Australia	0.00021312	0.009936	0.053601	−0.08554	9.811027	−0.60879
Belgium	0.000180872	0.012046	0.09334	−0.09168	9.845512	−0.15525
Denmark	0.000440809	0.012991	0.105853	−0.1923	20.32266	−0.78353
Germany	0.000398554	0.013657	0.107975	−0.1183	9.867267	−0.18562
Russia	0.000365696	0.021759	0.202039	−0.39454	38.62608	−1.65039
France	0.000178934	0.01363	0.105946	−0.11476	10.35057	−0.10197
Philippines	0.000529756	0.012929	0.131324	−0.13089	13.22437	−0.28913
Finland	0.00014869	0.01377	0.088	−0.12302	9.111103	−0.31114
UK Kingdom	0.000187913	0.011284	0.093843	−0.10327	12.60249	−0.23381
Singapore	0.000227348	0.01104	0.088659	−0.10628	11.98931	−0.1961
South Korea	0.000320125	0.01291	0.112844	−0.11172	11.01369	−0.58604
Netherlands	0.000179311	0.01316	0.100283	−0.12614	12.52358	−0.19825
Canada	0.000233094	0.010691	0.093703	−0.16999	29.31364	−1.4559
Czech	0.000208509	0.013616	0.123641	−0.16185	22.66821	−0.98643
Luxembourg	0.000168964	0.01407	0.152926	−0.16734	17.80594	−0.41434
Malaysia	0.000220867	0.007346	0.048869	−0.09979	15.90543	−0.76308
USA	0.000324398	0.011741	0.109572	−0.13777	17.70126	−0.57066
Mexico	0.000506444	0.012196	0.104407	−0.16278	16.89472	−0.49084
Norway	0.000548777	0.014095	0.091881	−0.15667	13.37254	−0.85664
Portugal	0.00018028	0.012294	0.183569	−0.17068	41.85238	−0.7964
Japan	0.000252219	0.015045	0.132346	−0.12715	11.61171	−0.63244
Sweden	0.00038072	0.012643	0.086289	−0.1232	10.05852	−0.33547
Switzerland	0.000218889	0.011052	0.107876	−0.0907	11.11371	−0.25009
China	0.000169464	0.015859	0.090345	−0.09256	7.504331	−0.50661
Thailand	0.000379686	0.012688	0.10577	−0.16063	18.31793	−1.08693
Spain	0.00010038	0.013885	0.137372	−0.13318	11.76595	−0.1321
Greece	−0.00017079	0.020025	0.196712	−0.19138	14.42364	−0.27617
Hungary	0.000436519	0.017229	0.356166	−0.36647	105.1957	−0.25989
Israel	0.000509695	0.089036	3.515917	−3.47592	1510.785	0.639923
Italy	$3.24E-05$	0.014445	0.106593	−0.14051	10.7802	−0.4434
Indonesia	0.000725063	0.013467	0.076231	−0.11306	11.01117	−0.63213
Poland	0.000364452	0.012984	0.176326	−0.20827	31.96476	−0.83331
Vietnam	0.00044173	0.015264	0.19903	−0.19918	20.97501	0.008044
Iceland	$-7.37E-06$	0.021051	0.060572	−1.0622	1697.964	−35.1124
New Zealand	0.000429481	0.006799	0.058146	−0.04938	8.720995	−0.60549
India	0.000641998	0.014345	0.1599	−0.11809	13.53421	−0.19143
Brazil	0.000600427	0.017617	0.136782	−0.18749	11.25471	−0.23355
Venezuela	0.002267143	0.161675	0.431492	−6.90285	1746.56	−40.8986
Turkey	0.000563264	0.019089	0.326883	−0.32566	50.54083	−0.29062
Egypt	0.001076359	0.019534	0.158032	−0.17992	10.36257	−0.51787
Nigeria	0.000184842	0.014365	0.346211	−0.35423	194.774	−0.16724
Lebanon	0.00013838	0.01036	0.084903	−0.10688	22.87406	−0.13297

on the financial system, such as the hike in the US Federal Reserve's interest rate, plummeting crude oil prices, and Brexit. We denote this period of economic recession (December 2013–March 2018) as Period IV.

(v) In March 2018, US President Trump decided to impose punitive tariffs on products imported from China. China responded immediately and announced additional tariffs on $3 billion worth of US goods. The effects of the trade war quickly spread throughout the world. In 2020, the COVID-19 pandemic spread around the world and was a huge shock to the international stock market. We denote the period of Sino-US trade friction and the COVID-19 pandemic (March 2018–July 2021) as Period V.

3.4. Rationale for Subsample and Full-Sample Analysis. Using our sample period subdivision, we explore the structure and topology of the international stock market network by performing subsample and full-sample analyses; these have distinct emphases and advantages.

The subsample analysis conducts an in-depth examination of the international stock market network over five

