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Risk Connectedness among International Stock Markets: Fresh Findings from a Network Approach

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Abstract: In this study, we analyze the upside and downside risk connectedness among international stock markets. We characterize the connectedness among international stock returns using the Diebold and Yilmaz spillover index approach and compute the upside and downside value-at-risk. We document that the connectedness level of the downside risk is higher than that of the upside risk and stock markets are more sensitive when the stock market declines. We also find that specific periods (e.g., the global financial crisis, the European debt crisis, and the COVID-19 turmoil) intensified the spillover effects across international stock markets. Our results demonstrate that DE, UK, EU, and US acted as net transmitters of dynamic connectedness; however, Japan, China, India, and Hong Kong acted as net receivers of dynamic connectedness during the sample period. These findings provide significant new information to policymakers and market participants.

Keywords: risk connectedness; value-at-risk; international stock market; extreme risk

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Citation: Choi, K.-H.; Yoon, S.-M. Risk Connectedness among International Stock Markets: Fresh Findings from a Network Approach. *Systems* **2023**, *11*, 207. https://doi.org/10.3390/systems11040207

Academic Editors: Wendong Yang, Jinpei Liu and Jianzhou Wang

Received: 18 March 2023
Revised: 17 April 2023
Accepted: 18 April 2023
Published: 19 April 2023

1. Introduction

In recent decades, there has been a significant increase in economic and financial interdependence alongside the liberalization of financial markets. Most companies worldwide import some of their intermediate inputs from foreign companies and obtain capital funds from foreign investors. In today's interconnected world, events in a country can quickly affect the global economy. Thus, when markets are connected, if one sector faces risk, this risk can affect others through strong links and contagion mechanisms, potentially causing the risk to spread to the entire stock market [1–4].

For years, the global stock market has fluctuated under the influence of geopolitical risk, energy price fluctuation, economic and monetary policies of large countries, infectious diseases, and financial shocks, such as the global financial crisis (GFC) and the European debt crisis (EDC); the impact of these events has been easily transmitted between markets. Therefore, over the past few decades, researchers have focused on spillover effects between international stock markets [5–11].

To this end, many researchers have conducted studies on the methodology, structure, and dynamics of these spillover effects [11–19]. However, most of these studies explored the overall spillover effects using returns and volatility and ignored the spread of tail risk. Although the overall spillover effects of stock market returns are important, in some cases extreme risk spillovers are more important. Extreme risks are unlikely to occur because they originate from extreme stock market events. Once they occur, they have a tremendous spillover effect on the stock market and economy as a whole. When market participants invest in international stock markets, it is crucial to understand the intensity and direction of the extreme risk connectedness between the markets as a whole.

Inspired by the growing financial literature focused on identifying risk networks in the financial system [10,20–22], these studies aim to identify the international stock price network and uncover the primary risk contributor and intensity of the interconnectedness of extreme risk within the network. Understanding the structure and dynamics of connectedness in the international stock market network by measuring extreme risk spillovers is of great significance, with this information being crucial for identifying early signs of systemic risk and enhancing the stock price network's resilience to systemic events. This information is also useful in terms of profit and loss management and systematic risk management, providing new information for assessing portfolio diversification opportunities and making decisions [11].

The DY approach has been applied to spillover studies on several financial markets. For example, Babar et al. [23] examined spillover effects among agricultural commodities and emerging stock markets during various crises, including the COVID-19 pandemic and the Russian–Ukrainian war. Hussain et al. [24] analyzed the volatility connectedness of GCC stock market returns and oil market returns. Li et al. [25] explored the returns and volatility spillovers between Chinese oil market and green energy stock markets.

Recently, a few studies investigated the connectedness between tail risks [26,27]. A previous study analyzed the connectedness of downside risks, whereas empirical analysis of upside risks is scarce. Upside risks, similar to downside risks, are another type of systemic financial risk as they can lead to future losses and high uncertainties [28]. In addition, market participants' ability to respond to market changes because of different information is bound to vary depending on upside and downside risks. Thus, analyzing and comparing upside and downside extreme risks together is useful in stabilizing the stock market network and helping investors' risk management strategies. In this context, it is worth investigating the connectedness of upside and downside risks between international stock markets.

Our findings provide evidence that the degree of connectedness is higher for downside risks than for upside risks. Moreover, in the dynamic results, we find that the magnitude of connectedness is more significant in the case of downside risks. Furthermore, we find convincing evidence that specific periods (e.g., the GFC, EDC, and COVID-19 pandemic) intensify risk spillover effects across international stock markets. Net connectedness also showed that developed stock markets, such as those in Germany, UK, the EU, and the US, were net transmitters of risk to all other markets, whereas Asian stock markets, including China, India, and Japan, Hong Kong, were net receivers for upside and downside risks during the sample period.

Our study contributes to the existing literature in the following ways: Firstly, we investigate the extreme risk connectedness of international stock markets based on the network approach, which differs from bivariate approaches, such as the correlation and Granger causality approaches, which focus on the relationship between the two markets. Secondly, we identify an international stock network from extreme risk connectedness using a value-at-risk (*VaR*) measurement, which contrasts previous studies that focused on the overall linkage of returns and volatility. To achieve our objective, we use the Glosten–Jagannathan–Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model [29] to calculate the *VaR* for stock market returns and apply Diebold and Yilmaz's methods [30,31] to examine extreme risk connectedness in the international stock market network. Thirdly, we measure downside and upside risks together, which can consider the asymmetry of connectedness in the upside and downside risks. This study differs from previous studies that have only examined negative risks by considering both downside and upside risks. Finally, we examine how the COVID-19 pandemic affects risk connectedness as our sample period includes the duration of the pandemic.

Our results present new evidence on how each market plays a role in the connectedness of extreme risks within the international stock market network. These findings are significant for policymakers and market participants who attempt to stabilize the financial market, manage risks and portfolio diversification, and make investment decisions. To the best of our knowledge, this study is the first to investigate connectedness in an extreme-risk network using the *VaR* of international stock markets.

The remainder of this paper is organized as follows: Section 2 reviews the literature; Section 3 explains the data employed and methods implemented in this study; Section 4 presents the empirical analysis; and Section 5 concludes the study.

2. Relevant Literature Review

For the past few years, the literature on risk connectedness in international stock markets has explored the interdependence of risks across stock markets globally. Several studies have found that risk connectedness tends to escalate during periods of market stress, such as financial crises. Studies have also found that the degree of risk connectedness between stock markets can vary depending on the specific markets considered and the time period studied. Overall, the literature highlights the need to better understand risk connectedness in international stock markets to inform investment strategies and public policy decisions. We now examine previous studies on this subject more closely.

