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Research Article

Time-Frequency Volatility Spillovers among Major International Financial Markets: Perspective from Global Extreme Events

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In the context of the gradual intensification of the Russia-Ukraine conflict and the continuous spread of the COVID-19 pandemic, this paper concentrates on the impact of global extreme events such as the COVID-19 pandemic and the Russia-Ukraine conflict on the risk spillovers among major international financial markets. First, to measure the impact of the extreme events the on the volatility spillovers among major international financial markets in the time-frequency domain, we combine the TVP-VAR-based connectedness method and BK frequency connectedness approach and focus on the total, directional, and net volatility spillovers. Second, the network visualization method is applied to outline the structural change in the risk contagion, paths, and roles among international financial markets during different periods of global extreme events. The empirical results indicate that the risk spillovers (total, directional, and net spillovers) among international financial markets and the roles played by each market in the process of risk contagion have changed significantly in different periods of global extreme events. Furthermore, volatility spillovers among international financial markets are driven mainly by the high-frequency component (short-term spillovers) during the full sample time. However, the effects of the extreme events also persist in the medium and long terms. Our findings may help understand the dynamics among international financial markets under extreme shocks and provide significant implications for portfolio managers, investors, and government agencies in times of extreme events.

1. Introduction

With the development of economic globalization, the integration process of financial markets is advancing. Although global economic integration has brought certain positive effects on international financial markets, speeding up the speed of information transmission, reducing the cost of market transactions, widening the access to financial assets, and improving the efficiency of global capital allocation [1]. However, financial activities between countries and markets penetrate and influence each other, and fluctuations in one financial market may affect the volatility of another financial market, that is, volatility spillover effects.

In recent years, we have witnessed several domestic and international financial extremes, such as the "International Financial Crisis" in 2008, the "European Debt Crisis" in 2011, the "China Stock Market Crash" in 2015, and the "China-US Trade Friction" in 2018. The shocks from these events have caused huge losses in the global financial markets. However, the international community is currently experiencing the double blow of the spread of the COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict. The uncertainty of global economic policies has risen sharply. It is difficult for financial markets to be immune to extreme events during a crisis period. Financial market fluctuations or risk transmission will be a more obvious and severe resonance phenomenon. An increasing number of scholars have also begun to pay attention to the contagion effect between financial markets, and there is a coordinated development trend [2]. Accurate understanding and effective identification of spillovers and related transmission mechanisms among financial markets are beneficial to mitigating financial risks across markets, countries, and regions. Relevant studies on information spillover effects are classified by Hong et al. [3] in terms of mean, volatility, and extreme risk, which are mean spillover effects [4, 5], volatility spillover effects [6, 7], and risk spillovers [8–10]. Tai [11] validates and measures the contagion of the 1997 Asian financial crisis from the stock market to the foreign exchange market. Bekaert et al. [12] analyze the contagion effect of the 2007 financial crisis. The study finds that the contagion effect was relatively lower in the US and global financial markets, while the contagion effect was more pronounced within countries. Trabelsi and Hmida [13] empirically test the market contagion effect in Greece and six European countries during the US subprime mortgage crisis. Wang and Zhang [14] find a significant increase in the spillover between the US and Chinese stock markets after the subprime mortgage crisis.

Extreme events hugely impact global financial markets, and the linkages between the markets also fluctuate [15]. Shah and Dar [16] examine extreme events during periods of market uncertainty; driven mainly by shorter time horizons, the level of cross-market spillovers is high. Several studies have demonstrated that the COVID-19 pandemic triggers changes in the degree of spillover between markets [17–23]. Aldawsari and Alnagada [24] find that the severity of COVID-19 affects the change in volatility of the US stock market. So et al. [25] construct a dynamic financial network based on stock returns, study the network linkages between the COVID-19 pandemic and the Hong Kong financial markets, and find a significant increase in network connectedness due to the outbreak. Zhang et al. [15] show that the COVID-19 pandemic impacts global financial markets, and the connectedness among markets appears to be differentiated. Bissoondoyal-Bheenick et al. [26] find a stronger association between stock returns and risk volatility as the duration of the outbreak increases. Pata [27] examines the relationship between the number of confirmed cases of the COVID-19 pandemic and the number of deaths in the G7 stock markets and finds that the COVID-19 pandemic harms all seven stock markets. Also, during the COVID-19 pandemic, Haddad et al. [28] and Kargar et al. [29] found severe liquidity problems in the bond market. Fasanya et al. [30] examined volatility spillovers between the COVID-19 pandemic and international exchange rate markets. Arif et al. [31] explored the time-frequency link between green and traditional financial markets during the COVID-19 pandemic; the results suggest that financial stability will be an essential factor in determining a smooth transition to green investments. Wang et al. [32], examining intermarket spillover effects, find that the largest intermarket fluctuations from the COVID-19 pandemic outbreak to the present occurred in March 2020 when the epidemic outbreak began. Naeem et al. [33] explore the volatility spillovers between markets during the COVID-19 pandemic and other economic periods of high uncertainty and the return spillover effects between sustainable and Islamic investments worldwide. Costa et al. [34] argue that the risk spillover in the US financial market increases with the epidemic outbreak. Due to the measures to prevent the spread of the epidemic, such as staying at home during the pandemic, which prevented all personnel from going out of the office during the closure, industrialized economic activities were at a standstill, causing the price of oil to fall sharply due to the shrinking global demand, with the average price of oil in the USA in 2020 at $39.68, setting a new 15-year record low with an annual decline of 20.64%. Umar et al. [35] focus on the impact of the Russia-Ukraine conflict on global financial markets and explore the dynamic linkages between important global stock and commodity markets through time-frequency analysis. Su et al. [36] examine the price linkages in energy markets under the role of the COVID-19 pandemic and the Russia-Ukraine conflict. Considering that Russia plays an essential role in the global energy market, the Russian-Ukrainian conflict may lead to risky changes in the commodity markets of oil and natural gas, the primary commodities it exports. Besides, the negative impact of extreme events such as the financial crisis on the world economy will lead to an upward trend in the price of gold. The main reason for the considerable risk response of oil, gold, and natural gas financial markets to extreme events is that oil is a highly volatile commodity [37]. Gold is a safe-haven asset [38] since investors usually use oil and gold as an asset portfolio to hedge their investment risk and achieve a reasonable allocation of their property. And natural gas is a clean and efficient fundamental energy source with high external dependence on the market supply and demand pattern [39]. Therefore, the gold, oil, and natural gas market are essential for the strategic decisions of investment groups, and the gold, oil, and natural gas market have a close connection with each country's stock market.

During this extreme event outbreak, how to accurately measure the changes among financial markets and identify and measure the spillover effects of time-frequency fluctuations among major international financial markets will help policymakers implement strategic plans as well as help investors and creditors analyze market behavior and minimize economic losses arising from the outbreak of extreme events. This study aims to examine how extreme events such as the spread of the global COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict would affect the dynamic spillovers of financial markets in six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as gold, oil, and natural gas to enrich the literature on risk contagion effects in financial markets. To this end, the time-varying connectedness and frequency connectedness among major international financial markets are explored based on the DY combined with the TVP-VAR model and the BK model.

The main contributions of this paper are as follows:

(1) In the context of the escalating Russia-Ukraine military conflict and the continuous spread of the global COVID-19 pandemic, we innovatively explore the impact of the multiple extreme events of the COVID-19 pandemic combined with the Russia-

Ukraine military conflict on the risk spillover of major international financial markets.

(2) We measure the volatility spillover effects of major international financial markets under the time-frequency model from static and dynamic perspectives, respectively; in the static spillover analysis, we innovatively classify all samples into three special periods (before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict) and deeply explore the impact of extreme events on the volatility spillover relationship major international financial markets.

(3) Based on the DY model, we innovatively combine the reason for employing the two approaches in this study. First, there are some shortcomings of using the rolling-window VAR-based connectedness method: (i) the size of the rolling window needs to be set arbitrarily, (ii) some observations are lost, and (iii) it is sensitive to the presence of outliers. Hence, by combining the TVP-VAR connectedness method and the BK method, we can explore the volatility spillovers among major international financial markets both in the time domain and frequency domain. Besides, we can also overcome the shortcomings of the rolling-window VAR-based BK connectedness method in many ways: (i) it overcomes the burden of the often arbitrarily chosen rolling-window size that could lead to very volatile or flattened parameters; (ii) it avoids the loss of valuable observations; and (iii) since it is based on a multivariate Kalman filter, it is less sensitive to the presence of outliers and thus adjusts immediately to events (Antonakakis et al. [40] and Gabauer and Gupta [41])). By combining the TVP-VAR model and BK model to explore the time-varying connectedness and frequency connectedness among major international financial markets both from the perspective of the time domain (time-varying) and frequency domain (short-term, medium-term, long-term) respectively, which helps to capture the dynamic evolution of risk contagion relationships among major global financial markets from a broader perspective, and thus effectively identify the risk contagion roles (risk exporters and risk receivers) played by each financial market at different times and frequencies.

The rest of the paper is organized as follows: the second part is the descriptive statistics of the sample data; the third part is the description of the research methodology; the fourth part presents and discusses the empirical results; the fifth part is the robustness check; and the last part draws the conclusions.

2. Sample Data

To explore the spillover effects of time-frequency volatility in major international financial markets based on the perspective of extreme events, the following stock indices are chosen: MSCI-France (France), MSCI-Germany (Germany), MSCI-Japan (Japan), MSCI-UK (United Kingdom), MSCI-USA (USA), and MSCI-China (China). Specifically, we choose MSCI-Japan and MSCI-China to represent Asian stock markets; MSCI-USA to represent the US stock markets; and MSCI-France, MSCI-Germany (Germany), and MSCI-UK to track the European market. Furthermore, the summation of the market capitalization of these countries accounts for more than 70% of the global stock market value [42]. We also include oil (WTI spot) and gold (XAU) as the most commonly traded commodities. The data is sourced from Wind Information on a daily frequency ranging from January 2019 to May 2022. To achieve the study aims, we split the sample data into three phases: before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, with two cutoff dates (23 January 2020 (according to Ashraf [43], our sample data starts from the day (23 January 2020) when the COVID-19 event caught the public eye and databases started reporting the COVID-19-related information) and 21 February 2022). The descriptive statistics for all the selected price returns are reported in Table 1, which exhibit serial correlation, non-normality of distribution, and stationarity of all series. The volatility series are calculated by the GARCH (1, 1) model since the GARCH (1, 1) model is widely used in estimating the volatility of variables [44, 45].

3. Methodology

3.1. TVP-VAR-Based Time-Varying Connectedness Approach. To explore the time-varying volatility spillovers among major global financial markets, we use the TVP-VAR methodology of Koop and Korobilis [46] and combine it with the DY method of [47]. This framework extends the original DY method by allowing the variances to vary over time via a Kalman filter estimation with forgetting factors. The Kalman filter algorithm is employed with forgetting factors chosen based on a Bayesian model selection, as introduced by Koop and Korobilis [46] and demonstrated in Antonakakis et al. [40].

Therefore, the TVP-VAR-based connectedness approach overcomes the shortcomings of using rolling window estimation in the VAR-based connectedness method [40, 41, 48, 49]. By doing so, this method improves the rolling-window VAR-based DY connectedness method in many ways: (i) it overcomes the burden of the often arbitrarily chosen rolling-window size that could lead to very volatile or flattened parameters; (ii) it avoids the loss of valuable observations; and (iii) since it is based on a multivariate Kalman filter, it is less sensitive to the presence of outliers and thus adjusts immediately to events (Antonakakis et al. [40] and Gabauer and Gupta [41]).

