International Journal of Power and Energy Systems, Vol. 46, No. 10, 2026
An Open Access Paper

RISK SPILLOVER EFFECTS OF CARBON, ENERGY AND PRECIOUS METALS MARKETS BASED ON MULTI-DIMENSIONAL AND TIME-FREQUENCY PERSPECTIVES

Baoshuai Zhang,* and Jia You**

Abstract

Risk spillover between financial markets is an important direction of financial risk research, which helps to identify and prevent financial risks. This article examines the spillover effects among the carbon market, oil, new energy, and precious metals from a multidimensional and time-frequency perspective. It achieves this by employing the GJRSK model and the quantile time-frequency linkage method. The primary focus is on inspecting the alterations in market risk spillover effects during extreme market conditions. The study reveals that noteworthy risk spillovers exist among the carbon market, oil, new energy, and precious metals, short-term risk spillovers surpass long-term risk spillovers. Furthermore, the spillovers among markets under different market conditions are heterogeneous, with significantly stronger risk spillovers observed during extreme upward and downward market conditions compared to normal states. Moreover, the risk spillovers in different dimensions exhibit an asymmetric status and display tail dependence.

Key Words

GIRSK model; quantile time-frequency model; spillover effect

1. Introduction

In the context of global financial integration, interdependence and risk contagion among financial markets are becoming increasingly prominent. The connectivity of financial markets is both a source of competitive benefits and an important mechanism for risk propagation [1]. From the 2008 financial crisis to the 2010 European debt crisis, a series of financial risk events have had an impact on the relevant regions and even the world's financial system, which has attracted widespread attention from countries around the world to financial risk contagion. In the context of economic globalization, risk contagion is an urgent and important issue that cannot be ignored.

In recent years, China has made "preventing and resolving major risks" the top priority of the "three major battles" and has made important deployments to prevent and control systemic financial risks multiple times [2]-[5]. As more and more evidence suggests, the financialization of commodities [6] has shown that the connectivity (spillover) of commodity markets has begun to receive widespread attention. Once it is recognized that commodities have become one of the core asset classes used by financial investors (i.e, gold melting), it is necessary to re-understand the operating mechanism of commodity markets.Due to their dual attributes as commodities and finance, precious metals and energy have long been highly regarded as the two most important types of commodities. After the shale revolution in the United States, the relationship between crude oil and natural gas became more complex [7]-[8] and it found that information overflow between the two has become more uncertain [9]. In recent years, there has been a linkage event between oil prices and precious metal prices in the international commodity market, which has attracted scholars' attention to the risk spillover effects between the two markets [10]-[11].

Current research typically analyzes the risk spillover between markets from the perspective of the first and second moments of the asset return distribution, namely returns, and volatility. However, the distribution of asset returns is usually nonnormal, indicating that asset returns are more likely to exhibit asymmetry or extreme returns, and the nonnormality, asymmetry, and fat-tailed nature of asset return distribution cannot be captured solely from the perspective of returns and volatility. It is worth noting that higher-order moments of the income distribution, such as

* School of Economics and Management, Chongqing Normal University, Chongqing 401331, China; e-mail: baoshuai8128@163.com
** School of Business Administration of Chongqing Vocational and Technical University of Mechatronics, Chongqing 402760, China; e-mail: yj1985113@163.com
Corresponding author: Jia You

Recommended by: Jen-Hao Teng
(DOI: 10.2316/J.2026.203-0613)

skewness and kurtosis, contain valuable information that can reflect asymmetric risk or tail risk events [12]. Therefore, skewness spillover describes the level of correlation between asymmetric returns between markets, while kurtosis spillover explains how extreme risk spreads between markets [13]. The returns of commodities are often affected by high market uncertainty or extreme returns due to periods of prosperity or depression. Extreme market risks may weaken the stability of the financial system. Therefore, it is not only necessary to consider risk spillover from intuitive indicators such as volatility, but also to study cross-market risk transmission from high-order moment perspectives such as skewness and kurtosis.