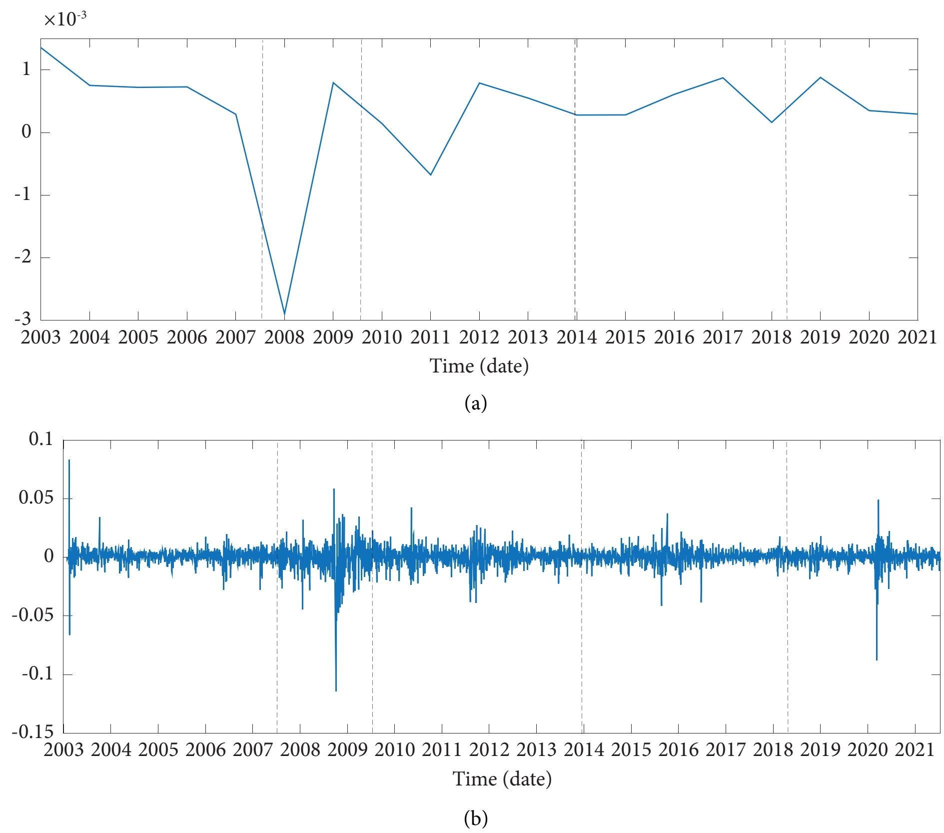

Figure 1: Average return of international stock indices. (a) Average annual return. (b) Average daily return.

periods. Similar to international economic fundamentals, stock market connectedness shows structural and cyclical regularity. The occurrence of major public events leads to variances in the network structure during the sample periods. Thus, the evolution of the connectedness among stock markets over periods of financial crises and stability can be investigated. The subsample analysis focuses on special clusters, links, and nodes from the micro perspective to examine the impact of major public events and the economic fundamentals of various countries.

The full-sample analysis focuses on the overall connectedness and connectivity efficiency of the international stock market network. The full-sample analysis uses the GE index and sliding window method, which can not only explore the topology of the international stock market network but also capture the dynamic impact of major public events from a systemic perspective.

4. Empirical Study

4.1. Construction of the International Stock Market Network. Figures 2–6 show the MSTs of the international stock market in five subperiods. The network consists of four clusters: the European, Middle Eastern, African, Asia-Pacific, and American clusters. In each MST, countries from different geographical regions are indicated in different colors.

4.1.1. Construction of the Network before the US Subprime Crisis. Figure 2 displays the international stock market network of Period I. France from Europe, Indonesia from Asia-Pacific, and Canada from America are the central nodes of their respective clusters. Asia-Pacific and America are divided into several groups.

We find that strong economies in the Asia-Pacific region are separate from their geographic cluster. For example, Japan, South Korea, and Singapore, located in the European cluster, are all Asia-Pacific countries. This result occurs for two reasons. (i) First, Japan and South Korea are economically developed countries with complete financial systems; indeed, Japan is called “ApacExJap” (i.e., “Asia-Pacific region except for Japan”). (ii) Second, the economic growth of Singapore, Japan, and South Korea has been deeply influenced by Western countries, and their financial systems are relatively independent of those of other Asia-Pacific countries.

Meanwhile, breaking away from the America cluster, Brazil enters the edge of the European cluster and becomes a node closely connected with China and Russia. This can be explained as follows: (i) as a BRICS country, Brazil is closely connected to China and Russia, also BRICS members. Thus, their economies are highly complementary, and they engage in close cooperation on energy, trade, agriculture, and food security. (ii) the Brazilian financial market is also highly

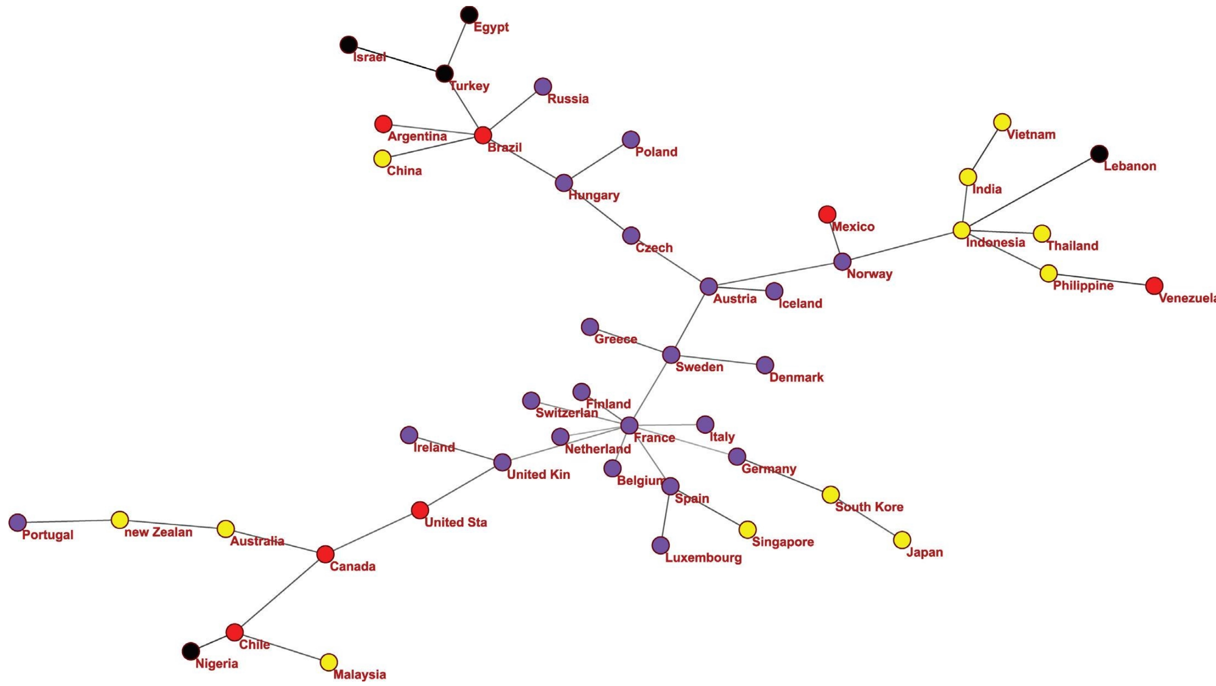

Figure 2: Network of period I, from January 2003 to June 2007. *Note*. Yellow represents Asia-Pacific countries, purple represents European countries, red represents American countries, and black represents Middle Eastern and African countries (the same applies to Figures 3–6).

