Research Article

A Study on Volatility Spillovers among International Stock Markets during the Russia-Ukraine Conflict

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This paper analyzes the dynamic time-frequency volatility spillovers among the international stock markets during the Russian-Ukraine conflict. We use the VAR-based connectedness framework to calculate the volatility spillovers. Results show that (1) the trend of the total spillover is consistent with the time of the Russian-Ukraine conflict; (2) Russian stock market is the primary source and net exporter of risk; (3) the Russian government has effectively controlled the further spread of risk through policy adjustments; and (4) Russian stock market may generate long-run volatility spillovers among the international stock market. We add research related to the impact of the Russia-Ukraine conflict on international stock markets by analyzing the results of the volatility spillovers.

1. Introduction

The Russia-Ukraine conflict has not only brought deep disaster to the people of both countries but also dealt a severe blow to the global financial markets. Investor sentiment in various countries was unstable, and financial asset price volatility increased significantly. This event became another major high-risk event in the global financial markets since the outbreak of COVID-19.

In the context of economic globalisation and financial integration, the linkage effects of national financial markets have become more pronounced. The financial markets of a particular country may have to bear price fluctuations caused by its shocks, which can be measured as spillover effects. Therefore, studying risk spillover effects between national financial markets is of great importance for the stable development of the global economy.

Measuring risk has been a hot topic in financial risk analysis. The connectedness method has been popular among scholars recently as a method for risk consideration. Diebold [1–3] proposed the DY index based on the vector autoregressive (VAR) model and improved it in subsequent studies. The method was widely used to calculate the spillover effects of multiple financial variables after it was proposed [4–6]. Barunik and Krehlik [7] proposed the BK index to study the level of risk spillover under uneven frequency shocks, making the connectedness method more comprehensive. This research method has also been applied in some studies [8, 9].

This paper analyzes the dynamic volatility spillovers among the international stock markets during the Russian-Ukraine conflict. Unlike the existing literature, which mainly analyzes only the intensity and direction using the DY index, this paper analyzes the impact of heterogeneous frequency shocks on the international stock markets by calculating the BK index.

The paper is structured as follows. Section 2 conducts a literature review. Section 3 briefly introduces the research framework of the connectedness framework. Section 4 describes the experimental data and tests the statistical properties. Section 5 conducts the empirical analysis. Finally, conclusions and some suggestions are given in Section 6.

2. Brief Overview of the Literature

There have been many results on risk propagation effects among financial assets, and the research results are summarised below.

Some studies use traditional econometric models to study risk propagation effects. Papathanasiou et al. [10] used a time-varying spillover approach to check the interactions between financial assets. Chen et al. [11] explored the extreme risk spillover from oil and exchange rates to the Chinese stock market based on upside and downside conditional value at risk (CoVaR) values. Xu et al. [12] estimated the risk spillover effect on the Chinese real estate sector based on a GARCH-time-varying-copula-CoVaR model.

Several scholars have proposed new modelling frameworks that combine them with traditional econometric models. Liu et al. [13] assessed the risk propagation effects of inter-regional environmental impacts of PM2.5 emissions based on multi-regional input-output analysis (MRIOA). Geng and Guo [14] used wavelet methods and wavelet-based Granger causality to analyze the uncertainty of financial and economic assets.

Today, a growing body of literature examines the risk propagation effects across financial assets under unexpected events. Tilfani et al. [15] applied a sliding window approach based on a detrended cross-sectional analysis of correlation coefficients to continuously assess cross-sectional relationships between markets in the context of financial crises. The results find differences in market correlations between the pre-crisis and post-crisis periods. In addition, risk propagation models have been widely used during COVID-19 dissemination (On 30 January 2020, the WHO issued the COVID-19 outbreak as a public health emergency of international concern). Baker et al. [16] assessed the leading causes and potential explanations for the strong impact of the outbreak using a text-based approach. Caggiano et al. [17] used a VAR model to estimate uncertainty shocks from an epidemic and calculated the peak negative response of world output. Zhang et al. [18] analyzed the potential consequences of policy interventions by general mapping patterns of country-specific and systemic risks. Wang et al. [19] used connectedness networks to study spillover effects across countries and showed that spillover effects are strongly associated with COVID-19.