Compared with existing literature, the marginal contribution of this paper is mainly reflected in the following aspects: firstly, this study will explore the spillover effects between markets based on volatility, skewness, and kurtosis indicators, and characterize the correlations between markets based on different risk measurement indicators, expanding the current research. Secondly, there is currently no consensus on the scale, direction, and dynamic changes of risk spillover in the precious metals and energy markets at different time scales. This study is based on the novel time-frequency domain spillover index framework proposed by Diebold and Yilmaz [14] and Barunik and Křehlik [15], combined with the rolling window method, which can simultaneously characterize the size, direction, and dynamics of risk spillover between markets, and capture the heterogeneity of risk spillover in the time domain and different frequency domains.

2. Literature Review

In the study of market risk spillover effects, scholars at home and abroad have conducted a lot of research, mainly focusing on commodity market risk spillover, market risk measurement, and risk spillover models.

Firstly, research on risk spillover in commodity markets. Morales and Andreosso-O'Callaghan [16] argue that the impact of financial crisis events on cross-regional and cross-market interdependence can be defined as a "spillover effect". Many scholars have focused on typical financial sub-markets, such as the stock market, bond market, money market, etc., to explore the risk spillover between markets. As Zhou [17] explored the spillover effects of returns and volatility in 14 Asia Pacific stock markets within the framework of spillover indices. Liu et al. [18] used generalized prediction error variance decomposition and complex network methods to explore the risk spillover effects of China's money market, capital market, foreign exchange market, gold market, and real estate market. With the acceleration of the process of commodity financialization, great attention has been paid to the exploration of risk spillover between financial markets and commodity markets, as well as between commodity markets [19]-[21]. Examining the issue of risk spillover between commodity markets has become a recent research hotspot. At present, there is no consensus on the nature of the information spillover effect between precious metals and energy markets. On the one hand, due to the connection between commodity channels and financial channels, crude oil price shocks are often considered as exogenous factors affecting the metal market in research [22]. In addition, some scholars have recently pointed out that there is a bidirectional effect between precious metals and energy markets [20]-[21]. Given that the spillover effects of precious metals and energy markets still need to be explored, this study will investigate the spillover effects of these two important commodity markets and further enrich the current literature.

Secondly, research on market risk measurement. The widely used measurement indicators for market risk are based on asset returns or volatility. Many studies investigate the spillover effects of systemic risk by examining the transmission relationship of returns or volatility between markets. For example, Tan Xiaofen et al. [23] studied the bidirectional spillover relationship between commodity markets and financial markets from the perspectives of return and volatility based on the BEKK-GARCH (Baba-Engle-Kraft-Kroner GARCH) model and spillover index method. They found that there is a bidirectional spillover effect between international commodity markets and financial markets, and the characteristics and trends of return spillover and volatility spillover are significantly different. A common limitation of current research is that their analysis of spillover effects is limited to the first and second moments of asset return distribution, namely returns and volatility. However, due to the nonnormality, asymmetry, and fat-tailed nature of asset return distributions, it is not comprehensive to limit spillover analysis only to first-order and second-order moments. Higher moments, such as skewness and kurtosis, contain valuable information that can reflect asymmetric risk or tail risk events [22]-[23]. High-order moment risk is associated with asymmetric risk and tail risk in the market, and risk research based on high-order moment measurement is an extension and expansion of traditional risk research. At present, research on high-order moment risk is focused on perspectives such as return forecasting, risk premium, risk measurement, and risk spillover. Langlois [24], Bevilacqua, and Tunaru [25] have approached this topic from different angles. The spillover effect of high-order moment risk between markets is gradually receiving attention. Early research on high-order moment risk spillover mainly focused on the stock and money markets [26]-[28]. Recently, scholars have also paid attention to high-order moment spillover effects in commodity markets. For example, Cui et al. [29] used the Diebold and Yilmaz [14] spillover model to study the spillover effects of realized skewness, realized kurtosis, and asymmetric volatility between WTI, Brent crude oil, and Chinese commodities.