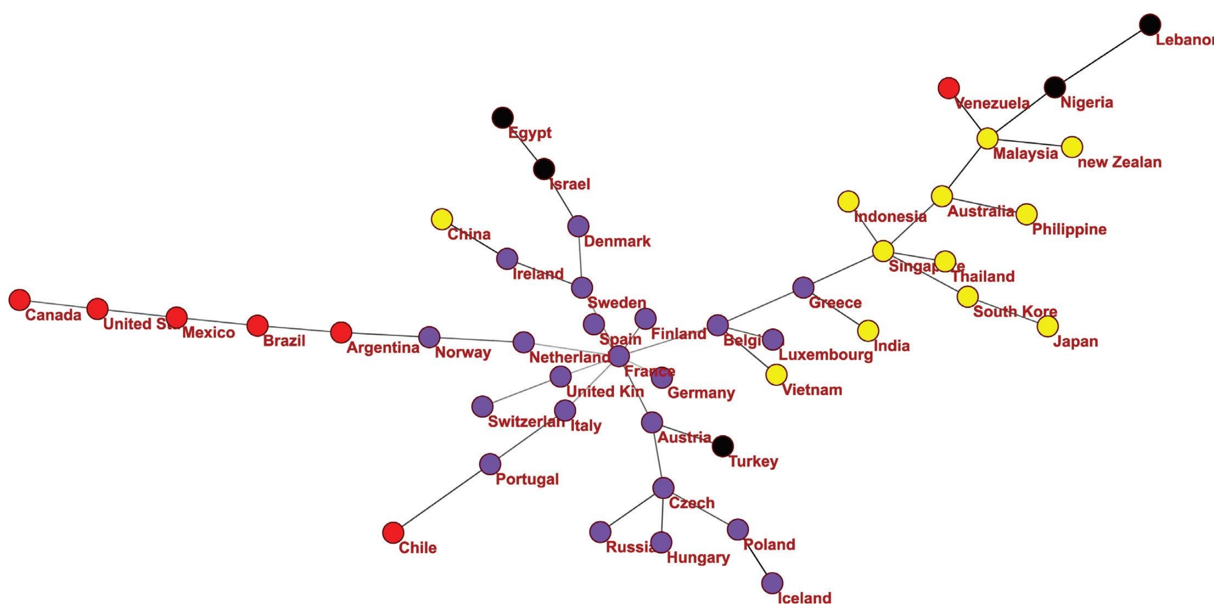

Figure 3: The network of period II, from June 2007 to June 2009.

internationalized. Taking average daily trading volume as the statistical parameter, foreign investors account for more than 40% of Brazil's stock market and derivatives market, and most are from the United States and Europe. The proportion of foreign investor shareholding is higher in the Brazilian stock market than in most other American countries. Furthermore, the Brazilian stock market offers a platform for international product trading. For example, the Brazilian Exchange and the US CME jointly issue cross-linked products.

4.1.2. Construction of the Network during the US Subprime Crisis. The network of Period II differs considerably from that of Period I, as shown in Figure 3. The number of central nodes decreases, and the links in the network become closer. As a result, the network consisting of several clusters can even be regarded as a large, unified cluster. The geographical aggregation effect is more obvious: (i) The Asia-Pacific cluster was concentrated during the US subprime crisis, and its central node is Singapore. (ii) The central node of the European cluster is still France. China is the only country

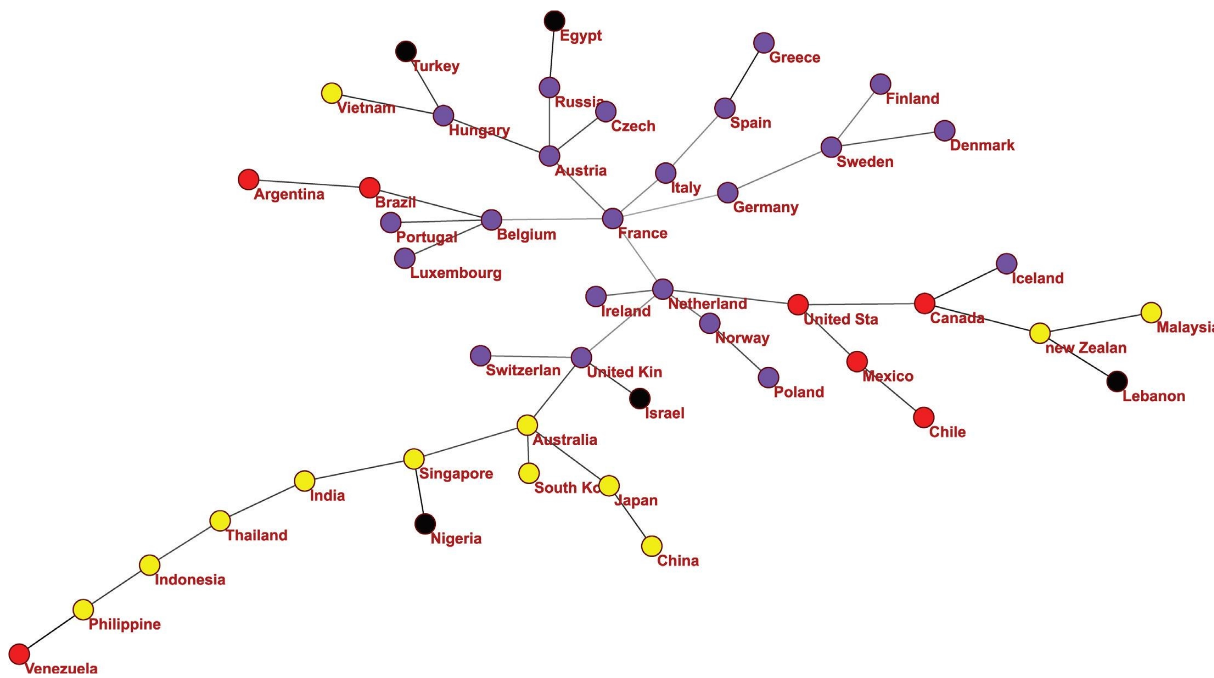

Figure 4: Network of period III, from June 2009 to December 2013.