According to the Bayesian information criterion (BIC), the TVP-VAR (1) model can be written as follows:

Table 1: Descriptive statistics.

	Mean	Median	SD	Skew	Kurtosis	LB test	JB test	ADF
USA	0.0006	0.0009	0.0146	1.0581	18.8107	214.62***	8693.95***	8.2276***
UK	0.0001	0.0008	0.0148	1.0582	19.2151	38.826***	9136.44***	29.2390***
JPN	0.0001	0.0003	0.0116	0.0124	7.2957	23.051**	630.49***	28.5190***
GER	0.0001	0.0008	0.0156	0.8347	19.3398	27.478***	9217.30***	28.1852***
FRA	0.0003	0.0009	0.0156	1.0361	17.6927	28.629***	7522.44***	28.4149***
CHN	0.0000	0.0004	0.0164	0.2869	10.0911	22.803**	1729.29***	26.0386***
Oil	0.0010	0.0020	0.0277	0.6767	14.5075	83.656***	4587.00***	39.3932***
Gold	0.0004	0.0011	0.0097	0.7094	6.7434	22.631**	547.55***	26.8155***
Gas	0.0268	0.0200	0.0257	2.2037	10.5218	177.06***	2593.61***	8.5760***

Note. ***, **, and * denote the null hypothesis rejection at 1%, 5%, and 10%, respectively.

$$\begin{cases} Y_t = \beta_t Y_{t-1} + \varepsilon_t, \\ \varepsilon_t \sim N(0, S_t), \end{cases} \quad \begin{cases} \beta_t = \beta_{t-1} + v_t, \\ v_t \sim N(0, R_t), \end{cases} \quad Y_t = \sum_{j=0}^{z} A_{jt}\varepsilon_{t-j}, \tag{1}$$

where Y_t, Y_{t-1}, and ε_t are $N \times 1$ dimensional vectors. The parameters β_t, v_t, and S_t are $N \times N$ dimensional matrices, whereas R_t is an $N^2 \times N^2$ dimensional matrix.

After estimating the time-varying coefficients and variance-covariance matrices, we need to transform the TVP-VAR to a TVP-VMA using the Wold representation theorem in (1). Next, using the generalized impulse response functions (GIRFs) that represent the responses of all variables under a shock in variable i, the impact of a shock in variable i on all other variables can be estimated. Since we do not have a structural model, the differences between an h-step ahead forecast with variable i is shocked and not shocked should be computed. The differences can be accounted to the shock in variable i, which can be calculated as follows:

$$\begin{cases} GIRF_t\left(h, \delta_{j,t}, F_{t-1}\right) = E\left(Y_{t+h} \mid \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(Y_{t+h} \mid F_{t-1}\right), \\ \Psi^{g}_{j,t}(h) = \dfrac{A_{h,t} S_t \varepsilon_{j,t}}{\sqrt{S_{jj,t}}} \dfrac{\delta_{j,t}}{\sqrt{S_{jj,t}}}, \\ \delta_{j,t} = \sqrt{S_{jj,t}}, \\ \Psi^{g}_{j,t}(h) = S^{-1/2}_{jj,t} A_{h,t} S_t \varepsilon_{j,t}, \end{cases} \tag{2}$$

where $\delta_{j,t}$ represents the selection vector with one on the $j - th$ position and zero otherwise, F_{t-1} is the information set until $t-1$, $\Psi^{g}_{j,t}(h)$ represents the GIRFs of variable j, and h represents the forecast horizon. Afterward, we can compute the GFEVD that is interpreted as the variance share one variable has on other variables j. The h-step ahead GFEVD $\widetilde{\varphi}^{g}_{ij,t}(h)$ can be calculated as follows:

$$\begin{cases} \widetilde{\varphi}^{g}_{ij,t}(h) = \dfrac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}(h)}{\sum_{j=1}^{N} \sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}(h)}, \\ \sum_{j=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h) = 1, \\ \sum_{i,j=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h) = N. \end{cases} \tag{3}$$

Using the GFEVD, the total connectedness index can be obtained:

$$C^{g}_{t}(h) = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)} * 100. \tag{4}$$

First, we focus on the spillovers of variable i to all others j, representing the total directional spillovers to others:

$$C^{g}_{i\% \longrightarrow j,t}(h) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\varphi}^{g}_{ji,t}(h)}{\sum_{j=1}^{N} \widetilde{\varphi}^{g}_{ji,t}(h)} * 100. \tag{5}$$

Second, we compute the spillovers of all variables j to variable i, representing the total directional spillovers from others:

$$C^{g}_{i\% \longleftarrow j,t}(h) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)}{\sum_{i=1}^{N} \widetilde{\varphi}^{g}_{ij,t}(h)} * 100. \tag{6}$$

Third, we subtract the total directional spillovers to others and total directional spillovers from others to get the net total directional spillovers:

$$C^{g}_{i,t} = C^{g}_{i\% \longrightarrow j,t}(h) - C^{g}_{i\% \longleftarrow j,t}(h). \tag{7}$$

If $C^{g}_{i,t} > 0$, it means that variable i influences the network more than being influenced by it. By contrast, if $C^{g}_{i,t} < 0$, it means that variable i is driven by the network.

3.2. BK Frequency Connectedness Approach. To examine the volatility spillovers among the major global financial markets in the frequency domain (long-, medium-, or short-term), we adopt the spectral representation of the variance decomposition method based on frequency responses to shocks following Baruník and Křehlik [50].

The scaled generalized FEVD on a frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$, and $a < b$ can be defined as follows:

$$\begin{cases} \left(\widetilde{\theta}_d\right)_{j,k} = (\theta_d)_{j,k} / \sum_k (\theta_\infty)_{j,k}, \\ (\theta_d)_{j,k} = \dfrac{1}{2\pi} \displaystyle\int_d \Gamma_j(\omega)(f(\omega))_{j,k} d\omega, \\ (\theta_\infty)_{j,k} = \sum_{d_s} \left(\theta_{d_s}\right)_{j,k}, \end{cases} \tag{8}$$

where $(\theta_d)_{j,k}$ denotes generalized variance decompositions on frequency band d, $\Gamma_j(\omega)$ denotes frequency share of the variance of the $j-th$ variable, $(f(\omega))_{j,k}$ represents the portion of the spectrum of the $j-th$ variable at frequency ω due to shocks to the $k-th$ variable, and d_s denotes an interval on the real line from the set of intervals D.

The frequency connectedness on the frequency band d can be obtained by

$$C_d^F = 100 \times \left(\frac{\sum \widetilde{\theta}_d}{\sum \widetilde{\theta}_\infty} - \frac{Tr\{\widetilde{\theta}_d\}}{\sum \widetilde{\theta}_\infty} \right), \tag{9}$$

where $Tr(\cdot)$ is the trace operator. This frequency connectedness framework allows us to identify the short-, medium-, and long-term volatility spillovers among the major global financial markets when setting frequency band d to different intervals.

4. Empirical Results

4.1. Static Analysis of Volatility Spillovers among Major International Financial Markets

4.1.1. Static Analysis of Spillover Effects under Different Stages

(1) Static Volatility Spillovers in the Time Domain. In this section, we first test the time-frequency volatility spillovers among the major international financial markets from the static perspective. About the parameters in the TVP-VAR-based connectedness and BK model, we keep the same forecasting horizon of $h = 10$ as in Diebold and Yilmaz [47]. The specific test results are shown in Table 2. The directional spillover index contains two categories, in which “From” represents the extent to which a financial market is influenced by other markets, denoting the inward inhalation spillover effect, and “To” represents the extent to which a financial market influences other markets, denoting the outward export spillover effect. According to the static analysis of time-domain volatility spillover effects in Table 2, from the perspective of the main international financial market variables as a whole, the total spillover index (TCI) represents the spillover effect of all other variables on one variable before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict at 55.63, 58.23, and 69.70, respectively, indicating that in addition to the effects of the market variables themselves, the 55.63% of the risk in financial markets before the COVID-19 pandemic comes from the spillover effect of correlated volatility between markets, while it rises to 58.23% and 69.70% during the COVID-19 pandemic and during the Russia-Ukraine conflict, respectively, indicating that COVID-19 and the Russia-Ukraine conflict were able to increase the linkages between gold, oil, natural gas, and the stock markets of six countries by 4.47% (2.60/58.23) and 20.19% (14.07/69.70), respectively.

From the perspective of specific variables, before the outbreak of the COVID-19 pandemic, the European debt crisis became the main factor plaguing the world economic development as the haze of the US subprime mortgage crisis had not yet wholly dissipated, with the USA (87.11%) and the European triumvirate of France (105.82%), the UK (93.48%), and Germany (91.45%), being the larger spillover propagators, which indicates that economies such as Europe and the USA have a substantial global influence in terms of extreme event outbreaks and stock market volatility. Furthermore, with the outbreak of extreme events such as the COVID-19 pandemic and the Russia-Ukraine military conflict, in order to cope with the liquidity crisis and avoid the financial crisis, on 15 March 2020, the Federal Reserve announced zero interest rates and launched a quantitative easing program of $700 billion and other countermeasures; the value of the contribution of spillover from the United States weakened, while financial markets such as Japan and Germany were unable to gain an interest rate advantage and their spillover influence increased. Affected by the conflict between Russia and Ukraine, gold, oil, and natural gas markets have not only shifted more spillovers but also have significantly been influenced by other markets. Where “Net” represents the “To” of each financial market as the result of subtracting the “From” of each financial market, it can be found that the natural gas market has become the recipient of the net spillover effect of volatility more and more affected by the COVID-19 pandemic. In contrast, the conflict between Russia and Ukraine has become increasingly tense. The global risk aversion has pushed the gold price higher and remained high. The spillover effect of the gold market rises from 12.39% during the COVID-19 pandemic to 91.66% during the conflict between Russia and Ukraine outbreak, making the gold market change from a net recipient of spillover effects to a spreader. In general, the static analysis of the time-domain volatility spillover effect found a strong interaction between the major international financial markets, which triggered a specific spillover effect after the outbreak of extreme events, providing investors with various investment strategies and portfolio schemes to avoid unexpected events.

(2) Static Volatility Spillovers in the Frequency Domain. In this study, the overall volatility spillover effect is analyzed separately according to different frequency domains, dividing the frequency bands into low, medium, and high frequencies and decomposing them into short-term frequency domain (1–5 days), medium-term frequency domain (5–20 days), and long-term frequency domain (more than 20 days) correspondingly. First, we focus on the volatility spillover effect of international major financial markets in the short-term

Table 2: Static volatility spillovers in the time domain.