Also, research on risk spillover models. The main methods for studying risk spillover effects between markets include VAR (Value at risk) models, GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, Copula models, CoVaR (Conditional Value at Risk) models, Granger causality, etc. (Maghyereh et al. [30], Ahmed and Huo [31], Sun et al. [32]). The above models all have certain measurement effects, but they also have their limitations. For example, GARCH models have the limitation of not being able to measure the size of spillover effects. The same GARCH model cannot simultaneously consider the directionality and dynamics of spillovers. Copula models are not easy to distinguish the direction of spillovers. GARCH-type models have the limitation of being unable to measure the magnitude of spillover effects. Moreover, the same GARCH model cannot simultaneously account for both the directionality and the dynamics of spillovers. Using GARCH-type models to characterize asset volatility is a relatively complex process. Additionally, the magnitude of asset volatility can vary depending on the model chosen, which is clearly not very reasonable. CoVaR models have the limitation of only considering one-way spillovers within a model. To overcome these shortcomings, Diebold and Yilmaz [14], [28] proposed a new overflow framework (referred to as the DY method), which combines a rolling window VAR model and a generalized error variance decomposition method to simultaneously characterize the dynamics, directionality, and size of overflow. More and more research has been conducted on market spillover effects based on this framework.

Through the review of existing literature, it is found that current research and analysis on risk transmission effects are mostly based on the first and second moments of asset return distributions. Spillover effects based on high-order moment risk indicators have not received much attention, and the overflow analysis models used in existing research, such as GARCH models, cannot simultaneously consider the strength, directionality, and dynamics of overflow, as well as capture the heterogeneity of risk overflow in the time domain and different frequency domains. The DY and BK time-frequency domain spillover models provide a good analytical framework for comprehensively evaluating high-order moment risk spillover between markets.

3. Model Construction

3.1 Time-Varying Higher-Order Moments Fluctuation Models

The present study utilizes the GJRSK model developed by Leon et al. [33] to analyze the dynamic properties of conditional skewness and conditional kurtosis across global energy markets. The model employed is outlined as follows:

$$\begin{cases} r_t & = \mu_t + \vartheta_t = \mu_t + h_t^{1/2} z_t \\ h_t & = \beta_0 + \sum\limits_{i=1}^{q} \left(\beta_{1,i} z_{t-i}^2 + \beta_{3,i} \vartheta_{t-i}^3 \varphi_{t-1,i}\right) + \sum\limits_{j=1}^{p_1} \beta_{2,j} h_{t-j} \\ s_t & = \gamma_0 + \sum\limits_{i=0}^{q_2} \left(\gamma_{1,i} z_{t-i}^3 + \gamma_{3,i} z^3 \varphi_{t-i,1}\right) + \sum\limits_{j=1}^{p_2} \gamma_{2,j} s_{t-j} \\ k_t & = \delta_0 + \sum\limits_{i=1}^{q_3} \left(\delta_{1,i} + z_{t-i}^4 + \delta_{3,i} z_{t-i}^4 \varphi_{t-i,1}\right) + \sum\limits_{j=1}^{p_3} \delta_{2,j} k_{t-j} \end{cases} \tag{1}$$

where, $\vartheta_t | I_{t-1} \sim D(0, h_t, s_t, k_t)$, and I_{t-1} is the information table at the moment t-1, $D(0, h_t, s_t, k_t)$ is any distribution containing the conditional mean, conditional variance, conditional skewness, and conditional kurtosis, s_t is the conditional skewness, k_t is the conditional kurtosis, and $\beta_{3,i}, \gamma_{3,i}$, and $\delta_(3,i)$ are the coefficients of leverage effects in the conditional variance equation, the conditional preference equation, and the conditional kurtosis equation, respectively.