As seen from the above literature, a large body of literature has examined the risk transmission effects between pairs of financial assets. Still, very little literature has dealt with the Russia-Ukraine conflict. Therefore, this paper is an essential addition to the existing research. Considering the abovementioned study, this paper improves on Diebold and Yilmaz's [1–3] and Barunik and Krehlik's [7] models based on VAR models to investigate the dynamic time-frequency volatility spillovers among international stock markets during the Russia-Ukraine conflict.

3. Methodologies

The literature review clearly shows that many methods can estimate spillover effects. Still, most of them (e.g., copula and VAR models) can only investigate spillover effects between two or a few financial assets. In contrast, the connectedness method based on vector moving average (VMA) coefficients proposed by Diebold and Yilmaz [2] can reasonably estimate risk spillovers between multiple financial assets. Barunik and Krehlik [7] used frequency-domain spectral decomposition based on Diebold and Yilmaz [2] to further evaluate the effect of dynamic connectivity frequencies on risk spillovers.

This paper calculates the volatility spillover effect on international stock markets based on the DY index and the BK time-frequency index. We begin below with a brief description of these two methods.

3.1. DY Index. Diebold and Yilmaz [2] performed a generalized forecast error variance decomposition of the VAR model and defined the variance contribution as the proportion in which the variance of the forward H-step prediction error can be explained by another variable X_j when the variable X_i is impacted. The equation is as follows:

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

where A_h denotes the coefficient matrix of the p-order vector autoregressive model expressed by moving average, $\sum$ is the variance matrix, σ_{ii} is the standard deviation of the error term of the first equation, and e_i is the selection vector.

In order to compare the pairwise connectivity between any two markets, the variance contribution is normalized by the following equation:

$$\widetilde{\theta}_{ij}^g (H) = \frac{\theta_{ij}^g (H)}{\sum_{j=1}^{N} \theta_{ij}^g (H)}. \tag{2}$$

This paper constructs TOTAL spillover that reflects the extent of volatility spillover in the financial system.

$$S^g (H) = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\theta}_{ij}^g (H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^g (H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\theta}_{ij}^g (H)}{N} \times 100. \tag{3}$$

The FROM spillover reflects the volatility spillover received by financial variable i from other variables.

$$S_{i\cdot}^g = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\theta}_{ij}^g (H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^g (H)} \times 100. \tag{4}$$

The TO spillover reflects the volatility spillover of financial variable i on all financial variables except itself.

$$S_{\cdot i}^g = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\theta}_{ji}^g (H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}^g (H)} \times 100. \tag{5}$$

TABLE 1: Notations of stock indices.

Country name	Stock index code	Stock index name
United States (USA)	SPX	S&P 500 index
Japan	N225	Nikkei 225 index
Hong Kong, China	HSI	Hang Seng index
United Kingdom (UK)	FTSE	FTSE 100 index
China	CSI	CSI 300 index
Russia	IRTS	IRTS index

TABLE 2: Descriptive statistics.

	Mean	Std	Skew	Kurt	ADF	JB	LB
USA	12.29	1.38	0.54	0.18	−4.14***	107.57***	10464.21***
Japan	16.73	1.16	0.19	0.16	−4.57***	15.16***	8239.91***
Hong Kong	17.52	0.90	0.30	0.40	−4.54***	44.87***	4920.33***
UK	14.74	0.92	0.42	0.96	−6.34***	145.75***	3442.22***
China	14.03	1.17	0.44	0.27	−4.01***	76.64***	11082.11***
Russia	12.46	0.95	0.61	1.65	−3.87***	372.46***	6344.09***

*** indicates rejection of the original hypothesis at 1% significance level.

The NET spillover reflects the net volatility spillover of a particular financial variable i on all remaining variables.

$$S_i^g = S_{\cdot i}^g - S_{i \cdot}^g. \tag{6}$$

3.2. BK Time-Frequency Index.
The BK time-frequency index is a method for evaluating the impact of dynamic connectivity frequencies (long, medium, or short term) on volatility spillovers by decomposing the variance spectrum of shocks at different frequencies.