2.1. Financial Risk Network at the Firm or Sector Level

The interconnectedness of financial risks within a firm or sector occurs when a firm's financial risk has an indirect or direct influence on the financial risks facing other firms within the same sector. For example, if a firm in a sector experiences financial difficulties, this can lead to a cascade of financial losses throughout the sector because of exposure to common risk factors, such as supplier disruptions or declining market demand. At the firm level, financial risk networks can be used to analyze and manage the interdependence of various financial risks, such as credit, liquidity, and market risks. Firms can use this information to identify and address sources of systemic risk and make informed investment decisions. At the sector level, a financial risk network analysis can inform public policy decisions aimed at promoting stability and resilience in the financial system.

Many studies have analyzed the formation and structure of financial risk networks at the firm or sector level. Among others, in a study on the stock market in China, Wu [32] identified the financial, industrial, and energy sectors as the most significant contributors to systemic risk, whereas Wu et al. [33] determined that the industrial sector had the greatest systemic importance among Chinese stock market sectors. Additionally, Zhang et al. [34] examined the tail risk network of Chinese sectoral markets and analyzed systemic risk linkages using the conditional *VaR* (CoVaR) approach. Ngene [35] explored asymmetric and time-varying volatility spillovers among US sector equities. Wu et al. [36] analyzed systemic risk connectedness in a network of global energy companies and revealed that US stock market volatility and financial market sentiment are the major drivers of time-varying risks. Shen et al. [37] investigated risk spillovers within Chinese sectors using the generalized variance decomposition framework of the vector autoregression (*VAR*) model.

2.2. Financial Risk Network Using a Bivariate Approach

To measure the network connectedness among financial markets, researchers have used various methods, such as correlation analysis, the Granger causality approach, the transfer entropy approach, and the variance decomposition of the *VAR* model. The most popular method in financial network analysis is calculating pairwise correlations. In a network, markets (sectors, institutions, or firms) are nodes and correlations are links. For example, Chi et al. [38] built a network of US-listed stocks using the calculated cross-correlations of price returns and trading volumes. Giroud and Mueller [39] used correlations to construct internal networks of firms and examined the transmission of local shocks across regions in the US through these networks. Zhou et al. [40] investigated special stock price behaviors in the Chinese A-share stock market using correlation-based stock networks.

The Granger causality network identifies causality by detecting the presence of information flow in a linear relationship, as proposed by Granger [41]. As this approach has the advantage of being based on statistical tests, many studies have applied this model. For example, by applying the Granger causality network, Billio et al. [42] analyzed the connectedness and system risk of four types of finance and insurance sectors, while Výrost et al. [43] analyzed the network between 20 stock markets. Wang et al. [44] employed *VaR* and Granger causality risk test to construct an extreme risk spillover network that measured connectedness among financial institutions and quantified the extent of extreme risk spillovers.

The Granger causality approach only considers the direction of causality and not the degree of causality in terms of the magnitude of information flow. If the quantity of information flow between the two markets is of greater importance, the transfer entropy approach becomes more relevant. A transfer entropy approach is a useful tool for quantifying information transfer within a network numerically [45]. Since Schreiber [46] proposed the concept of transfer entropy, it has been applied in many fields. Sensoy et al. [47] applied the transfer entropy method to investigate the intensity and direction of the information flow between stock prices and foreign exchange rates in emerging countries. Gong et al. [48] analyzed stock market connectedness and found that the total connectedness of the market increased during periods of crisis. Nicola et al. [49] used daily stock data from 74 listed US banks and investigated the US bank network. García-Medina and Luu Duc Huynh [50] examined the predictive power of the determinants of Bitcoin prices by employing the transfer entropy approach.

If tail risks are crucial, the copula approach is then suitable for building a tail-dependence network. For example, Münnix and Schäfer [51] investigated the statistical dependencies in the US stock market using a copula approach and revealed that many dependencies are from the tails of the marginal distributions. Changqing et al. [52] explored risk contagion between international and Chinese stock markets using a dynamic copula model and revealed that risk contagion is identified by lower tail dependence. Xixi et al. [53] utilized copula tail correlation to construct a complex network for the Chinese stock market and analyzed the network structure of the market. Wen et al. [54] employed a copula model to investigate the edge information of a stock price network.

2.3. Financial Market Risk Network Using a Multivariate System Approach

The pairwise correlation and Granger causality approaches focus only on bivariate linkage and, thus, fail to measure overall systemic connectedness. The *VAR* approach can analyze the relationship in a multivariate system as a whole. Diebold and Yilmaz (hereafter, DY) [12,30,31] suggest the most popular model of the *VAR* approach. Diebold and Yilmaz [31] suggested a network topology employing the variance decomposition method. They constructed stock returns and volatility networks by measuring the time-varying connectedness of the stock return volatilities of major US financial institutions using variance decomposition.

Recently, several techniques have been developed to improve the DY method. Demirer et al. [55] introduced the Least Absolute Shrinkage and Selection Operator (LASSO) method into high-dimensional networks to overcome the limitations of the *VAR* model in constructing low-dimensional networks. They constructed a network of publicly traded subsets of the world's top 150 banks. Du et al. [27] also investigated multiscale tail risk spillovers across global stock markets at different frequencies by employing LASSO-based network connectedness. Baruník and Křehlík [56] introduced the DY framework, which used the spectral representation of variance decompositions to measure the connectedness between financial variables resulting from heterogeneous frequency responses to shocks. Baruník and Kocenda [57] applied an extended DY approach to high-frequency intraday data and examined the total, asymmetric, and frequency connectedness between oil and foreign exchange markets. Youssef et al. [11] used the time-varying parameter VAR (TVP-VAR) of the DY method and investigated the dynamic connectedness between the eight stock indices affected by the COVID-19 pandemic. They also analyzed how economic policy uncertainty affected this connectedness. Chatziantoniou et al. [58] examined sectoral stock market connectedness in India by employing a TVP-VAR connectedness approach and revealed that connectedness was strongest during the GFC. Zhou et al. [59]

used a TVP-VAR DY model, constructed a network in Chinese sectoral stock markets, and analyzed sectoral risk spillovers based on high-frequency data.

Some studies have focused on measuring the system risk in a financial network. Adrian and Brunnermeier [60] introduced the CoVaR method to measure system risk according to the institutions' leverage, size, and maturity mismatch. Wu et al. [61] analyzed the tail risks of 28 stock markets using the conditional autoregressive value-at-risk model.