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	32.36	15.69	2.89	13.64	18.01	11.81	3.33	1.17	1.11	67.64
UK	15.08	29.85	0.59	18.75	20.87	12.24	0.95	0.34	1.34	70.15
JPN	16.55	10.86	35.26	8.68	11.86	6.86	4.76	1.56	3.62	64.74
GER	12.93	19.25	0.59	27.21	24.51	11.04	1.37	0.55	2.55	72.79
FRA	15.19	19.75	0.82	22.76	27.28	10.48	1.19	0.62	1.91	72.72
CHN	15.53	16.18	2.76	13.43	15.38	34.43	0.53	0.87	0.88	65.57
Gold	3.63	4.81	1.54	6.57	6.16	4.87	69.06	1.49	1.87	30.94
Oil	4.11	3.34	1.61	3.38	4.47	2.71	3.92	74.24	2.22	25.76
Gas	4.09	3.61	5.59	4.25	4.57	2.43	3.64	2.21	69.62	30.38
To	87.11	93.48	16.4	91.45	105.82	62.43	19.7	8.81	15.5	500.68
Net	19.46	23.33	−48.35	18.67	33.1	−3.14	−11.24	−16.95	−14.88	TCI = 55.63
Panel 1. (b) During the COVID-19 period										
USA	31.15	16	6.12	15.71	16.18	8.71	1	4.35	0.79	68.85
UK	13.42	24.95	5.8	19.85	21.05	7.47	1.39	4.9	1.18	75.05
JPN	13.55	13.3	28.32	15.29	14.77	7.06	2.75	3.63	1.33	71.68
GER	13.09	19.56	5.73	24.64	22.22	7.4	2.21	3.96	1.19	75.36
FRA	13.25	20.6	5.54	22.07	24.51	7.14	1.58	4.25	1.07	75.49
CHN	10.83	10.71	7.9	10.86	10.44	40.51	1.45	4.96	2.35	59.49
GOLD	2.72	4.04	3.28	6.42	5.11	2.03	73.67	1.55	1.18	26.33
Oil	7.48	9.44	4.61	7.78	8.54	6.3	1.08	53.38	1.39	46.62
Gas	2.74	4.09	3.26	3.84	3.56	4.63	0.93	2.18	74.78	25.22
To	77.07	97.75	42.24	101.79	101.86	50.74	12.39	29.77	10.48	524.09
Net	8.22	22.7	−29.44	26.43	26.38	−8.75	−13.94	−16.85	−14.74	TCI = 58.23
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	29.67	10.67	2.37	13.85	13.97	3.54	13.46	9.55	2.93	70.33
UK	11.5	20.33	7.56	17.86	18.45	3.46	10.71	6.61	3.53	79.67
JPN	12.8	10.59	22.71	12.16	11.88	7.83	7.47	6.53	8.03	77.29
GER	10.45	15.13	4.51	20.28	20.55	2.56	14.08	8.86	3.58	79.72
FRA	10.46	15.31	4.58	20.19	21.09	2.6	14.04	8.53	3.2	78.91
CHN	9.35	2.31	4.36	2.67	2.93	64.82	2.8	2.75	8.01	35.18
Gold	9.26	8.08	3.2	14.23	14.72	3	27.31	16.78	3.41	72.69
Oil	7.95	5.64	5.98	10.81	10.85	7.49	19.56	25.36	6.37	74.64
Gas	7.53	4.29	6.27	8.79	8.41	9.24	9.55	4.81	41.11	58.89
To	79.31	72.03	38.82	100.55	101.75	39.73	91.66	64.41	39.05	627.32
Net	8.98	−7.64	−38.47	20.83	22.85	4.55	18.97	−10.23	−19.84	TCI = 69.70

Note. (i) The TCIs (TCI = 55.63, 58.23, 69.70) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

frequency domain and measure the relevant static volatility index. The specific test results are shown in Table 3. From the overall level of volatility spillover effect in the short-term frequency domain, the total spillover index (TCI) is 41.78, 48.05, and 62.67 before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, respectively, indicating that there is a certain upward fluctuation trend in the volatility spillover effects of extreme events on major international financial markets in the short-term frequency domain. In specific analysis, it seems that before the COVID-19 pandemic, the spillover propagation contribution levels of the UK (69.56%), Germany (70.03%), and France (80.26%) were higher. When the extreme events broke out, they all showed a fluctuating trend of lower contribution values in the short-term frequency domain. The gold market, oil market, and natural gas market quickly become risk propagators for other market affiliates in the short-term frequency domain after the outbreak of extreme events; especially after the outbreak of the Russia-Ukraine military conflict, the spillover index of the gold market increases from 10.13 to 52.66, a rise of 80.76%; and the spillover index of the oil market increases from 25.42 to 67.59, a rise of 62.39%. The premium index of the natural gas market rose from 8.54 to 45.32, a rise of 81.16%.

When examining the financial market volatility spillover effect from the frequency domain perspective, there is a certain degree of cross-sectional correlation between the segment domains of medium, high, and low frequencies. Thus, medium frequency is examined as a transitional frequency band. Table 4 shows the volatility spillover effect of international major financial markets in the medium-term frequency domain. According to the results of the relevant static spillover indices, it can be seen that: from the overall perspective of the volatility spillover effect in the medium-term frequency domain, the total spillover index (TCI) was 7.01, 7.93, and 12.56 before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, respectively, indicating that as the outbreak of extreme events severity increases, the more pronounced the volatility spillover effect among major international financial markets. Among them, the USA, as the world's largest economy, had a positive net spillover index

Table 3: Static volatility spillovers in the frequency domain (short-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	24.47	11.77	2.17	10.97	14.33	8.8	2.49	0.8	0.8	52.12
UK	10.76	22.46	0.39	14.11	15.56	8.53	0.79	0.22	0.97	51.34
JPN	14.08	9.34	30.5	7.66	10.74	4.85	3.71	1.22	3.41	55.01
GER	8.83	13.67	0.4	20.56	18.09	7.42	1.17	0.39	2.03	52
FRA	11.26	14.98	0.67	18.13	21.56	7.62	1	0.45	1.53	55.64
CHN	10.34	10.7	1.97	9.02	10.24	24.1	0.42	0.61	0.52	43.81
Gold	2.83	3.71	1.25	5.07	4.78	3.84	60.18	1.23	1.59	24.31
Oil	3.28	2.66	1.06	2.23	3.31	2.03	3.33	66.33	1.7	19.6
Gas	2.92	2.76	4.29	2.83	3.2	1.68	2.75	1.79	59.52	22.22
To	64.32	69.56	12.2	70.03	80.26	44.77	15.65	6.72	12.54	376.05
Net	12.2	18.22	−42.81	18.03	24.62	0.96	−8.66	−12.88	−9.68	TCI = 41.78
Panel 1. (b) During the COVID-19 period										
USA	27.32	13.89	5.49	13.53	13.89	7.56	0.84	4.1	0.73	60.02
UK	11.25	20.75	4.75	16.38	17.31	6.12	1.14	4.16	0.94	62.04
JPN	10.46	10.19	21.96	11.62	11.16	5.42	2.11	2.67	0.95	54.57
GER	10.95	16.25	4.73	20.33	18.26	6.08	1.83	3.36	0.97	62.42
FRA	11.03	17.09	4.54	18.22	20.16	5.85	1.35	3.61	0.85	62.53
CHN	8.98	9.01	6.6	8.95	8.58	33.04	1.17	4.35	1.96	49.6
Gold	2.2	3.15	2.61	4.97	3.91	1.57	59.42	1.16	0.92	20.49
Oil	5.89	7.72	3.94	6.19	6.82	5.25	0.89	46.21	1.22	37.92
Gas	2.54	3.75	3.01	3.47	3.19	4.03	0.82	2.01	63.58	22.82
To	63.3	81.05	35.67	83.32	83.11	41.88	10.13	25.42	8.54	432.43
Net	3.27	19	−18.9	20.9	20.58	−7.72	−10.36	−12.5	−14.28	TCI = 48.05
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	16.09	5	11.63	3.84	4.98	15.9	3.47	6.38	4.27	55.47
UK	7.1	6.68	8.8	6.08	6.52	11.65	4.7	5.42	6.13	56.4
JPN	10.54	4.75	13.73	5.7	6.6	14.46	5.86	9.55	4.27	61.73
GER	5.37	6.39	12.33	12.25	10.58	7.3	8.27	6.73	5.81	62.78
FRA	5.64	6.36	11.69	11.56	11	8.73	8.04	7.05	4.89	63.96
CHN	13.06	5.86	8.41	4.02	5.47	24.56	4.16	9.94	4.97	55.89
Gold	7.4	3.87	11.95	7.86	7.38	7.47	14.97	13.8	7.32	67.04
Oil	8.3	3.27	9.25	6.41	6.22	7.94	11.98	22.12	7.65	61.04
Gas	12.7	4.74	20.72	5.1	6.82	14.73	6.18	8.73	13.72	79.73
To	70.11	40.25	94.79	50.57	54.58	88.18	52.66	67.59	45.32	564.04
Net	14.64	−16.16	33.06	−12.21	−9.38	32.29	−14.39	6.56	−34.41	TCI = 62.67

Note. (i) The TCIs (TCI = 41.78, 48.05, 62.67) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

Table 4: Static volatility spillovers in the frequency domain (medium-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	2.48	1.22	0.6	1.36	1.4	0.72	0.13	0.39	0.11	5.94
UK	1.65	2.65	0.72	2.22	2.4	0.81	0.19	0.6	0.19	8.78
JPN	2.19	2.25	3.55	2.63	2.57	1.11	0.43	0.6	0.22	12.01
GER	1.61	2.12	0.67	2.75	2.54	0.82	0.29	0.5	0.17	8.72
FRA	1.63	2.24	0.68	2.47	2.8	0.79	0.17	0.53	0.18	8.7
CHN	1.19	1.02	0.84	1.34	1.22	4.82	0.26	0.56	0.32	6.75
Gold	0.36	0.68	0.46	1.11	0.92	0.32	9.1	0.24	0.17	4.25
Oil	1.01	1.35	0.68	1.23	1.36	0.81	0.13	3.75	0.23	6.8
Gas	0.08	0.1	0.15	0.14	0.11	0.34	0.09	0.1	7.99	1.12
To	9.71	10.99	4.81	12.51	12.51	5.72	1.7	3.52	1.6	63.07
Net	3.78	2.21	−7.2	3.78	3.81	−1.03	−2.55	−3.28	0.47	TCI = 7.01

Table 4: Continued.

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (b) During the COVID-19 period										
USA	4.15	2.69	0.13	2.03	2.73	2.24	0.08	0.08	0.21	10.18
UK	2.72	4.44	0.06	2.52	2.97	2.33	0.03	0.04	0.19	10.87
JPN	0.98	1.22	2.2	1	0.94	1.85	0.02	0.06	0.13	6.21
GER	2.48	3.39	0.08	3.88	3.81	2.31	0.03	0.05	0.24	12.39
FRA	2.41	2.98	0.05	2.75	3.48	1.93	0.03	0.05	0.24	10.44
CHN	3.27	3.43	0.26	2.52	2.97	6.06	0.06	0.09	0.11	12.72
Gold	0.47	0.71	0.08	1.05	0.83	0.7	5.23	0.06	0.22	4.12
Oil	0.57	0.33	0.15	0.27	0.36	0.14	0.23	5.12	0.2	2.24
Gas	0.24	0.3	0.18	0.43	0.33	0.36	0.05	0.27	7.53	2.16
To	13.15	15.05	0.99	12.57	14.94	11.85	0.53	0.71	1.55	71.33
Net	2.97	4.18	−5.22	0.17	4.5	−0.88	−3.59	−1.53	−0.61	TCI = 7.93
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	2.67	3.51	2.66	3.2	1.68	1.49	0.77	0.56	1.06	14.93
UK	2.03	5.2	2.9	4.76	2.78	1.45	1.28	0.26	2.45	17.91
JPN	1.74	3.13	2.83	3.12	1.61	1.1	0.74	0.82	0.93	13.19
GER	1.42	3.51	3.17	4.53	2.31	1.39	1.25	0.32	1.42	14.79
FRA	1.5	3.42	3.04	4.08	2.2	1.23	1.08	0.31	1.43	16.08
CHN	2.13	1.99	2.24	1.6	0.97	3.48	0.52	0.5	0.56	10.51
Gold	0.64	1.89	1.74	3.54	1.74	1.3	2.21	0.67	1.09	12.61
Oil	0.83	1.22	1.32	2.43	1.31	1.82	1.74	2.05	0.58	11.25
Gas	0.12	0.38	0.17	0.38	0.24	0.09	0.23	0.14	0.62	1.75
To	10.41	19.06	17.23	23.11	12.64	9.86	7.6	3.59	9.5	113.01
Net	−4.52	1.15	4.03	8.32	−3.44	−0.64	−5	−7.66	7.76	TCI = 12.56

Note. (i) The TCIs (TCI = 7.01, 7.93, 12.56) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

before and during the COVID-19 pandemic, while when the Russia-Ukraine military conflict breaks out, the net value was −4.52, and the US financial market switches from being the transmitter of spillover effects to being the receiver of risk impacts, probably because the country's active response policy attenuates the degree of risk spillover. From the medium-frequency volatility spillover effect, it can be seen that with the outbreak of extreme events, both the spillover index and spillover of the gold, oil, and natural gas markets gradually show an increase, indicating that the three markets play an essential role in the overall international market risk contagion when faced with extreme events.