The following equation defines the generalized variance decomposition of the variance contribution over the frequency band $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$:

$$\left(\tilde{\theta}_d\right)_{j,k} = \frac{(\theta_d)_{j,k}}{\sum_k (\theta_\infty)_{j,k}}, \tag{7}$$

where $(\theta_d)_{j,k} = (1/2\pi)\int_d \Gamma_j(\omega)(f(\omega))_{j,k} d\omega$ denotes the overflow level of variable k to j, $\Gamma_j(\omega)$ denotes the power of the variance of the variable j, $(f(\omega))_{j,k}$ is the fraction of the spectrum of variable at a given frequency $\omega \in (-\pi, \pi)$ caused by the shock of variable k, and $(\theta_\infty)_{j,k}$ denotes the generalized variance decomposition in the full time domain.

This formula decomposes the DY index and realizes the calculation of short-term, medium-term, and long-term connectivity.

4. Data and Descriptions

In this paper, six representative stock markets are selected for the study (these six stock indices have a much longer history and more significant international influence; in addition, they are likely to be more closely related to the potential impact of the Russia-Ukraine conflict). The symbols of the stock indices are given in Table 1.

The paper chooses daily data of international stock markets from January 4, 2012, to May 21, 2022, with 2139 sets of observations for each submarket time series (this dataset contains the time dimension before and during the Russian-Ukraine conflict, a period that also includes major international events such as Brexit and the worldwide spread of the COVID-19 epidemic; therefore, we believe that there are sufficient observations to implement our proposed objectives). The data are sourced from the Wind financial database.

According to Garman and Klass [20], the following equation expresses the daily volatility:

$$\sigma = 0.511\left(H_t - L_t\right)^2 - 0.019\left[\left(C_t - O_t\right)\left(H_t + L_t - 2O_t\right) - 2\left(H_t - O_t\right)\left(L_t - O_t\right) - 0.383\left(C_t - O_t\right)\right]^2, \tag{8}$$
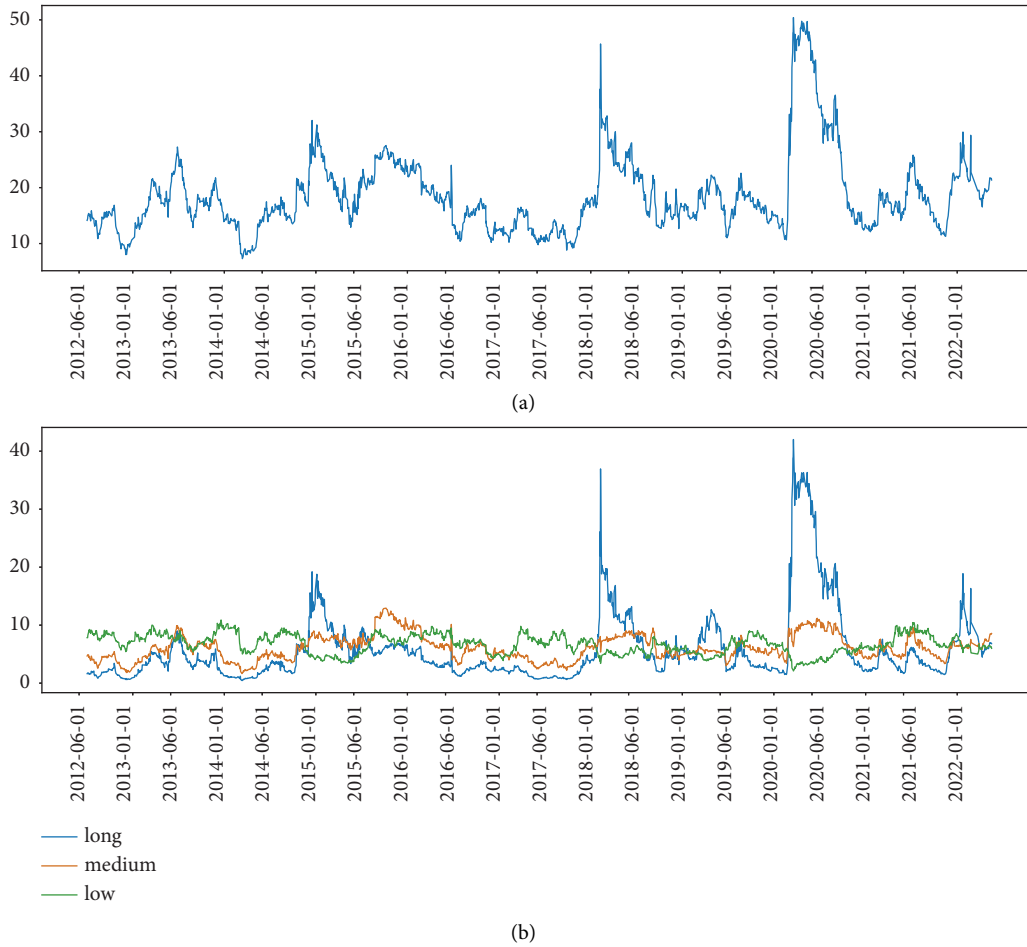
FIGURE 1: Total spillovers and frequency decomposition. (a) Total spillover. (b) Time-frequency decomposition of the total spillover.

where H_t, L_t, C_t, and O_t are the daily high, low, closing, and opening prices, respectively.

The results of descriptive statistical analysis are shown in Table 2. Each stock market passes the LB, JB, and ADF unit root test at a 1% confidence level, which is suitable for constructing the connectedness modelling.

5. Results and Analysis

This paper uses the VAR(2) model with a rolling window set to 200 and a forecast horizon set to 100 days, which are the same parameters as Barunik and Krehlik [7].

5.1. Total Spillover Results. This section calculates the total spillover among the international stock markets, and the results contain several unique spillover phenomena.

Firstly, Figure 1(a) shows that the total spillover changes significantly after a major international event such as the global spread of the COVID-19 epidemic, which is consistent with the results of Laborda and Olmo [21]. From Figure 1(a), it can also be found that the total spillover increased steeply during the Russian-Ukraine conflict, reaching a new high after 2020, indicating that the Russian-

Ukrainian conflict became another major event affecting the global economy after the COVID-19 epidemic.

Secondly, the trend of the total spillover is consistent with the time of the Russian-Ukraine conflict. It continued to increase after the escalation of the Russia-Ukraine conflict and peaked in 30% on February 24. After countries paid close attention and made policy adjustments, the negative impact of the conflict gradually decreased, and the total spillover drops to 19%. The above results suggest that volatility spillovers are closely linked to international policies and macroeconomics.

Finally, Figure 1(b) presents the results of the frequency-domain decomposition. The figure shows that the long-term and total spillovers are highly synergistic and significantly higher than the medium and short-term spillovers, indicating that the low-frequency component mainly drives the volatility spillover and that long-term factors such as economic fundamentals dominate the dynamic volatility spillovers.