In addition, by applying the dynamic model averaging approach, Dong et al. [6] explored how the interdependent structures between economic factors and stock markets changed during the COVID-19 outbreak. Their findings revealed that the dependence structures experienced significant changes during the COVID-19 outbreak and economic factors had a stronger impact on developed stock markets than on emerging Asian markets.

Remarkably, previous studies have mainly concentrated on examining the connectedness of downside risks and have not considered upside risks and asymmetry in risk connectedness. In the stock market network, upside risk connectedness is another type of systemic risk, which can lead to future losses and high uncertainty [28]. In this context, it is important to measure and analyze the upside and downside risk connectedness together and utilize the information in policy-making for stock market stabilization and international investors' risk management. There have been several studies on this topic. Baruník et al. [62] suggested a method to estimate asymmetries in volatility spillovers and revealed that asymmetries emerge because of bad and good volatility in the US stock market. BenSaïda [63] investigated asymmetric volatility spillovers across the G7 stock markets and discovered that asymmetric connectedness was time-varying. Li [64] dissected the influence of COVID-19 on global stock markets by employing the DY approach and discovered that volatility spillovers were time-varying, crisis-sensitive, and asymmetric. Mensi et al. [65] investigated the asymmetric volatility connectedness among stock markets by analyzing high-frequency data from 16 stock markets and found that bad volatility dominated good volatility. Mensi et al. [66], employing the DY spillover index, investigated the dynamic asymmetric volatility connectedness among US equity sector markets and revealed that the network of connectedness among sectors demonstrated asymmetric behaviors. Using high-frequency data from the COVID-19 period, Shahzad et al. [67] analyzed asymmetric volatility spillovers among Chinese stock markets and discovered that bad volatility spillover shocks dominated good volatility spillover shocks.

As mentioned in previous studies, various models have been applied and analyzed between markets (or industries) to determine the risk spillover effects. However, the model for calculating the extreme risks was not applied, while the analysis of the spillover effect was insufficient when applying the upper risk. Therefore, this study provides a new framework for computing networks and connectedness by applying the *VaR* model, which can estimate extreme risks (upside and downside risks).

3. Data and Method

3.1. Data

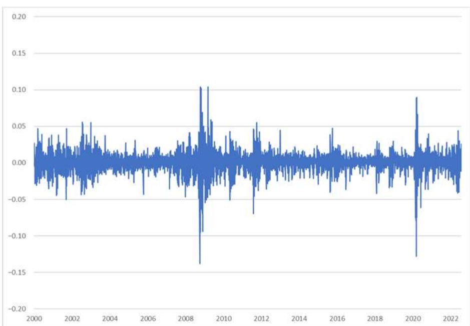
To discover international stock market risk connectedness, we analyzed the daily closing prices of 10 stock markets: the United States (US, S&P500), Japan (JP, Nikkei 225), China (CN, Shanghai Composite Index), Hong Kong (HK, HANG SENG Index), India (IN, BSE Sensex), the European Union (EU, EURO STOXX 50), Germany (DE, DAX), the United Kingdom (UK, FTSE 100), Switzerland (CH, Swiss Stock Market Index), and Canada (CA, S&P/TSX Composite Index). We selected stock exchanges with high market capitalization, focusing on Europe, Asia, and North America. The sample consisted of 10 stock markets operating between 5 January 2000, and 30 July 2022, with 4579 observations. Daily returns are calculated as the logarithmic difference between two consecutive daily prices. All data were obtained from Infomax (https://news.einfomax.co.kr, accessed on 5 August 2022).

Table 1 displays the summary statistics for all the stock returns. The UK, HK, and the EU had the lowest mean returns, whereas IN exhibited the highest mean returns. In addition, according to the standard deviation (Std. Dev), CN was the riskiest market, followed by DE and IN. By contrast, CH had the lowest risk, followed by CA and the US. As skewness had a negative value, all countries, except HK, were skewed to the left. It also had excessive kurtosis in all stock markets, indicating a thick-tailed leptokurtic distribution. According to the Jarque-Bera (J-B) statistics that test normality, all stock market returns deviate from a normal distribution. We conducted an augmented Dickey–Fuller (ADF) test to determine the presence of unit roots in each return series. The results are presented in the final column. All the stock market returns were stationary at the 1% level. Figure 1 shows the returns for the 10 stock markets. As demonstrated, the returns of all stock markets experienced abrupt fluctuations during the GFC and the COVID-19 pandemic. The financial crisis and pandemic had a greater impact on American and European stock markets than on Asian markets.

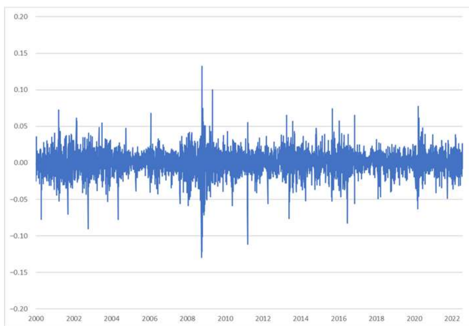
Table 1. Indicators of summary statistics.

	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis	J-B	ADF
US	−0.1378	0.1042	0.0002	0.0136	−0.5470	14.6547	26,144 ***	−32.9848 ***
JP	−0.1292	0.1323	0.0001	0.0161	−0.4801	9.8654	9168 ***	−67.6401 ***
CN	−0.0926	0.0940	0.0002	0.0167	−0.2386	7.6583	4183 ***	−67.3128 ***
HK	−0.1358	0.1680	0.0000	0.0161	0.1181	12.7150	18,017 ***	−66.5190 ***
IN	−0.1718	0.1611	0.0005	0.0162	−0.4024	13.3090	20,400 ***	−66.2381 ***
EU	−0.1324	0.1295	0.0000	0.0160	−0.1547	9.5916	8308 ***	−68.4671 ***
DE	−0.1305	0.1346	0.0002	0.0163	−0.1927	9.9620	9276 ***	−32.2282 ***
UK	−0.1276	0.1111	0.0000	0.0131	−0.3189	12.3819	16,871 ***	−69.8792 ***
CH	−0.1274	0.1576	0.0001	0.0128	−0.1021	16.2633	33,571 ***	−67.4280 ***
CA	−0.1700	0.1129	0.0002	0.0125	−1.1556	25.6797	99,156 ***	−32.6103 ***

Notes: Jarque-Bera normality test is denoted by J-B, while Augmented Dickey-Fuller unit root test is denoted by ADF. Symbol *** denotes rejection of null hypothesis at 1% significance level.