Table 5 shows the measurement results of the volatility spillover effect of major international financial markets in the long-term frequency domain. From the overall view of the volatility spillover effect in the long-term frequency domain, the total spillover index (TCI) is 3.54, 5.39, and 6.25 before the occurrence of COVID-19, during the epidemic, and during the outbreak of the Russia-Ukraine conflict, respectively, indicating that the degree of extreme events is positively correlated with the volatility spillover effect between financial markets. From the net spillover index, it seems that the net values of major international financial markets show differential changes. The results show that few markets can affect only other markets or receive only other markets at the risk of extreme events, indicating that most markets are switching roles between transmitters and receivers. It is difficult to be alone in the impact of extreme events, as markets are interconnected as a whole.

Overall, when extreme events break out, comparing the period before the COVID-19 pandemic and the period of double overlap between the epidemic and the outbreak of the Russia-Ukraine military conflict, the short-, medium-, and long-term total spillover indices of the frequency spillover effect increased by 33.33%, 44.19%, and 43.36%, respectively, which indicates that the change in the total impact on the original time series affected by extreme events is to some extent dominated by long-term spillover factors, which suggests that the variation of the total effect in the original time series affected by extreme events plays a volatile role in all frequency domains. From the directional spillover index, it seems that the financial markets of the USA, UK, Germany, and France have higher volatility spillovers in different frequency bands. The reasons for this are that the strong economic power and sound financial policy regimes in Europe and the USA have a profound impact on international financial markets. However, in the short term, it appears that the US market is a volatility transmitter with a positive net volatility spillover effect, while with the broadening of the event scale, the USA gradually begins to become a receiver of volatility under the influence of extreme events. In the long run, the USA maintains better risk-resilient stability under the double blow of the COVID-19 pandemic and the Russian-Ukrainian military conflict with a net value of 2.86. In the time-series volatility spillover effect test, the Japanese market shows a significant volatility net receiver characteristic. From the perspective of the frequency domain, it is found that in the short term, under the double blow of the COVID-19 pandemic and the Russian-Ukrainian military conflict, Japan's net volatility spillover index turns positive. It shows that the Japanese market will change from a receiver of volatility risk to a risk spreader in a sufficiently long period. The spillover effects of the Japanese market will remain relatively stable during the outbreak of extreme events, similar to the double superposition of extreme events such as the COVID-19 pandemic and the conflict between Russia and Ukraine in the

Table 5: Static volatility spillovers in the frequency domain (long-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	1.23	0.61	0.3	0.69	0.73	0.36	0.08	0.19	0.05	3.01
UK	0.82	1.33	0.36	1.13	1.23	0.41	0.09	0.3	0.09	4.44
JPN	1.11	1.15	1.79	1.35	1.34	0.56	0.21	0.3	0.11	6.13
GER	0.8	1.06	0.34	1.39	1.3	0.41	0.15	0.25	0.08	4.39
FRA	0.82	1.13	0.34	1.25	1.44	0.4	0.09	0.26	0.09	4.37
CHN	0.6	0.5	0.42	0.67	0.62	2.43	0.14	0.27	0.16	3.37
Gold	0.18	0.34	0.23	0.57	0.48	0.16	4.57	0.12	0.09	2.17
Oil	0.51	0.68	0.34	0.64	0.72	0.41	0.07	1.85	0.11	3.48
Gas	0.03	0.04	0.06	0.07	0.07	0.16	0.04	0.04	3.97	0.52
To	4.86	5.51	2.39	6.38	6.49	2.87	0.87	1.72	0.79	31.87
Net	1.85	1.06	−3.74	1.99	2.12	−0.5	−1.3	−1.75	0.27	TCI = 3.54
Panel 1. (b) During the COVID-19 period										
USA	1.36	2.21	2.76	1.11	1.22	0.2	0.3	0.11	1.57	9.48
UK	1.04	3.27	2.91	1.53	1.9	0.31	0.42	0.18	2.24	10.54
JPN	0.74	1.58	2.61	0.92	0.98	0.16	0.26	0.19	1.09	5.92
GER	0.29	1.14	1.42	0.95	0.87	0.25	0.1	0.08	0.55	4.69
FRA	0.42	1.35	1.74	0.95	1	0.23	0.12	0.06	0.89	5.76
CHN	1.12	1.26	0.57	0.37	0.58	0.58	0.17	0.09	0.82	4.99
Gold	0.07	0.23	0.23	0.64	0.4	0.28	0.64	0.51	0.18	2.53
Oil	0.29	0.07	0.11	0.12	0.06	0.25	0.82	1.19	0.63	2.36
Gas	0.18	0.36	0.76	0.07	0.22	0.12	0.46	0.1	1.9	2.28
To	4.15	8.19	10.5	5.73	6.23	1.8	2.65	1.32	7.97	48.55
Net	−5.33	−2.35	4.59	1.03	0.47	−3.19	0.12	−1.04	5.69	TCI = 5.39
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	2.59	1.69	0.15	1.27	1.69	1.4	0.05	0.08	0.16	6.49
UK	1.86	2.81	0.09	1.93	2.25	1.66	0.03	0.05	0.2	8.08
JPN	0.77	0.92	1.16	0.87	0.87	1.29	0.02	0.04	0.13	4.93
GER	1.69	2.2	0.1	2.62	2.65	1.6	0.02	0.06	0.22	8.54
FRA	1.58	1.86	0.04	1.73	2.17	1.27	0.02	0.04	0.17	6.71
CHN	2.21	2.31	0.25	2.06	2.38	3.72	0.05	0.1	0.22	9.57
Gold	0.34	0.49	0.15	0.98	0.83	0.52	2.58	0.08	0.19	3.57
Oil	0.49	0.38	0.33	0.96	0.94	0.39	0.14	2.7	0.39	4.03
Gas	0.4	0.46	0.34	1.19	1.08	0.58	0.04	0.24	4.23	4.35
To	9.35	10.32	1.45	11.01	12.69	8.72	0.37	0.68	1.68	56.26
Net	2.86	2.24	−3.47	2.47	5.98	−0.85	−3.2	−3.34	−2.67	TCI = 6.25

Note. (i) The TCIs (TCI = 3.54, 5.39, 6.25) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

time series volatility spillover. Net shows a negative state of the net receiver. Convergence: the gold market, oil market, and natural gas market all show a certain degree of short-term volatility under the impact of extreme events, while the long-term level of the gold market, oil market, and natural gas market is more vulnerable to risk spillovers from other financial markets during extreme events, with net values of −3.2, −3.34, and −2.67, respectively, becoming net receivers of risk spillovers.

4.1.2. Network Visualization Analysis under Different Stages. Furthermore, this paper examines the volatility spillover effects of the financial markets of six countries, including Germany, the United States, the United Kingdom, Japan, France, and China, as well as gold, oil, and natural gas, under the influence of extreme events. Specifically, the net pairwise spillover networks of major international financial markets are constructed to outline the structural change in the risk contagion, paths, and roles among international financial markets during extreme global events. The nodes in the network represent each financial market, and the edges between the nodes denote the volatility spillovers between financial markets. The strength of the volatility spillover effect is indicated by the thickness of the line and the direction of the arrow to describe the direction of risk transmission between different markets, where the more significant the radius and darker the color of the node, the stronger the ability of the corresponding market to influence other financial markets, and the more risk is transmitted externally. It can be seen from Figure 1 that in the time-domain spillover network, France with the largest size and the darker color of the node, followed by the United States, the United Kingdom, and Germany, and the degree of volatility spillover in the United States and the United Kingdom is also at a high level, indicating that the center of the volatility spillover network of major international financial markets is concentrated in Europe and the United States, the reason for which may be due to the geographical location, the degree of economic development, and the degree of perfection of financial policies. Asian financial markets such as Japan and China mainly acted as recipients

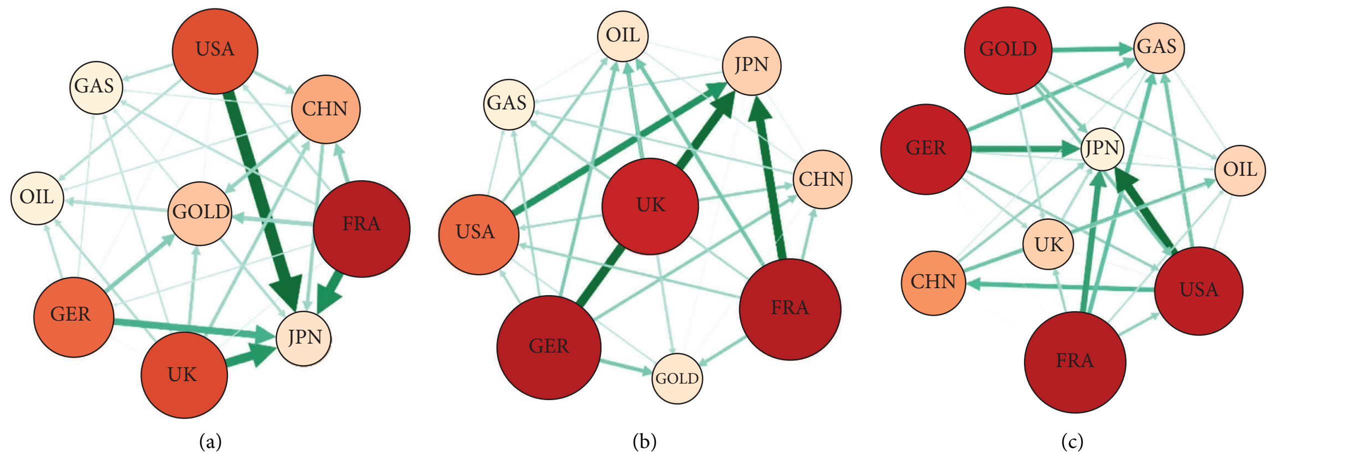


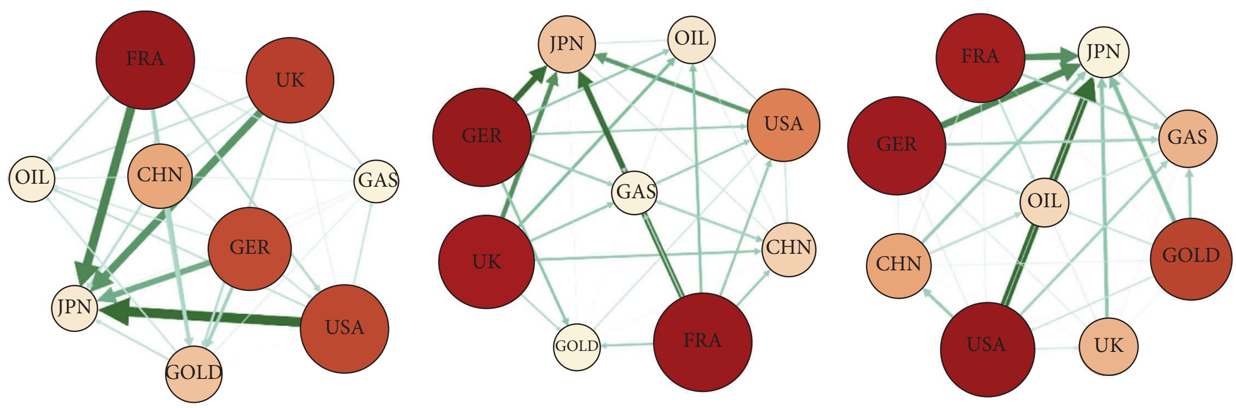
Figure 1: Time-domain volatility spillover network: (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