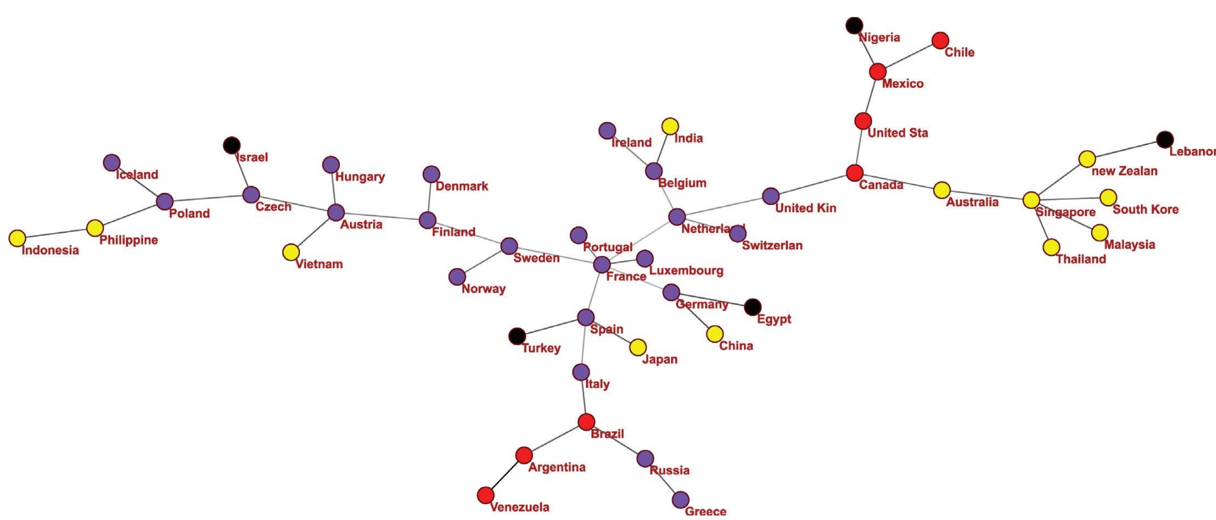

Figure 5: Network of period IV, from December 2013 to March 2018.

that is separated from the Asia-Pacific cluster, and it is directly linked to the European cluster via Ireland and Sweden. Another interesting finding is that China is closer to the center node than it was in Period I, and the Chinese position starts rising in the network.

Figures 2 and 3 show that Singapore is an important node in the Asia-Pacific cluster. As a financial center, Singapore became more prominent during the US subprime crisis. This may happen because its government promotes the development of Singapore as a "financial nation" and seeks to strengthen Singapore's position as an offshore US dollar center and preferred asset management center in Asia. Singapore also has a strong banking system and world-class port logistics. Facing the impact of the Asian financial crisis and US subprime crisis, the Singaporean financial market took effective action under the leadership of its government and continued its development as an international financial center. During the US subprime crisis, Singapore was the only Asian country that was rated AAA by the three major credit rating agencies (i.e., Fitch International, Standard and Poor's, and Moody's).

4.1.3. Construction of the Network during Crisis Recovery and the European Debt Crisis Period. Figure 4 shows the international stock market network in Period III. On the one hand, the closeness of the network is greatly reduced. The European and Asia-Pacific clusters are still centralized. France and the United States become central nodes of the network. Venezuela, Argentina, Lebanon, and other

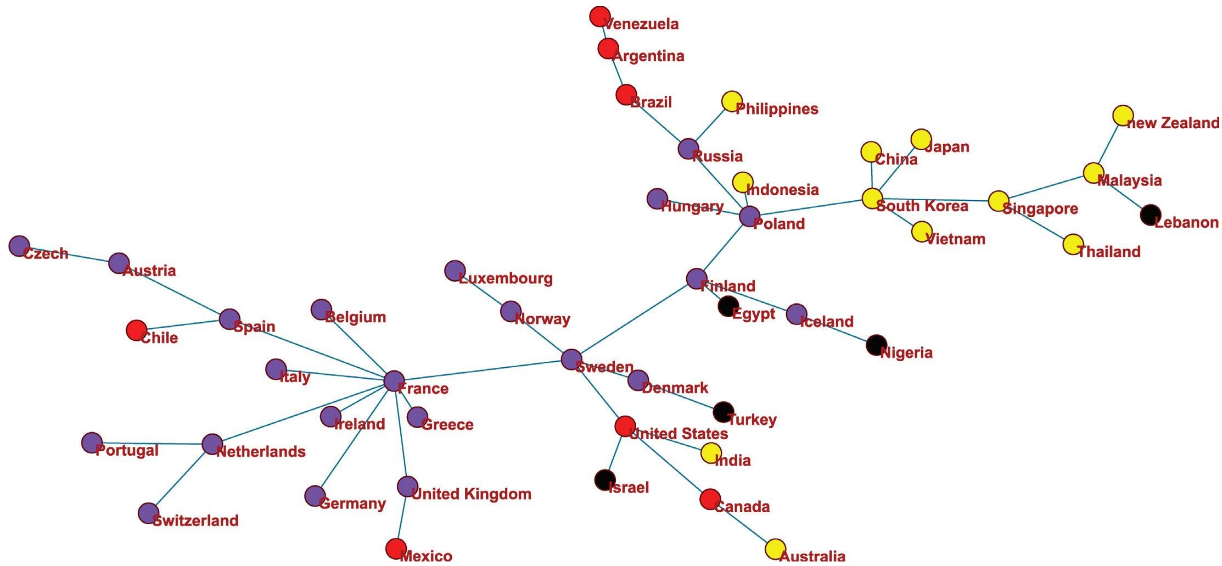

Figure 6: Network of period V, from March 2018 to July 2021.

countries in Latin America, the Middle East, and Africa are on the margins.