In accordance with common practice, the time-varying higher-order moments GJRSK model is estimated using a Gram-Charlier sequence expansion of the normal distribution density function truncated at the fourth moments as a conditional density function for z_t to ensure nonnegativity of the density and a integral of 1, the expanded density function is corrected, drawing on the practice of Leon:

$$f(z_t|I_{t-1}) = \frac{\phi(z_t)\psi^2(z_t)}{\Gamma_t} \tag{2}$$

where, $\psi^2(z_t) = (1 + \frac{s_t}{3!}\left(z_t^3 - 3z_t\right) + \frac{k_t - 3}{4!}\left(z_t^4 - 6z_t^2 + 3\right))^2$, $\Gamma_t = 1 + \frac{s_t^2}{3!} + \frac{(k_t-3)^2}{4!}$, $\phi(\bullet)$ represents the probability density distribution function of the standard normal distribution, by utilizing $\varepsilon_t = h_t^{1/2} z_t$, the logarithm of the likelihood function can be obtained by omitting the nonessential constants:

$$l_t = -\frac{1}{2}\ln h_t - \frac{1}{2} z_t^2 + \ln\left(\Psi^2(z_t)\right) - \ln \Gamma_t \tag{3}$$

Due to the high degree of nonlinearity of the model itself, in order to accurately determine the initial values of the parameters in the estimation of the maximum likelihood of the model, the method of "from simple to complex model" is used, firstly, the conditional mean and the conditional variance of the model are estimated, and the obtained parameters are taken as the initial values of the parameters of the two equations; then, the conditional mean and the conditional variance, as well as the conditional skewness are jointly estimated; finally, the conditional mean, the conditional variance, and the conditional skewness obtained by the previous estimation are taken as the initial values, and the joint estimation of the conditional mean equation, conditional variance equation, conditional skewness equation, and conditional kurtosis equation is realized.

3.2 Quantile Time-Frequency Modeling

The article adopts the quantile vector autoregressive model proposed by Ando et al. [34] to examine the quantile evolution characteristics of volatility spillovers between international energy markets, to refine the defects of the DY spillover index in the tail carving, and the specific framework of the quantile vector autoregressive model is as follows:

$$Y_t = \mu_t(\tau) + \sum_{i=1}^{p} \Phi_i x_{t-i} + u_t(\tau) \tag{4}$$

where, Y_t denotes the $\mathrm{N} \times 1$ dimensional column vector, Φ_i denotes the coefficient matrix of the QVAR (Quantile Vector Autoregression), τ denotes the quantile on $[0,1]$, p denotes the number of lagging periods of the QVAR, and $u_t(\tau)$ denotes the $\mathrm{N} \times 1$ dimensional error vector, which can be constituted as an $\mathrm{N} \times \mathrm{N}$ dimensional error variance matrix, Ω When the stability condition is satisfied by the QVAR(p), it can be transformed into a vectorial moving average of infinite order, QVMA(∞) process:

$$Y_t = \mu_t(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i} \tag{5}$$

where $A_i(\tau)$ is the coefficient matrix of the QVMA (Quantile Vector Moving Average), which obeys $A_i(\tau) = \Phi_1 A_{i-1}(\tau) + \Phi_2 A_{i-2}(\tau) + \cdots + \Phi_p A_{i-p}(\tau), A_0$ a unit matrix of order N and $A_i = 0$when i < 0. According to the generalized error variance decomposition, the estimate of variable j for the spillover effect of i is the proportion of the H -step prediction error variance of variable i that the proportion caused by variable $\underset{\mathrm{j}}{\mathrm{i}}$ is $\theta_{ij}(H)$:

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum\limits_{h=0}^{H-1} \left(e_i' A_h \Omega e_j\right)^2}{\sum\limits_{h=0}^{H-1} \left(e_i' A_h \Omega A_h' e_i\right)}, H \quad = 1, 2, 3 \ldots \tag{6}$$

where σ_{ii}^{-1} denotes the diagonal element of the error variance matrix, the i-th element of e_i is 1 and the remaining elements are $0, A_h$ denotes the coefficient matrix, and h denotes the forward prediction step, and further normalization yields:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum\limits_{k=1}^{N} \theta_{ij}(H)} \tag{7}$$

Simultaneously, we obtain two equations, denoted as $\sum\limits_{i=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i=1,j=1}^{N} \tilde{\theta}_{ij}(H) = N$. The augmentation of quartile τ leads to modifications in the coefficient matrix. This enables us to investigate the spillover impact of institution j on institution i in the presence of varying magnitudes of shocks, which is more in line with the reality of the economic performance, because the major event shocks tend to be stronger than the average shocks, and more likely to have spillover effects.