of volatility risks before the COVID-19 pandemic, while during the COVID-19 pandemic, risks were dispersed to other markets such as gold, oil, natural gas, and so on. With the outbreak of the Russia-Ukraine military conflict, the volatility spillover index of the gold market rose. The reason for this may be that the subconscious reaction of the market triggers a strong risk aversion due to the Russian-Ukrainian conflict, and the gold market shows a sharp surge higher, becoming a transmitter from the receiver of the risk spillover, which in turn have an impact on the risk volatility of other markets.

The changes in spillover network structure under different frequency bands are shown in Figures 2–4. It seems that the USA, the UK, France, Germany, and other developed countries in Occident play a dominant role in most of the time and frequency domains. The risk spillover propagation from these countries' financial markets is stronger even under the extreme events of the COVID-19 pandemic and the outbreak of the Russian-Ukrainian military conflict. Only the intensity of risk spillovers from the UK market to other markets weakened after the outbreak of the Russian-Ukrainian military conflict, probably because the Russian-Ukrainian conflict has a more significant impact on the exchange rate of the euro economy, which also affects the currency movements of the British pound, thus making the UK a risk receiver. From the short-term frequency domain volatility spillover effect, the gold market quickly becomes a risk propagator in the short term under the double impact of the Russian-Ukrainian military conflict and the COVID-19 pandemic. The volatility spillover index is significantly higher, and with the window period extension, the gold market's risk spillover capacity is further enhanced. After the outbreak of the conflict, European and American countries quickly make sanctions against Russia, and thus, there was a need for the Russian energy market to turn to the East. In the long run, Japan and China appear to have significantly higher volatility spillover indices after being affected by the overlapping Russian-Ukrainian military conflict and the COVID-19 pandemic, with Japan showing the propagation of risk to the natural gas market and China spreading risk to the oil and natural gas markets.

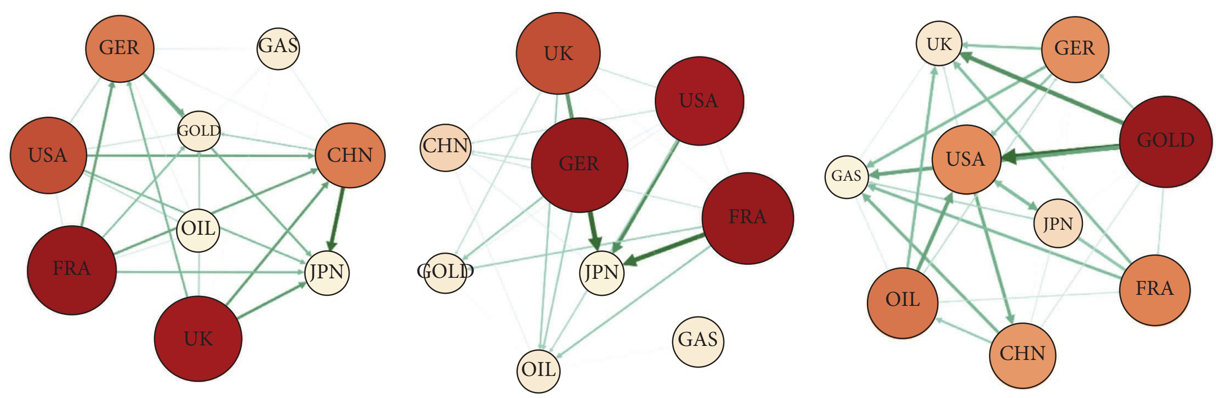
4.2. Dynamic Analysis of Volatility Spillovers among Major International Financial Markets. The static analysis of time-frequency volatility spillover effects described in the previous section refers to the analysis results measured under different stages of extreme global events. However, only from the perspective of static spillover analysis to analyze the changes in volatility spillover characteristics among major international financial markets by dividing three stages of the extreme global events cannot comprehensively explain the whole sample period. Consequently, to capture the secular and cyclical movements in the volatility spillovers, this section further analyzes the dynamic characteristics of time-frequency volatility in major international financial markets. The dynamic fluctuations of the relevant volatility spillover indices (TCI and net) are plotted considering the time domain. Besides, the dynamic fluctuations in the frequency domain (short-, medium-, and long-term) are also presented separately.

4.2.1. Total Spillover Analysis. Figure 5 shows the dynamic distribution of the total spillover effects in major international financial markets in the time and frequency domains (short-, medium-, and long-term). In general, the total spillover index is in a state of flat volatility before the COVID-19 pandemic. When the COVID-19 pandemic broke out in January 2020, the total spillover index showed an upward trend, indicating that the epidemic risk significantly impacted the global economic and financial markets. Such risk had strong intermarket linkages and increased



(a) (b) (c)

FIGURE 2: Frequency-domain volatility spillover network (short-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the short-term net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.



(a) (b) (c)

FIGURE 3: Frequency-domain volatility spillover network (medium-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the medium-term net pairwise directional volatility spillovers among theeight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

channels of risk spillover. The total spillover index reached its peak during the full period. After that, as countries become more experienced in facing the COVID-19 pandemic, the control strategy of the epidemic is gradually sound, and the relevant economic and regulatory policies operate effectively, the total spillover index shows a slow decline in the trend. The outbreak of the Russia-Ukraine conflict in February 2022 caused the total spillover index, which had fallen to its lowest point in terms of volatility, to rise again, and the war caused a global shortage of energy and rising costs, which affected the economic development of the major international financial markets. From the frequency domain distribution, it seems that all frequency domains show the same trend characteristics as the time-domain dynamic distribution at the critical points of the COVID-19 pandemic and the outbreak of the Russia-Ukraine conflict. The short-term level has the greatest volatility, and the long-term volatility is still pronounced, indicating that the impact of the COVID-19 pandemic and the outbreak of the Russia-Ukraine conflict lasted for a more extended period and that the shock was not the expected range of risk factors; thus, the total spillover index generates a larger volatility response to the shock of long-term structural factors.

4.2.2. Net Spillover Analysis. The net spillover index is the result calculated by subtracting the "To" of each financial market as the result of and the "From" of each financial

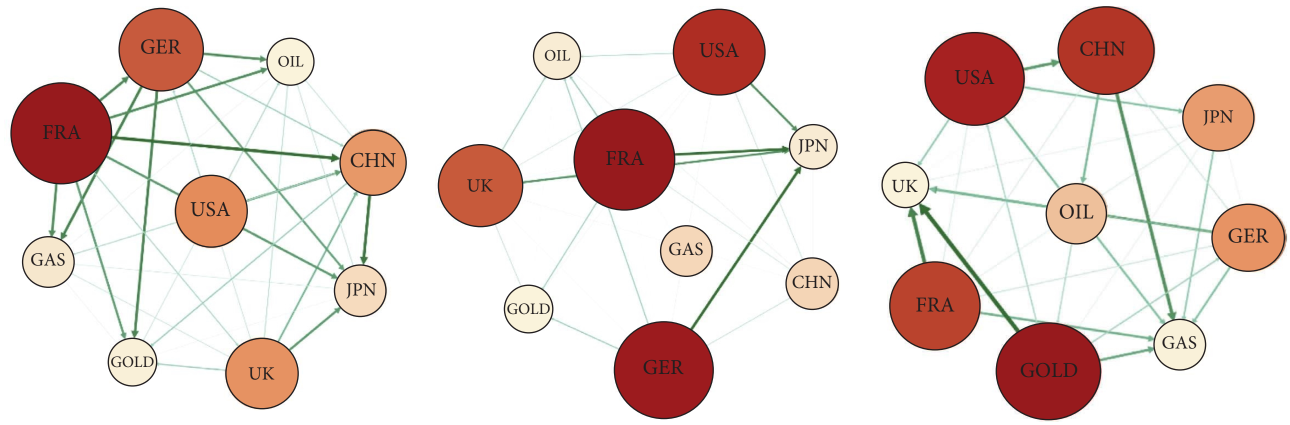
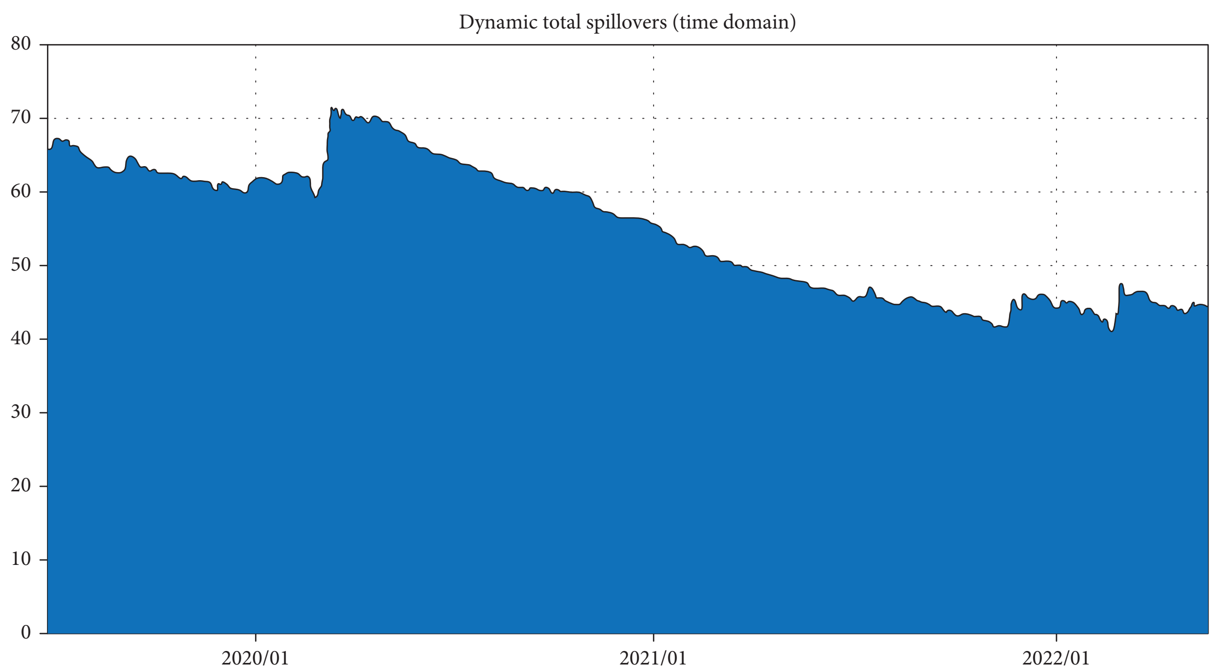
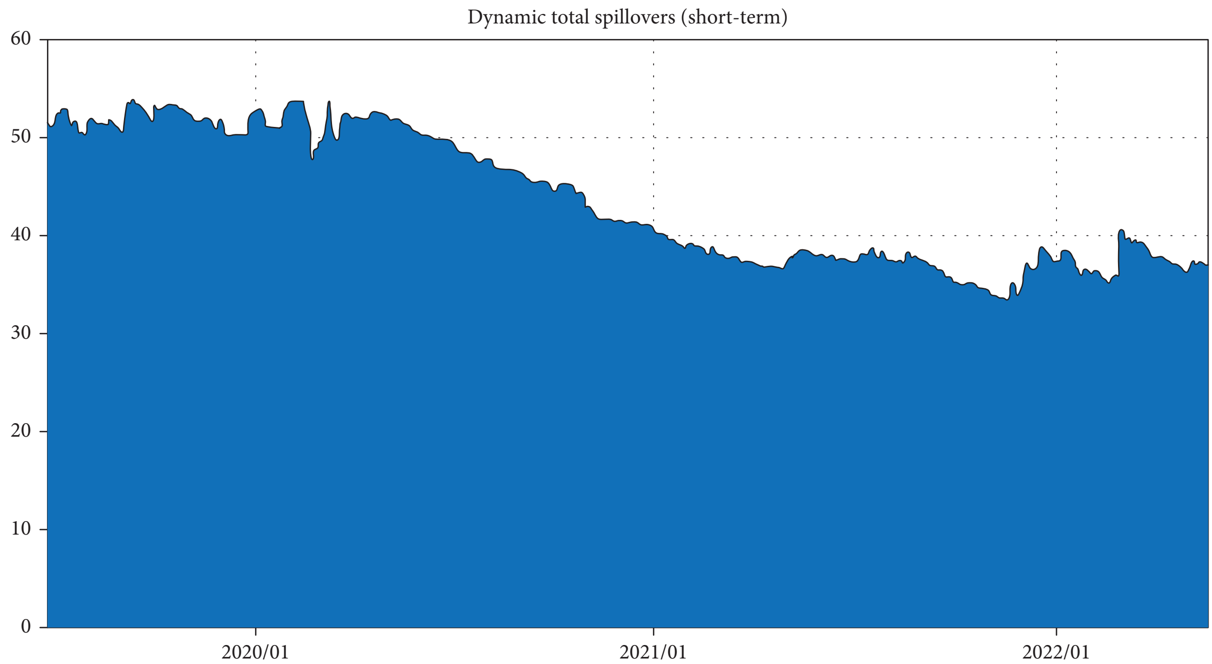