By contrast, China is reincorporated into the Asia-Pacific cluster and is connected to the European cluster through the United Kingdom, Japan, and Australia, which all have relatively close financial and trade links to China. The Asia-Pacific cluster is still clustered with Singapore as the central node. Simultaneously, the American cluster is divided into two parts: one is composed of developed countries in North America, which are closely linked to the European cluster via the United States; the other is comprised mainly of Latin American countries, on the margins of the network.

4.1.4. Construction of the Network during the Global Economic Recession. Figure 5 shows the international stock market network during the global economic recession. From a macro perspective, the network structure is closer than it was in Period III due to the hike in the US Federal Reserve's interest rate, the plunge in international crude oil, and China's A-share stock disaster. Aside from France, the Netherlands, Finland, and Belgium become central nodes of the network. The American cluster contains two parts: developed countries in North America and underdeveloped countries in Latin America. Moreover, the Asia-Pacific cluster no longer exists and is divided into several parts. China is linked to France via Germany. China's influence on the international stock market increases significantly due to the progress of the "Belt and Road" initiative.

4.1.5. Construction of the Network during the Sino-US Trade Friction and COVID-19 Pandemic Period. Figure 6 shows the MST during the time of Sino-US trade friction and the COVID-19 pandemic. The geographical aggregation greatly diminishes. Except for the European and Asia-Pacific clusters, which are still centralized, the other clusters no longer exist. Korea is connected to China, Japan, Singapore, and Vietnam, which highlights its important position. India and Australia are separated from the original Asia-Pacific cluster and are connected to the United States and Canada in the America cluster. Note that the United States and Canada are connected to the European cluster, while most other American countries are on the margins of the network.

4.1.6. General Features of Network. The international stock market network has noteworthy features in all periods.

(i) The stock markets are closely linked and move towards geographical aggregation in the following way: first, European markets exhibit the most obvious aggregation, and the European cluster occupies the core position of the network in all periods. Second, the American and Asia-Pacific clusters are located around the European cluster, which forms the international stock market network. Third, the Asia-Pacific cluster exerts a weak influence on the stock markets of other regions. Similarly, the Middle Eastern and African cluster is marginalized in the international stock market network.

(ii) The strong connectedness within every cluster confirms the significant geographical aggregation effect. The connectedness among stock markets in the same region is stronger than that among stock markets in different regions. This feature is more evident in the European cluster than in the others.

(iii) The structure of the international stock market network varies over time, and each cluster has a relatively fixed central node. In the European cluster, France is located in the center, and it exerts a significant influence on the European cluster and the entire network in the sample period. Singapore is the central node of the Asia-Pacific cluster, and the United States is the central node of the

American cluster. The Middle Eastern and African cluster has no central node because of its marginal position in the network.

(iv) A country's position in the network is closely related to its economic and financial development, and the distances between nodes reflect the financial connections between the countries. Developed countries are relatively concentrated and closely linked, while developing countries are on the margins of the network. It is worth noting that the connectedness of the international stock market increases markedly during major public events, indicating that financial crises are contagious.

4.2. System-Level Connectedness. We investigate the systemic connectedness of the international stock market at public events by combining the DTW-based network with the full-sample analysis and using GE as the statistical index. We also adopt the sliding window method to determine the time-varying property of GE. Following Liu and Wan's [60] judgment regarding time window width, we use a longer time window width in order to capture the long-term trend of the international stock market accurately. A shorter time window width should be used to analyze the short-term dynamic impacts of financial crises, economic cycles, and seasonal factors on stock markets. Following Liu and Wan [61], we set the time window width at 250 trading days (approximately one year) and the step length at five trading days (one week).

As shown in Figure 7, the GE of the international stock market network fluctuates in a range of [0.06, 0.08] during the sample period. In Period I, the GE maintains a low level, from 0.062 to 0.071, because the international stock market is stable. In Period II, the GE soars and reaches its peak value at the end of 2008. Afterward, it gradually declines and returns to a normal value by the end of the US subprime crisis in 2009. During Period III, the GE declines but then increases relatively rapidly in mid-2011. During Period IV, the GE rises and then falls, declining to its lowest value at the beginning of 2018. During Period V, the GE once again presents an upward trend and reaches its second-highest peak in 2020 during the COVID-19 pandemic.

Thus, the sharp increase in GE occurs in four of the five periods, which correspond to the following public events: (i) the US subprime crisis from 2007 to 2009; (ii) the European debt crisis in 2011; (iii) the US Fed's first interest rate hike in 10 years and China's A-share stock disaster in 2015; and (iv) the period of Sino–US trade friction in 2018 and the COVID-19 pandemic in 2020. By contrast, the GE remains low with small fluctuations during Period I and other periods when no major public events occur. We find that public events exacerbate the volatility of stock markets at a certain stage and strengthen their linkages, which increase aggregation in the network and cause GE to reach its peak.

In terms of change amplitude, the most violent increase in GE happened during the US subprime crisis, followed by the world economic recession triggered by the hike in the US Federal Reserve's interest rate, the Chinese A-share stock disaster, and, finally, the European debt crisis. Among these, the European debt crisis imposes a significant impact on Europe but has limited global spread. Therefore, global public events (such as the US subprime crisis) exert a much greater impact on stock markets than do regional public events (such as the European debt crisis).