At the same time, time series data are often characterized by "sharp peaks and thick tails", and the tails contain substantial risk information, implying that quantile estimation is superior to conditional mean estimation because it not only reveals the risk spillover relationship in the tails, but also its estimation is more robust in the extreme cases.

According to Ando et al. [34], the total spillover index (TSI) and the directional spillover index (SI) can be computed under quartile τ:

$$\begin{aligned}
TSI^{\tau} &= N^{-1} \times \sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{ij}(H) \times 100 \\
SI_{i\to j}^{\tau} &= \sum_{i=1;i\neq j}^{N} \tilde{\theta}_{ij}(H) \times 100 = TO \\
SI_{j\to i}^{\tau} &= \sum_{i=1;i\neq j}^{N} \tilde{\theta}_{ij}(H) \times 100 = FORM \\
NSI_i^{\tau} &= SI_{i\to j}^{\tau} - SI_{j\to i}^{\tau}
\end{aligned} \tag{8}$$

3.3 Spillover Index Measure in Frequency Domain - BK Spillover Index

Based on the frequency response function $\Psi\left(e^{-i\omega}\right) = \sum\limits_h e^{-i\omega h} \Psi_h$, the spectral density $S_X(\omega)$ of X_t at frequency ω is:

$$\begin{aligned}
S_X(\omega) &= \sum_{h=-\infty}^{\infty} E\left(X_t X_{t-h}'\right) e^{-i\omega h} \\
&= \Psi\left(e^{-i\omega}\right) \sum \Psi'\left(e^{i\omega}\right)
\end{aligned} \tag{9}$$

where $\Psi\left(e^{-i\omega}\right)$ is Fourier transformed from $\Psi_h, i = \sqrt{-1}. S_X(\omega)$ portrays how the variance of X_t is distributed at frequency ω, which is a key parameter for understanding the frequency dynamics. The generalized causal spectrum at frequency ω can be defined as:

$$(f(\omega))_{jk} \equiv \frac{\sigma_{kk}^{-1} \left| \left(\Psi\left(e^{-i\omega}\right)\Sigma\right)_{jk} \right|^2}{\left(\Psi\left(e^{-i\omega}\right)\Sigma\Psi\left(e^{i\omega}\right)\right)_{jj}} \tag{10}$$

$(f(\omega))_{jk}$ denotes the fraction of the spectrum of variable j that is caused by shocks to variable k at a given frequency ω. Since the denominator of the above equation is the spectrum of variable j at a given frequency $\omega, (f(\omega))_{jk}$ can be interpreted as intra-frequency causality by further introducing the frequency share of the variance of j as a weighting function:

$$\Gamma_j(\omega) = \frac{\left(\Psi\left(e^{-i\omega}\right) \sum \Psi'\left(e^{i\omega}\right)\right)_{jj}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} \left(\Psi\left(e^{-i\lambda}\right) \sum \Psi^{\Psi'}\left(e^{i\lambda}\right)\right)_{jj} d\lambda} \tag{11}$$

$\Gamma_j(\omega)$ denotes the power of variable j at a given frequency, and the generalized variance decomposition over frequency band d is:

$$\theta_{jk}(d) = \frac{1}{2\pi} \int_d \Gamma_j(\omega) (f(\omega))_{jj} d\omega \tag{12}$$

Where, $d = (a, b), a, b \in (-\pi, \pi), a < b$, and $\theta_{jk}(\infty) = \frac{1}{2\pi} \int_d \Gamma_j(\omega)(f(\omega))_{jk} d\omega$, are equal to $H \to \infty$ at $\theta_{jk}(\infty)$ under the time domain, $\theta_{jk}(d)$ can be further normalized as:

$$\tilde{\theta}_{jk}(d) = \frac{\theta_{jk}(d)}{\sum k\theta_{jk}(\infty)} \tag{13}$$