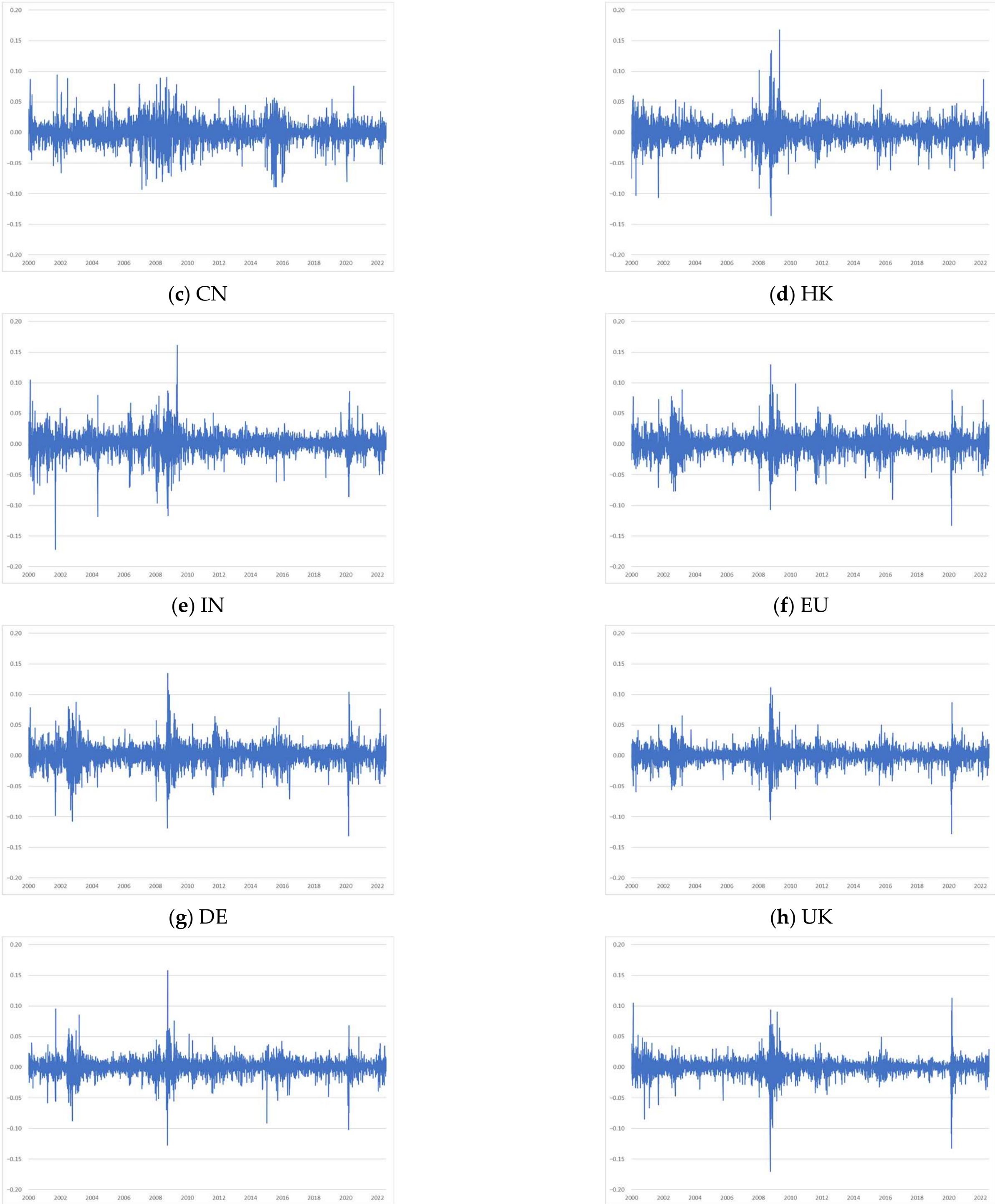


(**a**) US



(**b**) JP

Figure 1. *Cont*.



(**c**) CN (**d**) HK
(**e**) IN (**f**) EU
(**g**) DE (**h**) UK
(**i**) CH (**j**) CA

Figure 1. Daily returns of international stock markets.

3.2. Methodology

VaR is widely used to calculate the risk for stock markets; a common approach to *VaR* measures is to use econometric models. Thus, to estimate the upside and downside *VaR* of stock markets, we used the ARMA $(1,1)$-GJR-GARCH $(1,1)$ model. The upside and downside risks for the log-returns of the stock markets are given as follows:

$$VaR_{i,t}^{U} = \mu_{i,t} + t_v^{-1}(1-\alpha)\sigma_{i,t} \quad (1)$$

$$VaR^D_{i,t} = \mu_{i,t} + t_v^{-1}(\alpha)\sigma_{i,t} \tag{2}$$

Equations (1) and (2) are the upside and downside risk equations, where $\mu_{i,t}$ and $\sigma_{i,t}$ represent the average returns and the standard deviation of stock market returns, respectively. $t_v^{-1}(1-\alpha)$ and $t_v^{-1}(\alpha)$ are the $(1-\alpha)$th and αth quantiles of a Student-t distribution with v degrees of freedom, respectively.

The approach used in this study was developed by Diebold and Yilmaz [30,31] and is widely applied in many areas of economic analysis. Based on this approach, we analyzed the risk connectedness of international stock markets using the *VaR* estimates obtained from Equations (1) and (2). This approach relied on the use of the VAR model and generalized forecast error variance decomposition (GFEVD). This approach analyzed the total, directional, and net connectedness among international stock markets. The VAR (p) model with n variables is expressed as

$$Y_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t \tag{3}$$

where Y_t is the vector of endogenous variables at time t. Φ_i, $i = 1, \cdots, p$, are matrices of autoregressive coefficients, and ε_t is the vector of the error terms. This VAR model can be expressed in terms of the vector moving average (VMA) model as follows:

$$Y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{4}$$

where A_i is the matrix of the coefficients of the moving average representation. This coefficient was used to generate the variance decomposition. Thus, the H-step ahead GFEVD was calculated using the generalized approach proposed by Koop et al. [68] and Pesaran and Shin [69]. The variable j's contribution of variable j to H-step-ahead GFEVD for variable i is defined as

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{5}$$

where σ_{jj} is the standard deviation of the jth equation in the VAR model and $\sum$ is the variance matrix of the error vector ε_t. e_i is the selection vector, which has values equal to 1 for element i and 0 elsewhere. A_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR.