4.3. Region-Level Connectedness. The stock markets cluster in each of the regions. Following Wang et al. [59], we propose a measure of regional connectedness, shown in equations (6) and (7), to explore the commonly found geographical aggregation (the regional clustering effect in our case) in the international stock market. Table 3 displays the estimations of regional connectedness, where the connectedness between one region and all others (total connectedness) is equal to the corresponding off-diagonal row sums (or column sums). The within-region connectedness (diagonal elements) is significantly stronger than the cross-region connectedness (off-diagonal elements), with the exception of that between the Middle East & Africa and America. The major reason why these two regions have high connectedness is the frequent oil trade between the United States and Middle Eastern countries.

We find that the stock markets of 22 countries in Europe are highly interconnected. By contrast, the Middle East and Africa have the lowest within-region connectedness, indicating a weak influence on the international stock market. Furthermore, the American, Middle Eastern, & African regions are the two highest in terms of total connectedness, manifesting the powerful influence of the US dollar and oil exports. Europe and Asia-Pacific show the third and fourth highest total connectedness levels, respectively. Although Japan and Singapore exert a strong influence on the network, most Asia-Pacific countries are emerging markets with weak influence. Thus, the total connectedness of this region is not high.

4.4. Market-Level Connectedness

4.4.1. Assessment of Systemically Important Stock Markets. Risk contagion speeds and intensities differ among the nodes in the international stock market network when a public event breaks out. Based on the scale, relevance, and globality of the systemically important stock markets, we conduct a comprehensive assessment of risk contagion speed and intensity to analyze their influence.

The measure of risk contagion speed is defined as the number of stock markets infected by the source of risk (a single stock market) within a certain time. The degree of a node is defined as the number of edges directly connected to it, which can be used to represent risk and contagion speed. We can also measure the intensity of risk contagion by calculating the connectedness between one stock market and other stock markets that are connected to it in the network.

We select the IS index, which considers the degree of a node and the weight of the edges (the correlation coefficient between stock markets), to examine the influence of

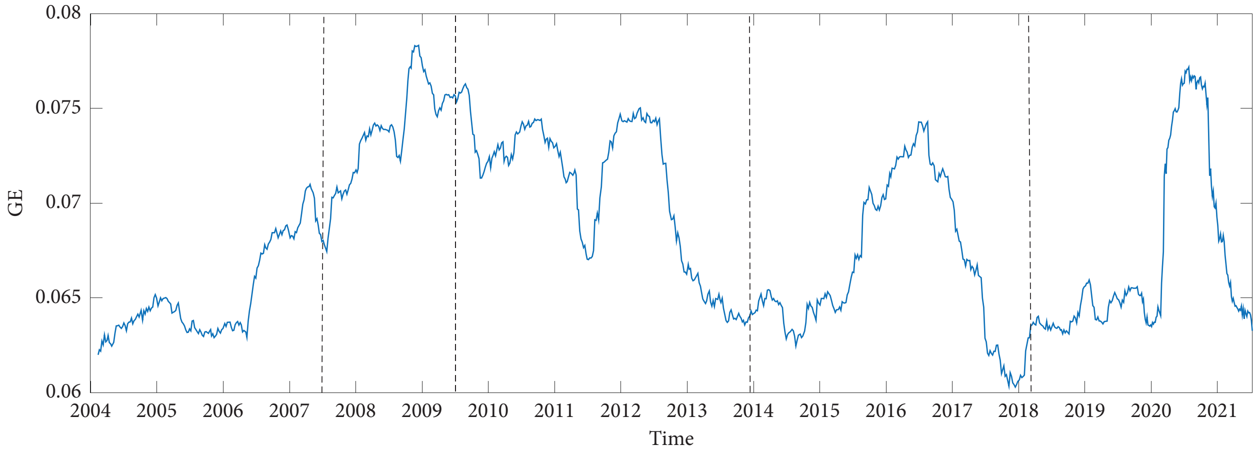

Figure 7: Time-varying global efficiency of the international stock market network.

Table 3: Regional connectedness.

	Europe	Asia-Pacific	Middle East and Africa	America	Total connectedness
Europe	0.8207	0.7336	0.5653	0.7689	2.0678
Asia-Pacific	0.7336	0.7937	0.5792	0.7829	2.0957
Middle East and Africa	0.5653	0.5792	0.7596	0.9679	2.1124
America	0.7689	0.7829	0.9679	0.7667	2.5167

Note. Indicators in the table are normalized as in equations (6) and (7) to eliminate the sample size bias arising because the numbers of countries differ across the four regions.

the stock markets. The greater the IS of a stock market, the stronger its effects on the international stock market network.

We calculate the IS of each node to identify the systemically important stock markets and analyze their network structure over different time periods. The top five nodes in each period are shown in Table 4. At public events, the top five nodes of the network are different across the five periods. The IS in Period I with no public events is significantly lower than that in Period II. Furthermore, Periods III, IV, and V correspond to the European debt crisis, the hike in the US Federal Reserve's interest rate, and the period of Sino-US trade friction, and the COVID-19 pandemic, respectively. The harm of these events is less intense than that of the US subprime crisis. Therefore, the IS in the latter three periods is higher than that in Period I and lower than that in Period II. This indicates that public events make the international stock market network more compact and the IS accordingly higher, which matches the conclusion drawn from the time-varying GE curve.

Meanwhile, we find that the top five nodes based on IS in all periods are all from the European cluster, which coincides with the powerful influence of Europe. Consistent with the outcomes shown in Figures 2–6, the European cluster is in the center of the international stock market network, and it dominates the other nodes and clusters. France is in the top five nodes in all periods and is extremely important in the network. Moreover, the United Kingdom entered the top five during the US subprime crisis. Afterwards, it declines and withdraws from the top five; thus, the leading position of the United Kingdom is highlighted during this period. The Netherlands ranks among the top five nodes in four of the five periods and is especially high in Periods III and IV, reflecting its significant influence. Germany, Sweden, Belgium, Switzerland, and Spain are also among the top five nodes in the five periods, which demonstrates that these countries significantly affect the international stock market.