$\tilde{\theta}_{jk}(d)$ measures the level of spillover from variable k to j over frequency band d. The total spillover index TSI over frequency band d, the directional spillover index SI are respectively:

$$\begin{aligned}
TSI^d &= \frac{\sum\limits_{j,k=1;j\pm k}^{N} \tilde{\theta}_{jk}(d)}{N} \times 100 \\
SI_{j\to k}^d &= \sum_{j=1;j\pm k}^{N} \tilde{\theta}_{jk}(d) \times 100 \\
SI_{k\to j}^d &= \sum_{k=1;j\pm k}^{N} \tilde{\theta}_{jk}(d) \times 100 \\
NSI_j^d &= SI_{j\to k}^d - SI_{k\to j}^d
\end{aligned} \tag{14}$$

$TSI^d, SI^d_{j\to k}, SI^d_{k\to j}$ and NSI^d_k decompose the gross spillover TSI^τ, directional spillover $SI^\tau_{j\to k}$, $SI^\tau_{k\to j}$ and net spillover NSI^τ_j in the time domain into different frequency bands respectively.

4. Analysis of Empirical Results

4.1 Data Sources and Descriptive Statistics

To investigate the spillover effects among traditional energy, new energy, the carbon market, and the precious metals market, this paper selects oil, new energy, the carbon market, and gold as research objects.The data included in this study originates from the WAND database. Based on the data presented in Table 1, the following information can be derived: firstly, except the mean value of the price index of the precious metal market is negative, the mean value of the price indices of the new energy, crude oil and Hubei carbon trading market are all positive, which indicates that the mean value of the price indices of the new energy, crude oil and Hubei carbon trading market is increasing, while that of the precious metal market is decreasing. At the same time, we find that the market price index of the Hubei carbon trading market price index has the largest variance of the market price index, followed by the crude oil market index and precious metal market index, while the variance of the new energy market index is the smallest, the size of the variance of the price index can be regarded as the price volatility during the sample study period, that is the price change of carbon trading market is the largest, and the change of market price of new energy is the smallest; secondly, the skewness of the price indexes of the four markets are constants that are not 0, in which the new energy price index and precious metal price index is less than 0, that is, there is an obvious leftward bias, and the skewness of the crude oil price index and the carbon price index is greater than 0, that is, there is an obvious rightward bias. In addition, from the kurtosis coefficient, it can be seen that the new energy, crude oil and carbon price indexes show a sharp distribution, and the precious metal market price index shows a low peaked distribution; thirdly, through the ADF unit root test, the results show that the series are considered to be smooth significantly at the 1% level, and the conditional returns of the four kinds of price indexes do not obey the standardized normal distribution as shown from the J-B test, and the LM test shows that the variances of the four price index series are inhomogeneous, that is, autocorrelation in the residual series can be fitted by the GJRSK model.

4.2 Empirical Results

4.2.1 Static Risk Spillover Analysis

The GJRSK model is utilized to calculate the conditional return, conditional variance, conditional skewness and conditional kurtosis for each index and the estimation results are shown in Figure 1:

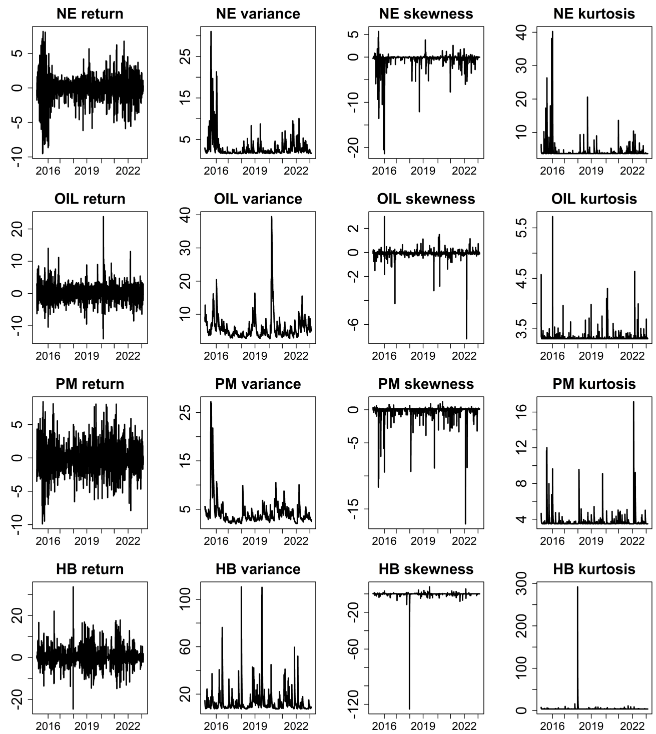

Figure 1. Time Series of Conditional Return, Conditional Variance, Conditional Skewness and Conditional Kurtosis

As can be seen from the time series charts, there are obvious differences in the conditional variance, conditional skewness and conditional variance for each index's return: The conditional variance is small when the market is running smoothly, and the conditional variance rises sharply in oscillation and smoothes out quickly when there are sharp fluctuations in the market; the conditional skewness is mainly negative and widens with the expansion of fluctuations in return; and the conditional kurtosis has a characteristic that is similar to the conditional variance's, when the return of the market index fluctuates around 0, the conditional skewness is smooth, and when the conditional return has a sharp rise and fall, the conditional kurtosis will change sharply. Variations in the order moments of the market index can indicate disparities in the operational attributes of diverse marketplaces.

Because the traditional OLS regression can only reflect the average spillover effect between markets and cannot capture the diversity spillover effect between markets, especially it is difficult to portray the extreme volatility risk spillover between markets, in order to better study the spillover effect of individual markets on each other, the article adopts the quantile time-frequency connectivity method proposed by Ando et al. (2022) to calculate the connectivity and spillover effect of individual market indexes at different quartiles. The low quartile ($\tau = 5\%$), the middle quartile ($\tau = 50\%$) and the high quartile ($\tau = 95\%$) are used to characterize the risk spillovers between different markets at different quartiles, respectively. Considering the model parsimony and the persistence of correlation between markets, according to the AIC criterion, the article chooses the lag period p=1 and the forecasting step

Table 1
Results of descriptive statistics

	Min.	Mean	Max.	skewness	kurtosis	Std.Dev	J-B	ADF	LM(10)
NE	-9.53	0.03	8.19	-0.54	5.24	1.83	1824.15***	-10.33***	466.11***
OIL	-14.03	0.11	23.85	0.75	6.92	2.65	3189.80***	-11.00***	243.67***
PM	-9.89	-0.02	8.44	-0.03	2.24	2.18	320.23***	-9.84***	248.63***
HB	-24.60	0.16	33.65	0.69	7.06	4.05	3292.13***	-12.23***	232.51***

h=100 to measure the risk spillover level of markets under different quartiles from the directional spillover level and the total spillover level, respectively, in which, the total spillover index (TCI) measures the total size of spillovers between markets under different quartiles, and the directional spillovers indexes (TO and FORM) indicate the size of direct spillovers from the market itself to other markets and the size of acceptance of spillovers from different markets, respectively; the net spillover index (NET) measures the net recipients of spillovers between markets (NET<0) and the net senders of spillovers (NET>0). Table 2 shows the gross spillover, directional spillover, and net spillover indexes between the new energy, crude oil, precious metals, and carbon market indexes for different quartiles(Due to space limitations, the graphical display of overflow effects under different quantiles, skewness overflow effects under different quantiles, and kurtosis overflow effects under different quantiles has been omitted here. If necessary, please contact the author).