Figure 4: Frequency-domain volatility spillover network (long-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the long-term net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

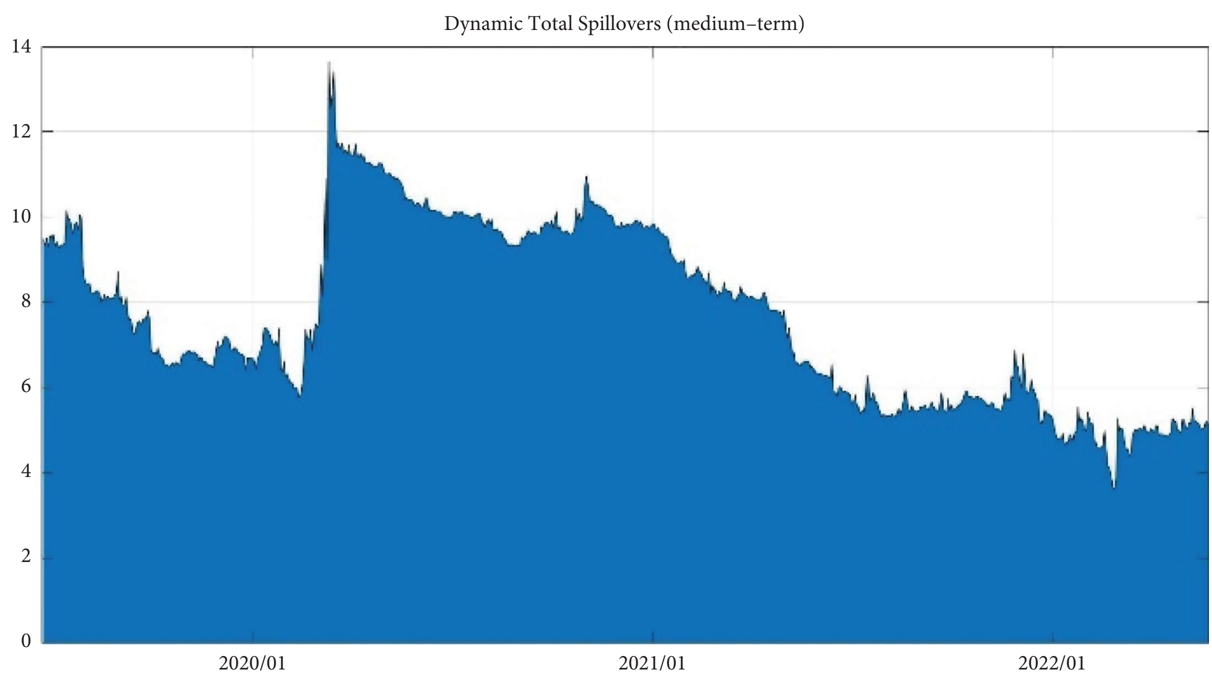


(a)

Figure 5: Continued.



(b)



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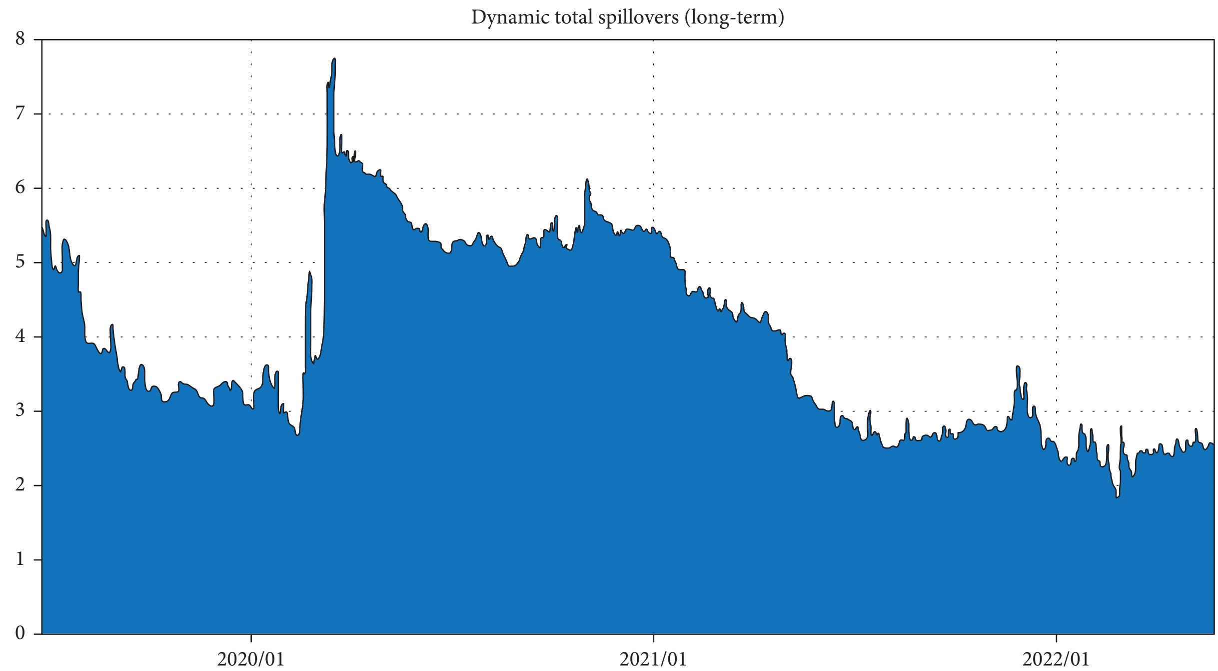
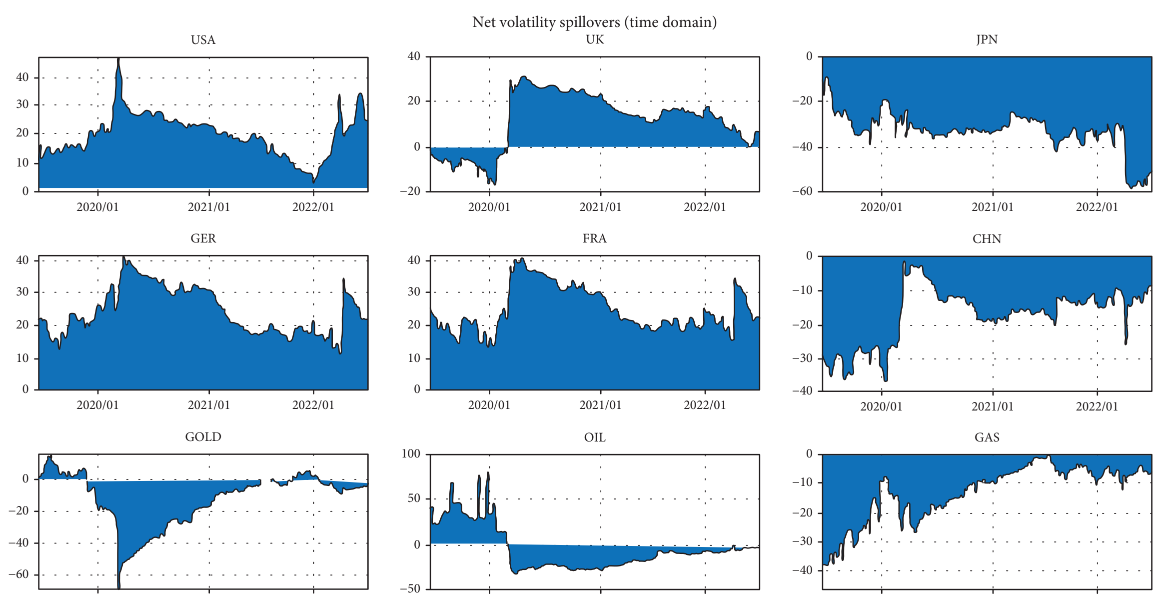