5.2. Directional Spillover Results. This section calculates the directional spillovers. As shown in Figure 2(a), the stock markets in each economy exhibit different characteristics after the Russia-Ukraine conflict.
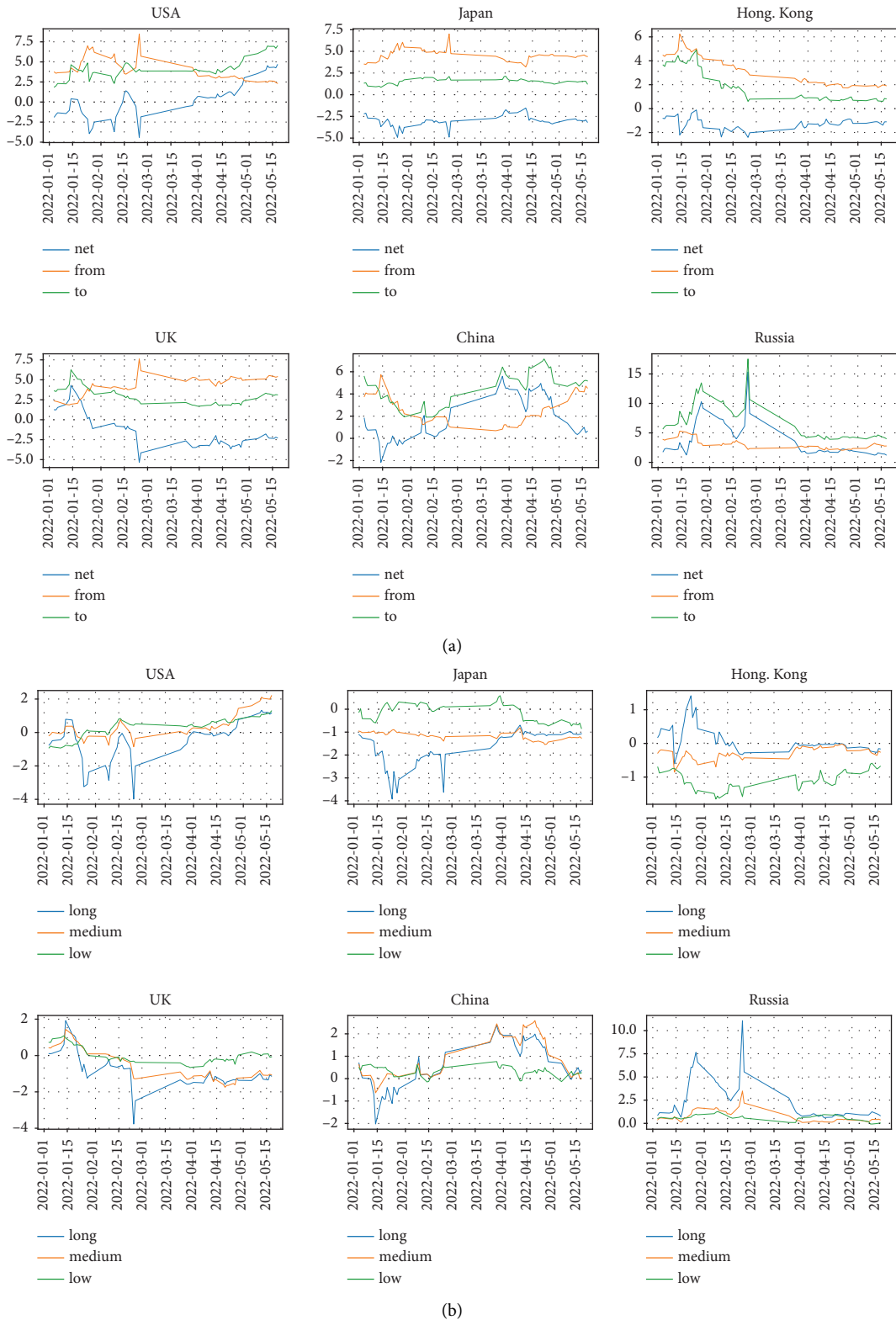
FIGURE 2: Directional spillovers and frequency decomposition. (a) Directional spillovers. (b) Time and frequency decomposition of directional spillovers.