However, the row sums of the variance decomposition matrix are not necessarily equal to 1. Thus, the normalized H-step ahead GFEVD can be expressed as

$$\widetilde{\theta}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{n} \theta_{ij}^{H}} \tag{6}$$

where $\sum\limits_{j=1}^{n} \widetilde{\theta}_{ij}^{H} = 1$ and $\sum\limits_{i,j=1}^{n} \widetilde{\theta}_{ij}^{H} = n$. $\widetilde{\theta}_{ij}^{H}$ is the variance share of the other variables. Using Equation (6), we constructed several types of connectedness indices. The total risk-connectedness index is calculated as follows:

$$TS^H = \frac{\sum_{i,j=1, i\neq j}^{n} \widetilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{n} \widetilde{\theta}_{ij}^{H}} \times 100 \tag{7}$$

Additionally, we can gauge the directional spillovers of risks. The FROM directional connectedness $\left(DS^H_{i\leftarrow\blacksquare}\right)$ estimates risk spillovers from all other stock markets to ith stock market as

$$DS^H_{i\leftarrow\blacksquare} = \frac{\sum_{j=1, j\neq i}^{n} \widetilde{\theta}_{ij}^{H}}{\sum_{i,j=1}^{n} \widetilde{\theta}_{ij}^{H}} \times 100 \tag{8}$$

The TO directional connectedness $(DS^H_{i\rightarrow\blacksquare})$ estimates risk spillovers from *i*th stock market to all other stock markets as

$$DS^H_{i\rightarrow\blacksquare} = \frac{\sum_{j=1,j\neq i}^{n} \widetilde{\theta}^H_{ji}}{\sum_{i,j=1}^{n} \widetilde{\theta}^H_{ji}} \times 100 \tag{9}$$

In addition, the net total directional connectedness of risks for *i*th stock market can be computed as the difference between Equations (9) and (8) and is expressed as

$$NS^H_i = DS^H_{i\rightarrow\blacksquare} - DS^H_{i\leftarrow\blacksquare} \tag{10}$$

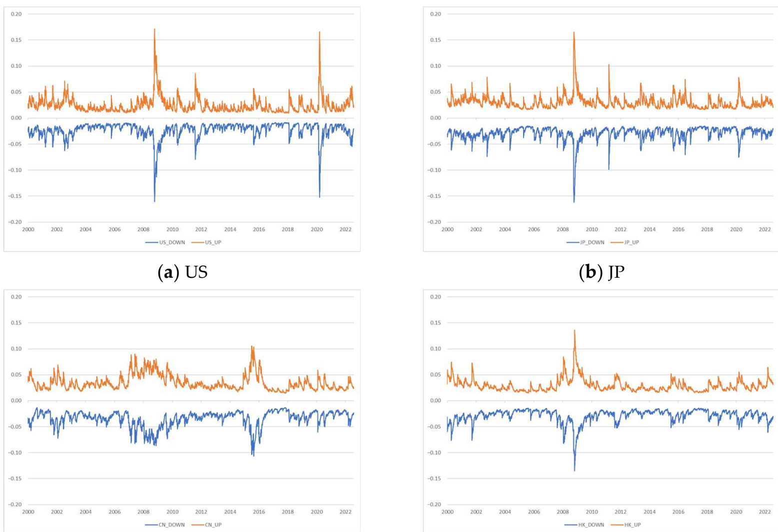
This index determined whether a given stock market is a recipient or transmitter of risk. If $NS^H_i > 0$, the risk of *i*th stock market affected the stock market risk more than it was affected by all other stock market risks. If $NS^H_i < 0$, then the opposite was true. Finally, the net pairwise directional connectedness of risk was calculated using the following formula:

$$NPS^H_{ij} = \left(\frac{\widetilde{\theta}^H_{ji}}{\sum_{i,k=1}^{n} \widetilde{\theta}^H_{ik}} - \frac{\widetilde{\theta}^H_{ij}}{\sum_{j,k=1}^{n} \widetilde{\theta}^H_{jk}} \right) \times 100 \tag{11}$$

4. Empirical Results

4.1. Upside and Downside VaR Measurement Results

Using the GJR-GARCH (1,1) model, we measured the downside and upside risks associated with all the stock markets. Figure 2 shows the upside and downside *VaR*s of the 10 international stock markets. Based on the figures, changes in *VaR* estimates for downside and upside risks were basically similar, though the range of fluctuations in the upside *VaR* (absolute value) was higher than the downside *VaR*. Additionally, the downside and upside *VaR*s underwent significant fluctuations during the initial phases of the GFC and the COVID-19 pandemic. Unlike the other two events, all countries experienced significant fluctuations during the GFC. However, during the COVID-19 outbreak, while there were significant fluctuations in the Americas and Europe regions, CN, HK, and JP experienced relatively small fluctuations. In particular, JP experienced significant fluctuations during the GFC. Moreover, CN showed great fluctuations between 2015 and 2016 because of the stock market bubble and the decline in the economic growth rate. Furthermore, the rapid changes that occurred in 2002 and 2004 were driven by factors such as economic openness, increased foreign investment, and political instability.



(**a**) US (**b**) JP

(**c**) CN (**d**) HK

Figure 2. *Cont.*

(**e**) IN (**f**) EU

(**g**) DE (**h**) UK

(**i**) CH (**j**) CA

Figure 2. Dynamics of downside and upside *VaR*s.

4.2. Connectedness Results

The results in this section were calculated using the VAR (2) model and a 10-step ahead GFEVD. The risk connectedness results based on *VaR* among the 10 global stock markets are presented in Tables 2 and 3. The finding presented in Table 2 for upside risk shows that the total upside risk connectedness reaches 68.99%, which suggests international stock markets are exposed to high levels of upside risk contagion and are not independent of each other. We find that the US, EU, DE, UK, CH, and CA stock markets are net risk transmitters, whereas the remaining stock markets are risk receivers. DE is the highest transmitter of connectedness, whereas the EU is the highest receiver of connectedness. By contrast, CN is the least significant transmitter and receiver of connectedness in the risk network. CN has the highest contribution of risk to its own market (67.02%), whereas, in the case of other stock markets, own market risk connectedness is approximately 20–30%. According to Table 3, the total downside risk connectedness reached 69.66%. As with the upward risk results, it was found that there was downside risk contagion and that these results were not independent of each other. We find that the US, EU, DE, UK, CH, and CA are net risk transmitters, whereas the remaining stock markets are risk receivers. This is similar to the results in Table 2. In addition, CN is high (72.29%) according to the contribution of risk to its own market. This indicates that the risk of CN is influenced more by its own risks than by external market risks in the upside and downside risks.