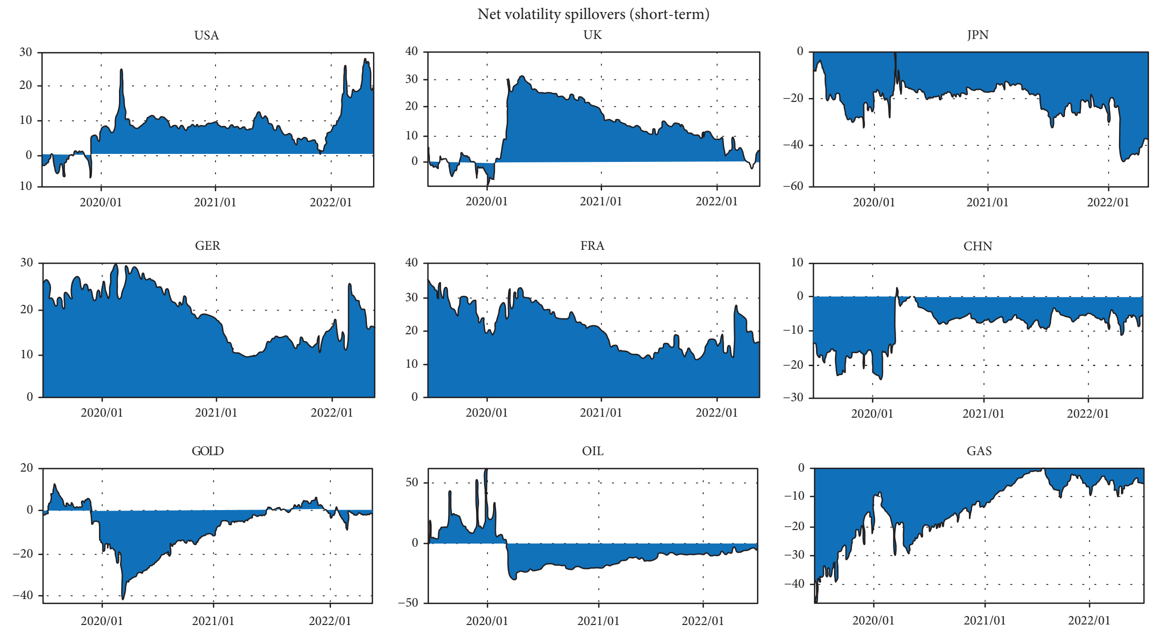
(d)

Figure 5: Total spillover index in time and frequency domains: (a) TCI (time-domain), (b) TCI (short-term), (c) TCI (medium-term), and (d) TCI (long-term).

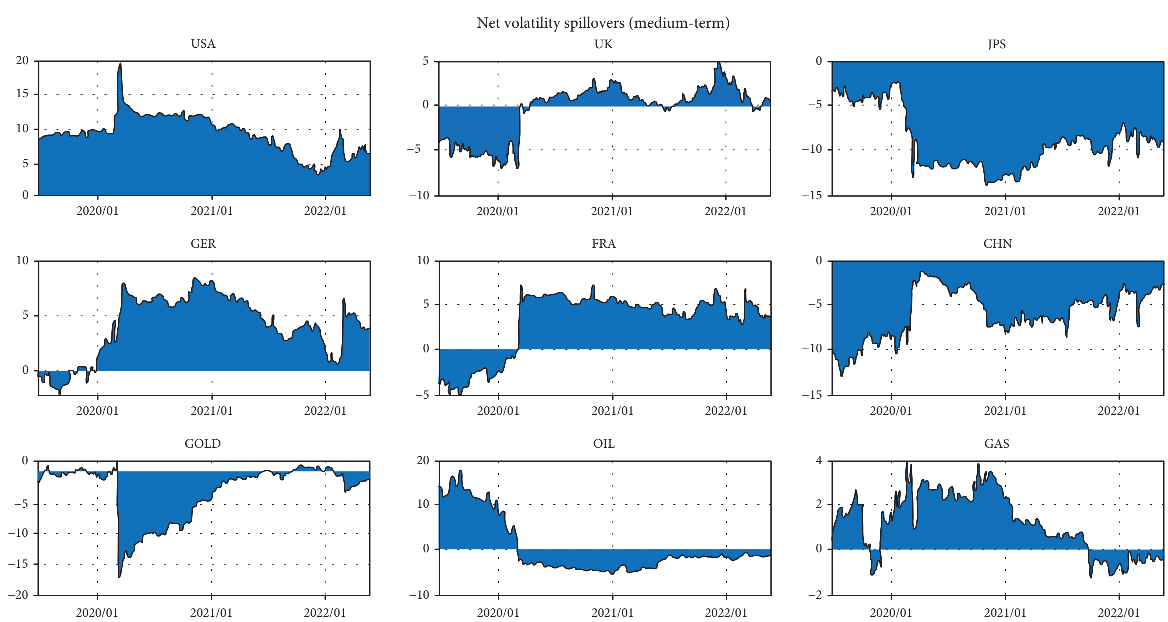


(a)

Figure 6: Continued.

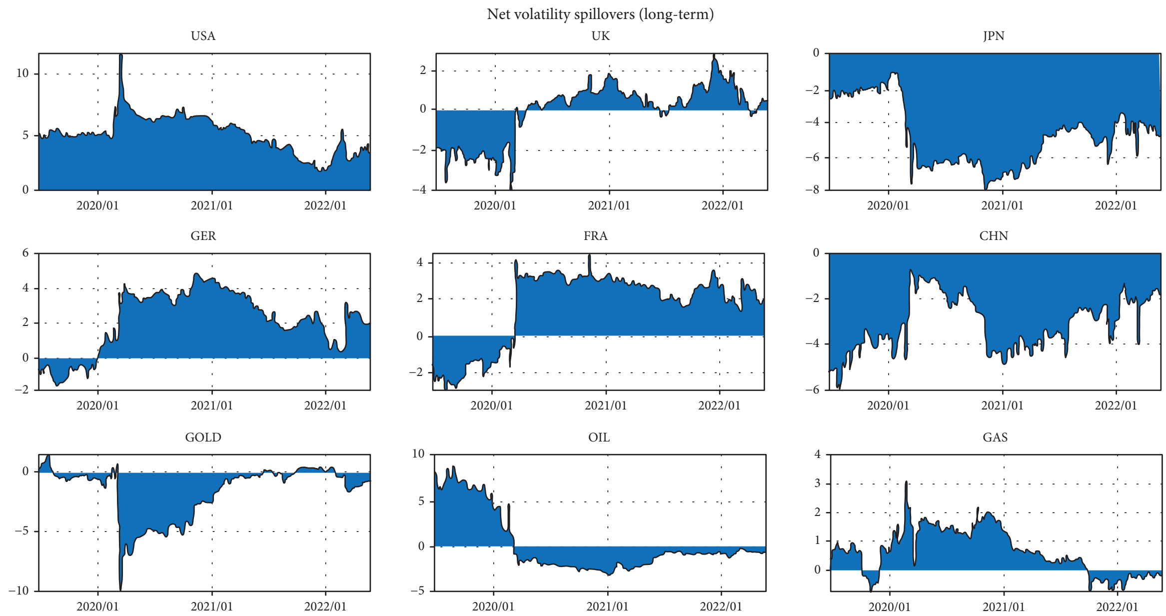


(b)



(c)

FIGURE 6: Continued.



(d)

Figure 6: Net spillover index in time and frequency domains: (a) net (time-domain), (b) net (short-term), (c) net (medium-term), and (d) net (long-term).

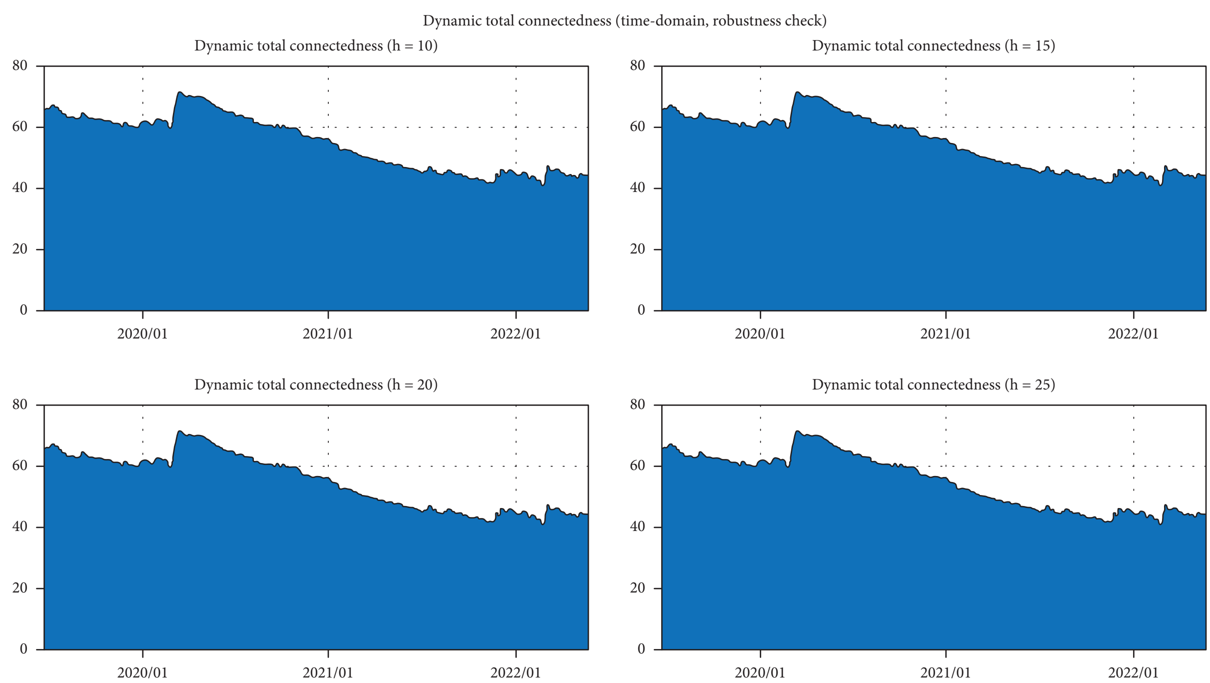


Figure 7: TCI in the time domain (robustness check).

market. According to the dynamic distribution of the net spillover index in Figure 6, it can be seen that six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as the financial markets for gold, oil, and natural gas, show significant changes in their characteristics in the face of the outbreak of extreme events. From a time-domain perspective, it is found that the values of the net spillover indices for the French and German markets are positive, the net spillover indices for the USA and the UK are positive over most of the period range, and the USA has a brief negative value in November 2021, probably related to the most significant increase in US inflation rate in 40 years of history during that period, indicating an increase in the natural gap in the US economy

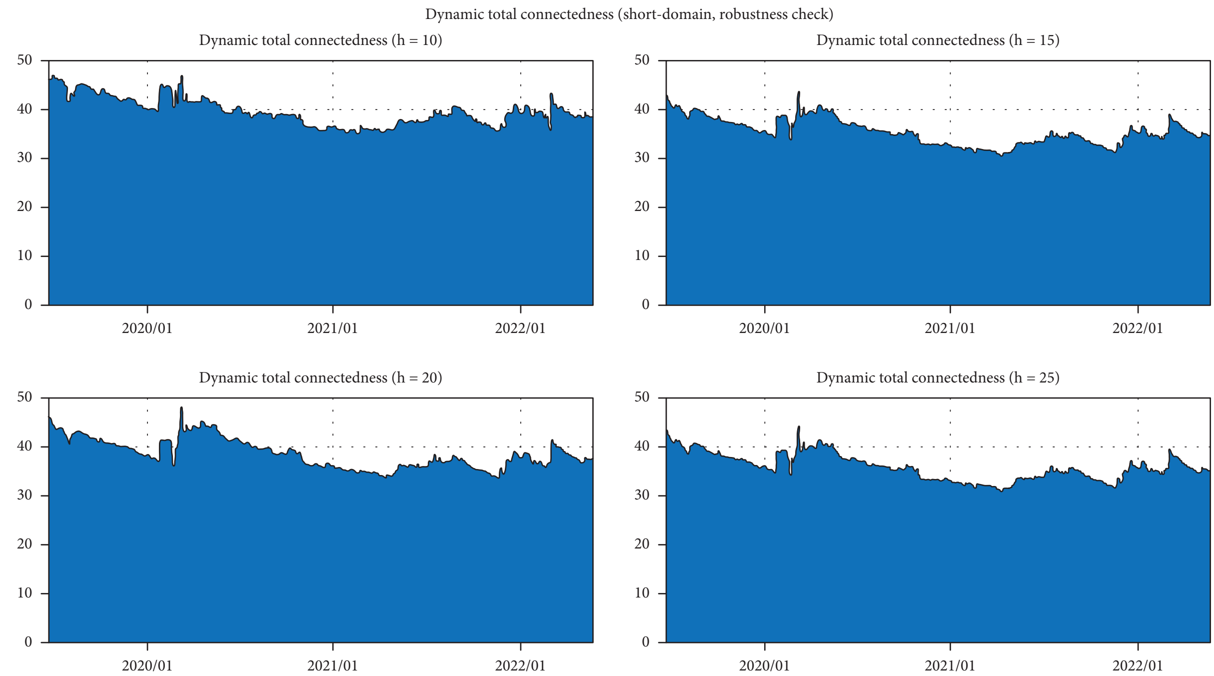


Figure 8: TCI in the short term (robustness check).