Firstly, the net spillover of the China stock market continued to increase after February 15, which could be related to the second round of the outbreak of the Omicron epidemic in early 2022.

Secondly, the trend of the Russian stock market is consistent with the international stock market, which may be related to Russian government policy adjustments. The volatility spillovers increased significantly after the conflict when
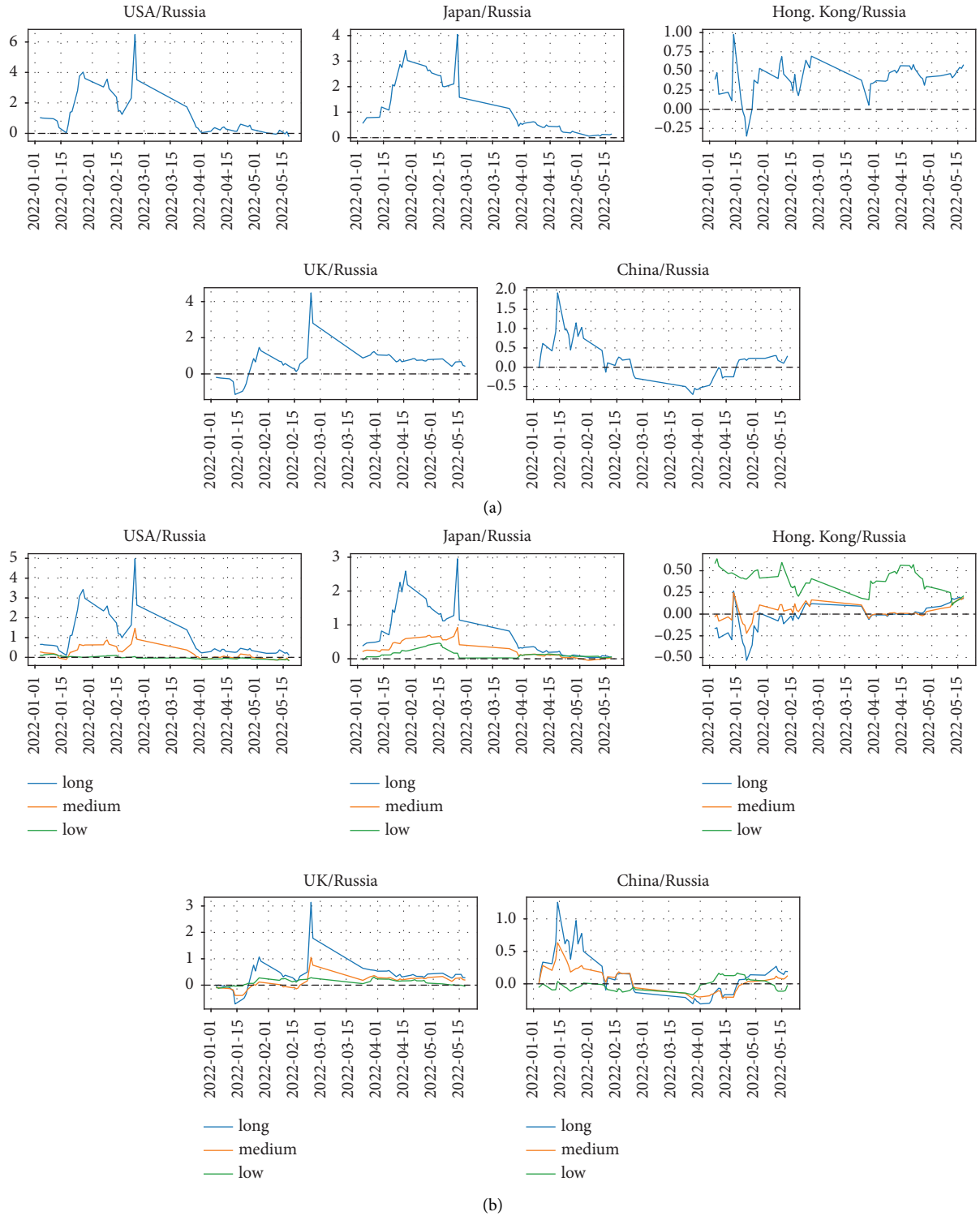
(a)