Taken together, these results show that, first, the international stock market is greatly impacted by France and that Europe is the most important cluster in the network. This result occurs for two reasons. Europe's economy and finance are exceedingly integrated within the European Union, and stock markets in Europe have strong internal connectedness and thus have a significant influence on the stock markets of other regions. Second, the United States and Singapore have the highest IS in the American and Asia-Pacific clusters, respectively, because the United States is the world's largest economy and holds an extremely important position in the international financial market, and Singapore is the financial center of Asia. Third, Japan's IS exceeded Singapore's during the global economic recession, and it is prominent in the Asian financial market. Thus, Singapore and Japan are the most influential nodes in the Asia-Pacific region.

4.4.2. Analysis of Systemically Important Stock Markets. The findings show that France, the United States, and Singapore/Japan are the most systemically important stock markets in their respective regions. China is the world's

Table 4: Top 5 stock markets in international stock market network ranked by IS.

	Country	IS
Period I	France	38.91
	Sweden	38.88
	Switzerland	38.63
	Germany	38.62
	Spain	38.58
Period II	France	40.48
	Sweden	40.36
	Belgium	40.36
	UK	40.30
	Netherlands	40.27
Period III	Netherlands	39.92
	Belgium	39.85
	UK	39.67
	Germany	39.62
	France	39.59
Period IV	Netherlands	39.33
	Finland	39.28
	Belgium	39.27
	France	39.24
	Sweden	39.19
Period V	France	39.53
	Finland	39.46
	Sweden	39.45
	Netherlands	39.43
	Belgium	39.39

second-largest economy and has a growing influence on the international financial system. Thus, we next explore the importance of these markets in the international stock market network. The importance index we select is the tree length, which is the shortest distance when one stock market merges into the MST. We obtain it by calculating the connectedness between the node and its neighboring nodes in the network. We take the average importance indicator of the international stock market as a baseline. The normalized tree length (NTL) can be used to measure the average distance among nodes in order to explore the overall connectedness strength of the international stock market after redundant relationships are "filtered out."

As mentioned, we adopt the sliding window method to detect the time-varying property of the tree length and set the sliding time window width to 250 trading days. To measure market importance in the network, we calculate the time-varying NTL as well as the FRTL, USTL, SGTL, JPTL, and CNTL, as shown in Figure 8. We conclude that their stock markets are more important than the average level in the network if the tree lengths are below the NTL; otherwise, their stock markets are less important.

(i) The average NTL for the full-sample period is 0.3355, and the values in the five periods are 0.3462, 0.3142, 0.4301, 0.3431, and 0.3385, respectively. Since 2004, the NTL curve has fluctuated around 0.35 in a relatively high position. Affected by the US subprime crisis, it shows a downward trend during Period II from 0.3309 to 0.3084. Afterward, the NTL in Period III rises because the global financial environment is resurgent at the end of the US subprime crisis. It displays a short-term decline in 2012 and quickly recovers due to the European debt crisis. Then, the NTL first descends and then rises from 2015 to 2016 because several Black Swan events in the international financial system, such as the US Fed's first rise in interest rates in a decade, the plummeting crude oil price, Brexit, and the Chinese stock market disaster, run through Period IV. Furthermore, the NTL declines slightly during the period of Sino–US trade friction in 2018, and it falls sharply after the COVID-19 outbreak. Next, it rises again in late 2020 and early 2021 as the COVID-19 epidemic is gradually brought under control. In general, the NTL during the sample period experiences three falling/rising cycles.

(ii) The FRTL is the lowest, and its fluctuation range is the largest among all five tree lengths. As the core of the European cluster, France is much more important than the average level of the international stock market. Furthermore, the FRTL is low during public events, indicating that France is highly sensitive to them. It is noteworthy that the importance of France rose fastest from mid-2014 to the end of 2015, and the range of this increase was more dramatic than that of the average importance level.

(iii) The USTL is the closest to the NTL, but its fluctuation range is greater than the NTL's. The USTL is also highly sensitive to public events, and its sharp decline occurred during the US subprime crisis and the Sino-US trade friction period. By contrast, the emergence of the European debt crisis in 2012 and the hike in the Federal Reserve's interest rate in 2016 triggered only a small drop, which indicates that the connectedness between the United States and other markets is only weakly influenced by these events. Furthermore, the US subprime crisis in 2007 and the period of Sino-US trade friction in 2018 exhibit a significant influence on the importance of the United States. As the birthplace of these public events, the United States is obviously greatly affected by them.

(iv) The JPTL and SGTL are exceedingly close, and both are slightly higher than the NTL; this happens because Japan and Singapore have similar importance levels, and these are lower than the average. The fluctuation of the JPTL during the European debt crisis is greater than that of the SGTL, indicating that the Japanese stock market is more sensitive to the European debt crisis than are other markets.

(v) The CNTL is much higher than the NTL, and it fluctuates within a small range after the US subprime crisis. In addition, the importance of China is lower than the average level, and its sensitivity to public events is weaker than that of other