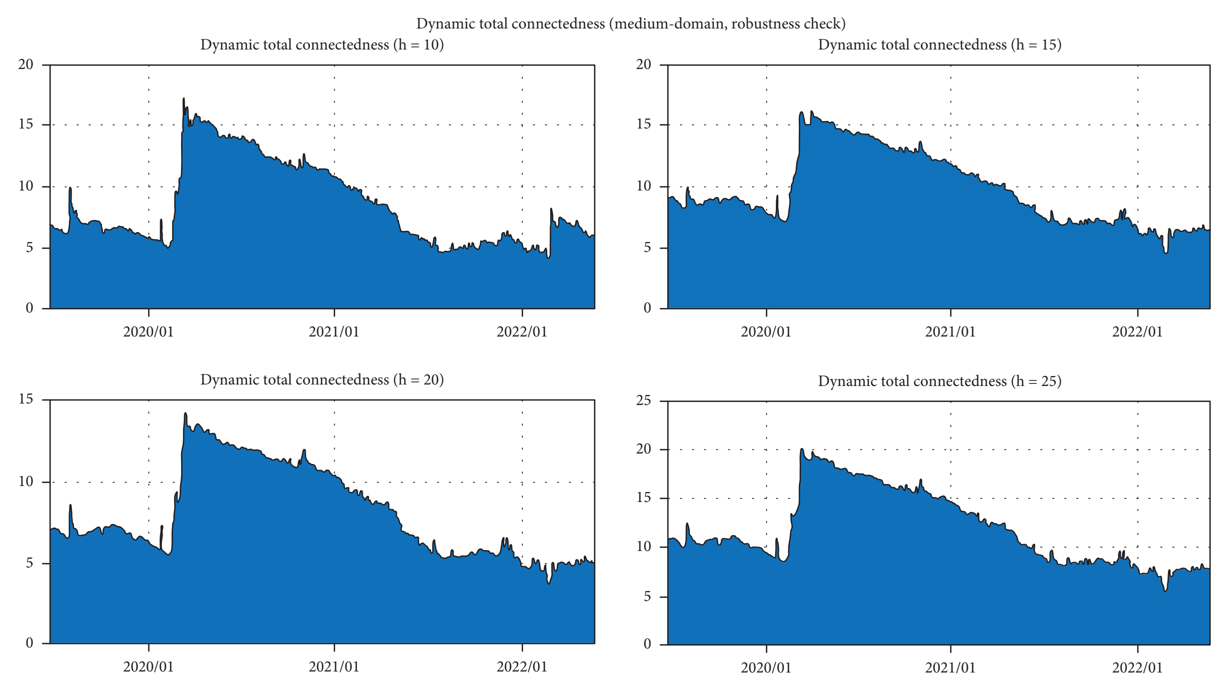


Figure 9: TCI in the medium term (robustness check).

during that period; the UK released a coexistence with the COVID-19 pandemic in early 2022 "lie flat" prevention policy in early 2022, which led to elevated UK input risk in other markets, thus briefly making the two markets net receivers of risk volatility in international markets. In contrast, Japan, China, gold, oil, and natural gas markets have almost always been in the role of risk receivers, among which the gold market, except for a profound volatility change at the time of the COVID-19 outbreak, gradually fluctuates smoothly in the middle range of risk receivers and risk transmitters with the occurrence of extreme events, reflecting the risk aversion property characteristics of the gold market. The COVID-19 pandemic and the epidemic response initiatives significantly worsen the US government deficit and debt problems, widen the income gap between residents and the rich-poor divide, reduce economic growth

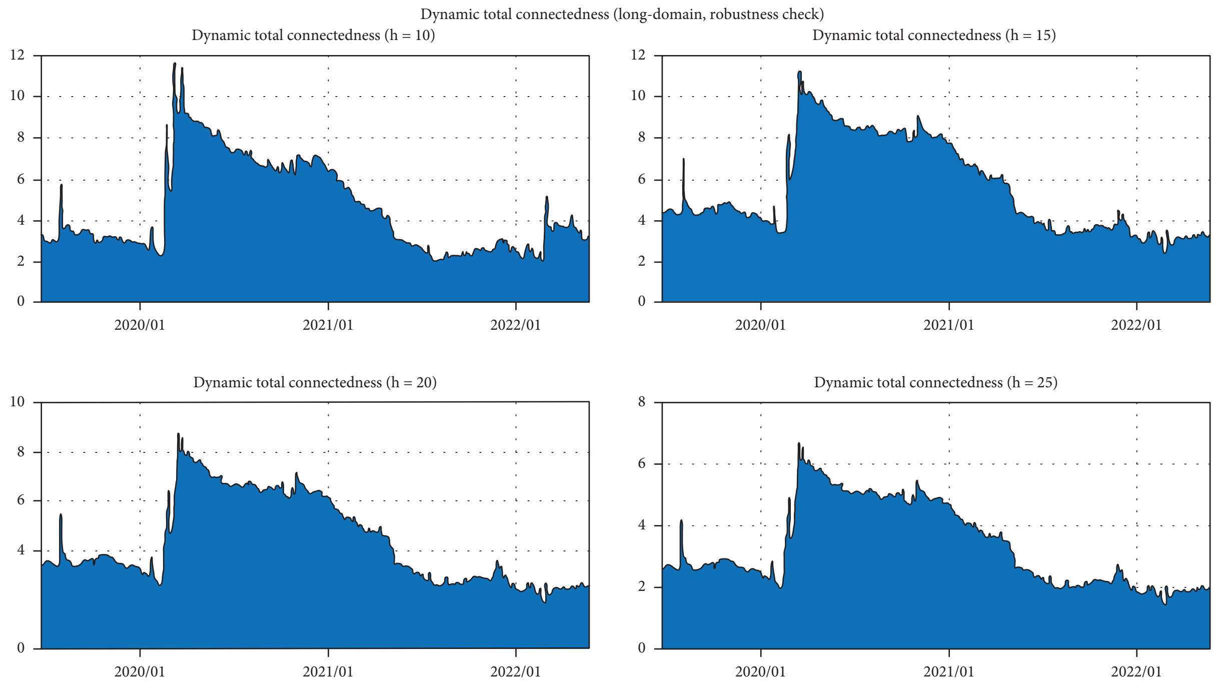


Figure 10: TCI in the long term (robustness check).

potential, and exacerbate the long-term unresolved structural problems of the US economy. Analyzed from the frequency domain perspective, the USA appears to have the highest increase in dynamic net spillover effect in the long term due to the impact of the COVID-19 pandemic, and other markets also reached a peak in the net spillover effect over a period of time range due to the influence of extreme events.

5. Robustness Check

In this section, we conduct robustness checks by setting different forecast horizons (h). Specifically, in the diagnostic tests, we choose $h = 15$, $h = 20$, and $h = 25$ to compare with the original TCI (other robustness check results are available if requested; dynamic total connectedness index) results by setting $h = 10$. The TCIs (dynamic total connectedness index) under the time domain and the frequency domain (short-, medium-, and long-term) are displayed in Figures 7–10. These figures show that the same results still stand under different forecast horizons, which supports the robustness of our results.

6. Conclusions

This paper examines the impact of multiple extreme events, such as the spread of the global COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict, on the financial markets of six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as gold, oil, and natural gas based on the time- and frequency-domain perspectives. First, to measure the impact of the extreme events the on the volatility spillovers among major international financial markets in the time-frequency domain, we combine the TVP-VAR-based connectedness method and BK frequency connectedness approach and focus on the total, directional, and net volatility spillovers. Second, the network visualization method is applied to outline the structural change in the risk contagion, paths, and roles among international financial markets during different periods of extreme global events.

First, we conduct the static spillover analysis. From a time-varying perspective, it appears that the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict led to higher volatility spillover risks during the outbreak; from the frequency domain, it seems that when extreme events broke out, the total spillovers among the international financial markets are affected significantly by the extreme events in each frequency domain.

Furthermore, net pairwise spillover networks are constructed to explore the impact of extreme events overlapping the COVID-19 pandemic and the Russia-Ukraine military conflict on the changes in the risk contagion paths and roles of the major international financial markets. From the time-domain net pairwise spillover networks, the French stock market with the highest level of volatility spillovers to other markets, followed by the United Kingdom, Germany, and the United States, indicate that the center of the volatility spillover network of major international financial markets is concentrated in Europe and the United States; in the frequency-domain network, the US market is the volatility transmitters in the short term, but as the window period lengthens, the level of spillover risk decreases under the impact of extreme events. The gold, oil, and natural gas markets all exhibit some degree of short-term volatility during extreme events. In contrast, at a long-term level, the gold, oil, and natural gas markets are more susceptible to risk spillovers from other financial markets during extreme events.

Finally, the dynamic spillover analysis reveals that the total spillover index rises rapidly with the outbreak of the COVID-19 pandemic, and the Russia-Ukraine conflict puts the total spillover index, which has fallen to its lowest point with fluctuations, rising again. The frequency-domain distribution appears to show the same trend characteristics as the time-domain dynamic distribution at the critical points of the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict, whereas the short-term dimension has the greatest volatility spillovers, suggesting that volatility spillovers among international financial markets are driven mainly by the high-frequency component (short-term spillovers) during the full sample time. In terms of the net spillover index, France, Germany, the USA, and the UK are the main risk transmitters, while Japan, China, gold, oil, and natural gas markets have almost always been risk receivers.

Our results can provide some reference for researchers and investors worldwide to analyze market behavior and make investment decisions. On the one hand, it is a critical period for the outbreak of extreme events such as the COVID-19 pandemic and the Russia-Ukraine military conflict, enabling investors to avoid highly connected investment markets and categories, choose the portfolio solution with the lowest risk cost, and minimize the economic losses suffered due to unexpected events; on the other hand, it can help financial regulators and policymakers to identify the risk transmission fully and connectedness between international financial markets and other markets after an extreme event; identify the risk transmission linkages, paths, and spillover scale; analyze the time-varying connectedness and frequency connectedness among major international financial markets; and propose strategic guidance recommendations that are most in line with the current policy and financial system.

Data Availability

All the data used in this study are obtained from the Wind Database.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

All authors have made equal contributions to the paper.

Acknowledgments

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