(b)

FIGURE 3: Net pairwise spillovers and frequency decomposition. (a) Net pairwise spillovers. (b) Time-frequency decomposition of the net pairwise spillovers.

the Russian stock market plunged by more than 40%, and the RUB/USD dropped to record low. To offset ruble depreciation and inflation risks, the Russian government raised the benchmark interest rate from 9.5% to 20% and forced the settlement of 80% of corporate income, reducing the risk premium. This changing trend suggests that Russia may be the primary source and net exporter of international stock markets from the events of the Russia-Ukraine conflict.

Finally, Figure 2(b) shows the frequency decomposition results. It shows that the volatility spillover within one week significantly impacts the Hong Kong stock market. However, the low-frequency component is still the main driving

part of the directional spillover index, which is the same result as in the previous section.

5.3. *Pairwise Spillover Results.* From the conclusions of the previous two sections, it is clear that the Russian stock market may be the sender of risk. Therefore, we chose the pairwise spillover of the Russian stock market for our analysis, and the results are shown in Figure 3.

On the one hand, Figure 3(a) shows an apparent asymmetry in the pairwise spillover risk results. Before the Russia-Ukraine conflict, the volatility spillovers of each country's stock market to the Russian stock market were small. After the conflict, the pairwise spillovers all increased to different degrees. After one month, each country's pairwise spillover decreased to a value near zero, indicating that the volatility spillover from the Russian stock market to each country has become negligible.

On the other hand, Figure 3(b) shows that the level of long-term spillover mainly drives the pairwise spillover. This may be because Russia has an important position in the commodity market. Conflicts can cause sharp increases in energy and metal prices, chronic shortages in the global food supply, and ultimately destabilize global trade chains. Therefore, as the conflict continues, Russia could have a long-term (more than one month) volatility spillover on international stock markets.

6. Conclusions and Implications

Based on the connectedness method, this paper empirically analyzes the dynamic volatility spillovers among the major international stock markets during the Russia-Ukraine conflict in 2022.

The results show that the total spillover continues to grow and peak after the conflict and gradually decreases after countries make policy adjustments, a trend consistent with the timing of the Russia-Ukraine conflict. The directional spillovers indicate that each country was affected by the Russia-Ukraine conflict to varying degrees. When risks such as ruble devaluation occurred, the Russian government took decisive measures to prevent the spread of risks effectively. The pairwise spillovers show that Russia significantly correlates with each country in the Russia-Ukraine conflict. The time-frequency decomposition of the volatility spillovers indicates that the long-run component mainly drives the volatility spillovers. The Russian stock market may generate long-run volatility spillovers from the international stock market.

Based on the study's results, this paper provides some suggestions.

Countries should strengthen their market communication capabilities and reasonably guide financial expectations. On the one hand, the market guidance effect can be strengthened through public research reports; on the other hand, the authority of the results can be increased by increasing the integration of market information to avoid the adverse effects of poor communication.

At the same time, every effort should be made to improve regulatory and risk warning systems. Experiments have shown that when a specific economic or political event occurs, that event may generate long-term volatility spillover to international stock markets. Therefore, the relevant government departments should improve the regulatory system from both macro and micro perspectives to maintain the stability of financial markets. In addition, the relevant authorities should further strengthen the risk early warning system, especially the risk transmission of uncertainty due to long-term asset allocation, and regulate the financial market volatility system to avoid generating systemic financial risks.

Data Availability

The data are all from the Wind database.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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