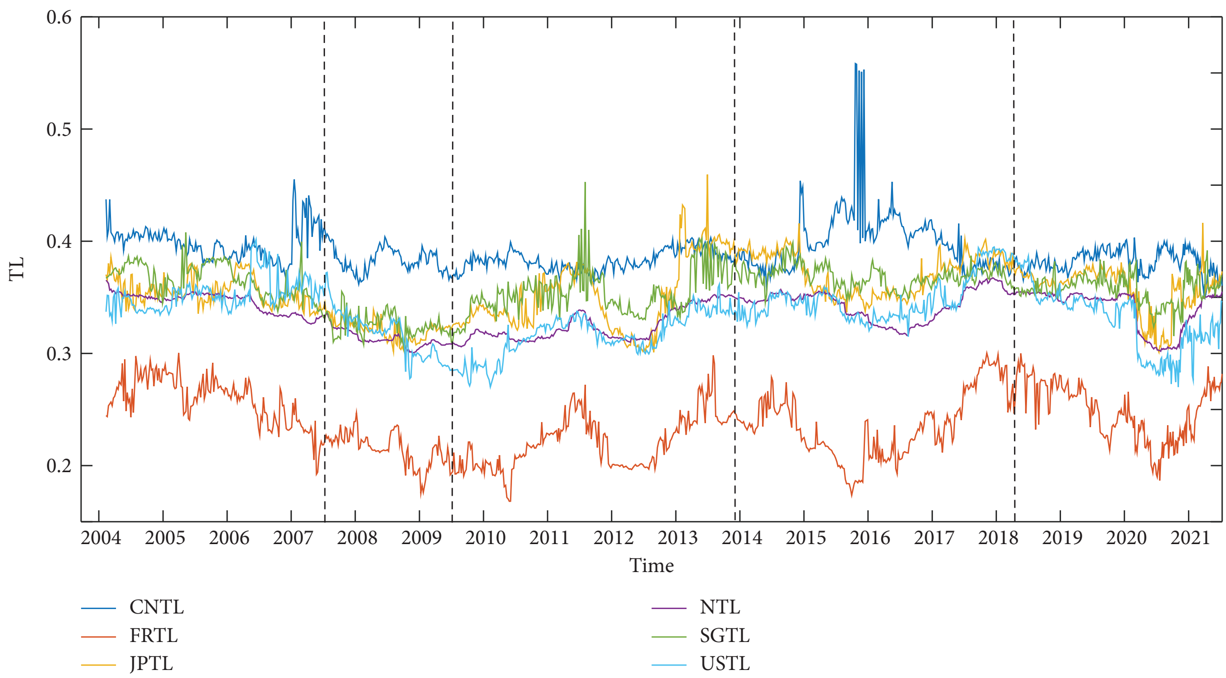

Figure 8: Tree lengths of systemically important stock markets. *Note*. NTL represents the normalized tree length of the international stock market network, and FRTL, USTL, SGTL, JPTL, and CNTL represent the tree lengths of France, the United States, Singapore, Japan, and China, respectively.

systemically important stock markets. It is worth noting that the gap between the CNTL and NTL was widest during the US subprime crisis. Thus, the importance of China is lower during the US subprime crisis than in other periods, which minimizes the extent of economic recession and the risk of contagion during the crisis. The Belt and Road Initiative also has a profound impact on the CNTL. During its implementation in 2015, the CNTL deviates from the NTL and declines; it approaches the NTL after the period of Sino-US trade friction. At that time, the importance of China reaches its peak. The world's two largest economies, China and the United States, are in conflict, which may continue to increase the China's importance. Moreover, the CNTL becomes relatively stable after the COVID-19 pandemic instead of declining sharply, as in other countries. One major reason for this is that China controls the risk of contagion caused by the COVID-19 pandemic effectively through its strong epidemic prevention measures.

5. Conclusions

We build correlation networks using the DTW model and investigate the connectedness of the international stock market at public events at the system, region, and market levels.

(i) At the systemic level, the public events increase market volatility and synergies among the stock markets. During times of stability, the network is relatively loose, and the connectedness among nodes is weak. By contrast, the network becomes integrated and compact after public events, indicating that a sharp increase in network connectedness may signal the emergence of financial crises. Additionally, the GE during the US subprime crisis was significantly higher than it was during the European debt crisis, indicating that global events have a greater impact on network connectedness than regional events have.

(ii) At the regional level, Europe always occupies a core position in the network. Affected by strong within-region connectedness, the network structure shows geographic regionalization. Stock markets in Europe are the most interconnected because of the integration of European finance and economy. Contrariwise, stock markets in the Middle East and Africa have the lowest within-region connectedness, due to their chaotic political situations and backward financial systems. America, the Middle East, and Africa are top-ranked in terms of total connectedness manifesting the powerful influence of the US dollar and oil exports. Europe and Asia-Pacific are ranked lowest in terms of total connectedness.

(iii) At the market level, France, the United States, and Singapore/Japan are the systemically most important stock markets in their respective regions. In particular, France exhibits the strongest influence in all five periods. Moreover, the influence of China increases rapidly, reaching its peak during the period of Sino-US trade friction, which shows that public events exert an important impact on the countries involved and that the dominance of the international financial system by European and American countries is changing.

Our research studies offer insights useful for investment strategies and systemic risk warning measures for the international stock market, while also providing regulatory authorities with important suggestions regarding financial supervision.

(i) Considering the periodicity of risk contagion among stock markets, governments need to make discretionary choices regarding risk sources, event processes, and categories (i.e., global vs. regional events). Public events are most intense in their early stages, which is often accompanied by a dramatic increase in stock market connectedness. During this stage, authorities should implement policies designed to strengthen bailout efforts, control market liquidity, curb capital outflow, and stabilize investor sentiment.

(ii) Investors should pay more attention to the European stock market, especially the French stock market, when making investment decisions, given the significant influence of Europe in the international stock market network. China's influence on the international stock market has been rising since the Belt and Road initiative began in 2015. It reached its peak during the period of Sino-US trade friction and the COVID-19 pandemic. As the world's largest emerging stock market, China is having an increasingly significant impact on other stock markets due to its openness.

(iii) Amid the increasing risks in the international financial system, authorities should implement rescue policies to reduce the breadth and depth of public events in consideration of the regional clustering effect. Since within-region connectedness is higher than cross-region connectedness in most instances, all countries should pay more attention to the stock markets in their own region, especially those that are systemically important. Stock markets with high IS rankings should also be taken seriously. Additionally, as the Middle East and Africa was closely linked with America, countries in these two regions should focus on their connectedness to prevent financial risks. For example, the Middle Eastern and African countries should be cautious about financial risks coming from America, particularly the United States, whose stock market is systemically important.

Data Availability

The data on the closing prices of stock market indices used to support the findings of this study were supplied by the Wind database under license and requests for access to these data should be made to Wind (https://www.wind.com.cn/).

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Nature Science Foundation of China (Grant nos. 71971079 and 72271087), the National Social Science Foundation of China (Grant no. 19BTJ018), and the Major Projects of National Social Science Foundation of China (Grant no. 21ZDA114).

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