Table 2. Connectedness for upside risks in international stock markets.

	US	**JP**	**CN**	**HK**	**IN**	**EU**	**DE**	**UK**	**CH**	**CA**	**From**
US	24.86	3.17	0.73	3.49	3.06	12.46	13.01	13.43	9.94	15.84	74.12
JP	8.73	26.25	1.38	9.07	4.75	10.47	12.05	10.45	8.45	8.40	73.33
CN	1.59	2.24	67.02	10.56	3.15	3.30	3.29	3.64	3.66	1.56	27.71
HK	7.30	7.52	3.78	29.22	9.13	8.41	9.10	10.97	6.27	8.30	71.22
IN	6.82	4.89	1.52	10.80	36.85	7.14	8.58	8.27	5.53	9.58	61.82
EU	10.50	4.21	0.85	3.89	2.86	21.57	19.55	15.47	13.10	8.00	78.05
DE	10.42	4.54	0.76	3.98	3.26	18.91	22.46	14.21	12.82	8.65	77.20
UK	11.14	3.59	0.94	4.66	3.29	15.81	14.84	22.34	13.33	10.05	77.53
CH	10.18	4.83	0.91	3.59	2.83	15.45	16.03	14.98	24.26	6.95	76.80
CA	16.80	3.04	0.72	4.33	4.83	10.42	11.20	12.51	7.59	28.56	72.13
To	90.82	43.22	10.29	45.24	28.74	105.13	109.00	106.46	74.82	76.18	68.99
Net	16.70	−30.11	−17.42	−25.97	−49.31	27.08	31.47	29.66	2.69	7.19	

Table 3. Connectedness for downside risks in international stock markets.

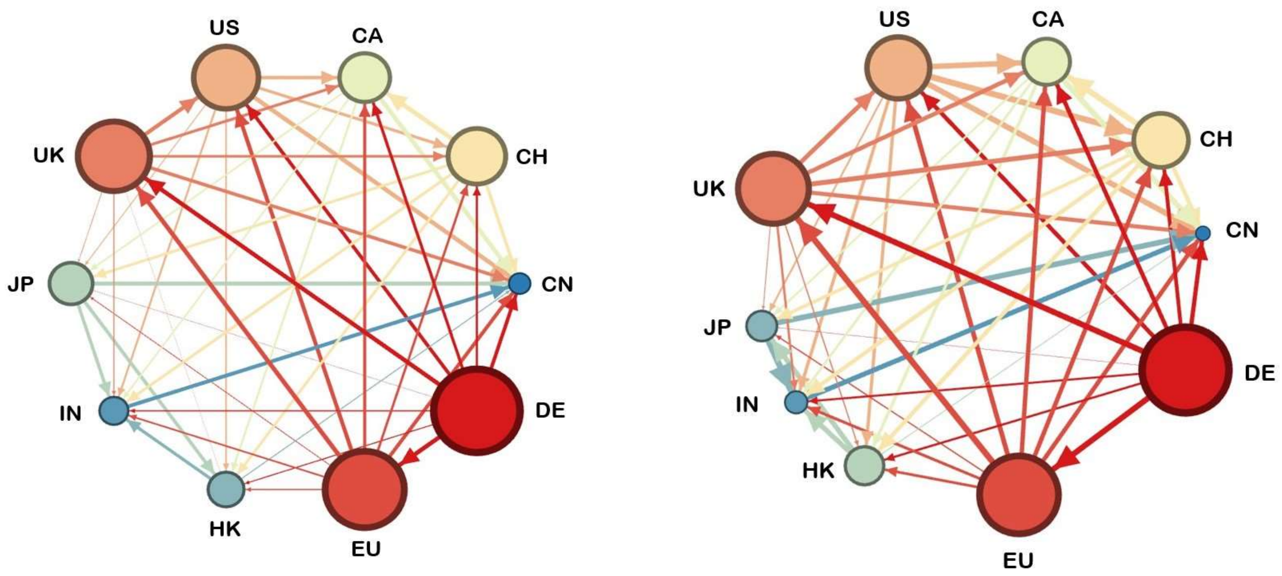
	US	**JP**	**CN**	**HK**	**IN**	**EU**	**DE**	**UK**	**CH**	**CA**	**From**
US	25.88	3.61	0.54	2.54	2.01	13.24	13.59	14.08	8.90	15.60	75.14
JP	9.87	26.67	1.06	7.14	3.58	11.12	12.48	11.03	8.53	8.52	73.75
CN	1.07	2.09	72.29	9.87	3.05	2.38	2.44	2.62	3.11	1.08	32.98
HK	7.69	9.18	3.71	28.78	8.06	8.63	9.05	10.98	5.75	8.17	70.78
IN	6.59	5.88	1.73	10.59	38.18	6.81	8.10	8.25	4.80	9.08	63.15
EU	11.99	4.58	0.61	2.73	1.77	21.95	20.09	16.04	12.16	8.08	78.43
DE	11.65	4.92	0.59	2.87	2.26	19.51	22.80	14.78	12.04	8.56	77.54
UK	12.88	4.06	0.69	3.40	2.18	16.44	15.39	22.47	12.29	10.19	77.66
CH	11.67	5.35	0.74	2.40	1.81	16.02	16.39	15.51	23.20	6.90	75.74
CA	17.41	3.56	0.61	3.70	4.02	10.96	11.46	13.16	7.24	27.87	71.44
To	83.48	38.02	11.59	54.37	37.15	102.38	107.65	103.93	80.69	77.34	69.66
Net	8.34	−35.72	−21.39	−16.41	−41.28	23.95	29.99	28.19	9.25	7.68	

By comparing Tables 2 and 3, we obtain some noteworthy results. Firstly, the degree of total connectedness for downside risks is relatively higher than that for upside risk connectedness, indicating a high level of risk contagion for downside risks. Therefore, downside risks have a greater impact on connectedness strength than upside risks in an international stock market network. In addition, the risk contribution to one's own stock market is higher for downside risks.

Secondly, there is a change in the connectedness between some stock markets. Our results show that the risk transmission for major stock markets to other markets reduces the downside risk. For example, the TO directional risk connectedness of the US fell from 90.82% (Table 2) to 83.48% (Table 3). This result persists for five stock markets (US, JP, the EU, DE, and the UK), whereas for other stock markets the TO directional risk connectedness increases. In contrast, the FROM directional risk connectedness of the US increased in the case of downside risks from 74.12% (Table 2) to 75.14% (Table 3). This means that there is an asymmetric spillover effect in the international stock market, which suggests that the response of market participants to positive and negative news may differ depending on the country due to variations in the underlying economic and financial conditions.

Thirdly, these results display that while the importance of Asian stock markets in the global economy is growing, the influence of Asian stock markets on developed stock markets remains relatively insignificant. The results also confirm the importance of distinguishing between upside and downside risks when analyzing risk connectedness and risk management.

Figure 3 displays the estimation results of the net pairwise directional connectedness within the international stock market network. The size of a circle (or node) indicates the level of connectedness. If the circle's color is red, it denotes that the stock market is a risk transmitter; if it is blue, it implies that the stock market is a risk receiver. The arrow (or link) indicates the direction of risk connectedness, whereas the thickness of the arrows indicates the intensity of the net pairwise connectedness. For upside risks, the net connectedness of DE is the largest, followed by the EU and the UK. Thus, the European stock market is the network's major market for pairwise risk connectedness. However, CN and IN have been shown to act as risk receivers. Figure 3b illustrates that the net risk connectedness of the stock market remains unchanged even at downside risks. The intensity of net pairwise connectedness from developed economies (DE, the EU, and the UK) to other countries appears similar in both upside and downside risk networks.



(**a**) Upside risk (**b**) Downside risk

Figure 3. Net pairwise connectedness within international stock market networks.

However, with the exception of HK, Asian countries have shown a decrease in their size of connections. This connectedness between Asian countries is lower in the case of downside risk networks. The findings revealed that the degree of connectedness depends on the risk situation. It is also observed that developed stock markets are closely associated with both risk networks.

To investigate how extreme risk connectedness between international stock markets varies over time, we estimated the dynamic connectedness of extreme risk using the rolling-window method. We chose 200 days (approximately one year) as the rolling window length.

The time-series plot in Figure 4 illustrates the total connectedness within the upside and downside risk networks over time. Blue and gray indicate the results for the downside and upside risks, respectively. Overall, we observe that, in the case of downside risks, the strength of connectedness is larger; however, we can conclude that movements and magnitudes in the total connectedness for upside and downside risks are similar. The total connectedness for the upside and downside risk networks varies over time but is higher than 50% during the sample period. We observe higher total connectedness during specific periods (e.g., the GFC, EDC, and the COVID-19 pandemic). Our analysis reveals that the total connectedness within both networks reached the highest level (over 87%) during the GFC, followed by the COVID-19 pandemic. These results indicate that the international stock market exhibits strong interconnections and that interdependence increases significantly during periods of crisis.

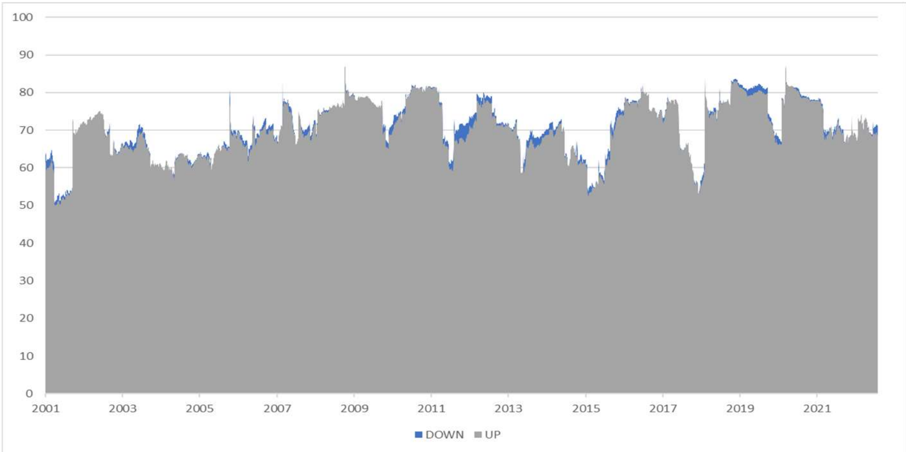
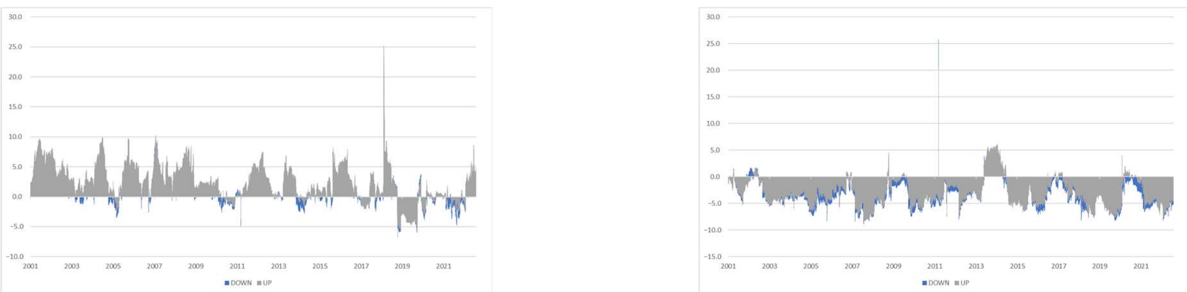


Figure 4. Total dynamic connectedness for upside and downside risks.

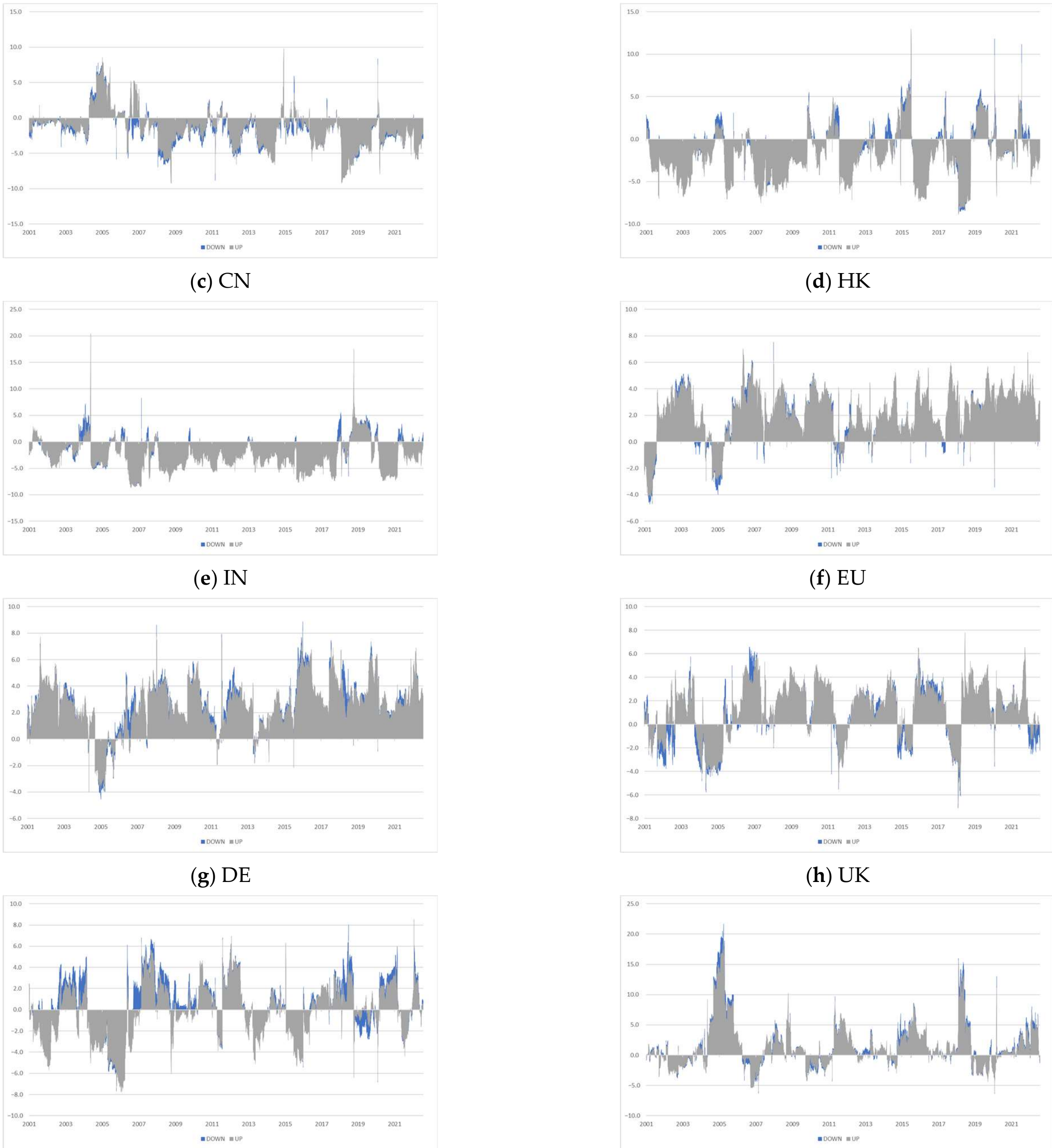
To better understand the time-varying movements of connectedness, we investigated net connectedness, revealing information about the direction of connectedness for the 10 stock markets. A positive value refers to a transmitter of risk to other stock markets; negative values are the opposite. Figure 5 shows the net dynamic connectedness between international stock markets for upside and downside risks. The plot distinguishes between upside and downside risks using gray and blue, respectively. We observed that all stock markets showed significant time-varying patterns; however, they were found to have a greater magnitude on the stock market in the case of downside risks. Our results show ample evidence of asymmetric connectedness. Each stock market shows this pattern because it is event-driven or affected by the way it responds to crises, economic characteristics, and geographical proximity. Although the net connectedness of all stock markets fluctuates between positive and negative values in response to specific events, overall, the US, the EU, DE, and the UK are the net transmitters and JP, CN, HK, and IN the net receivers of upside and downside risks. These results indicate that the European stock markets are less affected by spillover effects from other stock markets and confirm that the German stock market has the greatest influence on other stock markets. This finding aligns with the results of Youssef [11] and Zhang [70,71]. Thus, the developed stock markets continued to be net transmitters of risk during the sample periods, except for CH and CA, whereas Asian stock markets were net receivers. Although the importance of Asian stock markets has been growing recently, their influence on developed countries is relatively weak and has not increased significantly over time.



(**a**) US

(**b**) JP

Figure 5. *Cont*.



(**c**) CN (**d**) HK (**e**) IN (**f**) EU (**g**) DE (**h**) UK (**i**) CH (**j**) CA

Figure 5. Dynamics of net connectedness of upside and downside risk networks.

5. Conclusions

This study analyzed the dynamic connectedness of the international stock market network based on extreme risks (upside and downside risks) measured using the *VaR*. To the best of our knowledge, this was the first study to examine an extreme-risk network in international stock markets. We applied the DY model and used daily prices between 5 January 2000, and 30 July 2022.

This study obtained several important results. Firstly, for the static analysis approach the connectedness level of downside risks is relatively higher than that of upside risks, which implies that international stock markets are more sensitively associated with the fall of global stock prices. The dynamic results also show that the magnitude of connectedness is more significant in the case of downside risks, indicating that stock market networks are more likely to transmit downside risks. This finding is similar to the results of BenSaïda [70], who found that stock markets transmit more bad volatility than good volatility. Secondly, we revealed that economic crisis periods (e.g., the GFC, EDC, and the COVID-19 pandemic) intensified risk spillover effects across international stock markets. This indicates that the international stock market network is strengthened during crisis periods. Thirdly, the results of the net dynamic connectedness of extreme risks show that the EU, DE, and the US act as net transmitters of dynamic spillovers, whereas JP, CN, and IN act as net receivers of dynamic spillovers. DE is the most influential international stock market in the world. Thus, developed stock markets are net transmitters of risk for all other markets, whereas Asian stock markets are net receivers of upside and downside risks.

These findings provide significant new information to policymakers and market participants. Under upside and downside risks, policymakers and risk managers should devise measures to stabilize the stock market and minimize the risk impact on the global stock market. Investors need risk management skills to minimize losses. Our analysis will be valuable for investors in mitigating significant losses and developing strategies for long-term profitability. In particular, as shown in Figure 5, the dynamics of net connectedness of upside and downside risk networks are time-varying. Therefore, investors should continuously monitor changes in market risk and its cross-border connectivity and incorporate them into their portfolio optimization.

Author Contributions: All the authors contributed to the entire process of writing this paper. K.-H.C. and S.-M.Y. conceived the idea and designed the structure of this paper, K.-H.C. collected and examined the data and devised the methodology, K.-H.C. wrote the draft of Sections 1, 2 and 3, S.-M.Y. wrote Sections 4 and 5, and S.-M.Y. performed a final revision for the entire paper. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A5B8103268).

Data Availability Statement: All data that support the findings of this study were obtained from Infomax (https://news.einfomax.co.kr, accessed on 5 August 2022).

Conflicts of Interest: The authors declare no conflict of interest.

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