Table 2
Connectivity of return spillovers across quartiles

	NE	OIL	PM	HB
tau=0.05	TCI=62.16			
TO	66.33	60.98	65.77	55.56
FROM	63.97	62.03	63.11	59.52
Net	2.36	-1.05	2.66	-3.96
tau=0.5	TCI=8.68			
TO	13.71	4.66	13.66	2.7
FROM	13.33	6.29	13.12	1.98
Net	0.38	-1.63	0.53	0.72
tau=0.95	TCI=62.49			
TO	64.19	61.3	66.57	57.9
FROM	63.51	62.71	63.03	60.71
Net	0.68	-1.41	3.55	-2.82

Based on Table 2, first, the business links between various markets and the timely feedback of market information from participants make the markets have a strong linkage between them, and the total spillover index is precisely to portray the overall linkage between the markets, under different quartile conditions. There is a large difference in the total spillover index between the markets, and the size of the total spillover in the low and high quartiles is higher than that of the median, in the case of normal shocks (τ = 50%), the conditional return, conditional variance, conditional skewness, and conditional kurtosis of the total spillover are 8.68%, 12.09%, 6.08%, and 6.31%, respectively, which indicates that the overall linkages among the new energy, crude oil, precious metal, and carbon markets are weak. But in the case of a shock from an extreme event (τ = 95%), the conditional return, conditional variance, conditional skewness, and conditional kurtosis of the total spillover of 62.49%, 74.63%, 16.76% and 55.70% respectively, the risk spillover between the markets is more serious, which may be due to the fact that China's carbon trading market is still in the initial stage, and the connection between the carbon trading market and the other markets is not particularly close, resulting in a lower level of risk spillover between the markets in the case of normal shocks, but it is more prone to inter-market risk spillover in the case of extreme shocks. However, in the case of extreme shocks, inter-market risk infection is more likely to occur, especially more sensitive to extreme market shocks.

Second, despite the presence of thick tails among the four markets, the spillover effects of low-order and high-order moments are different for the left and right tails at different quartiles; the total spillover indexes of the conditional returns at the low quartile (τ = 5%) and the high quartile (τ = 95%) are 62.16% and 62.49%, respectively, which are much higher than that of the normal case (τ = 50%) at 8.68%; the conditional variance and the conditional kurtosis spillover indices in the high quartile (74.63% and 55.70%) are significantly higher than those in the low quartile (13.24% and 6.32%), suggesting that spillovers are asymmetric between markets [35], and that the market is affected by extreme positive shocks more than extreme negative shocks. The spillover index of conditional skewness is just the opposite. The difference in total spillovers between markets with different order moments and different quartiles. It also shows that the risk spillover between markets cannot be accurately portrayed when only first-order moments and second-order moments are considered.

Third, examining the directional spillover indexes of each market, the spillover effects of the four markets at different order moments in the low and high quartiles are larger than those in the median, indicating that the risk spillover from extreme shocks is higher than that from ordinary event shocks among the four markets. Taken together, the new energy index has the strongest spillover effect, followed by the precious metals and crude oil indexes, the worst spillover effect is the carbon trading market index. This indicates that the new energy market has obvious cross-market spillover benefits, while the precious metals and crude oil indexes also play an important role in the directional spillover effect. It is worth noting that at high scores (τ=95%), the conditional variance and conditional kurtosis of the carbon trading price index exhibit 102.99% and 117.46% spillover effects.

Fourth, in terms of the net spillover index, the level of net spillover among the four markets is low under normal conditions and significantly higher under extreme conditions, and the net spillover index for crude oil is less than 0 under both different order moments and different quartiles, indicating that crude oil is a net recipient of market risk among these four markets. The new energy price index has a net spillover index greater than 0 under all quartiles of conditional expectations, indicating that it is a net spillover, which is consistent with Dan Nie et al. [35].'s use of the DY model to measure risk spillovers in the case of normal shocks with lower-order moments, where new energy plays the role of a net spillover in the energy market. However, in the article, we find that at high quartiles of conditional variance and conditional kurtosis, and at low quartiles of conditional skewness, new energy is a net recipient. The precious metal index is a net spillover under the quartiles of conditional expectation and conditional skewness, and plays the role of a net receiver under the median and high quartiles of conditional variance, as well as the high quartile of conditional kurtosis; the spillover effect of the carbon trading market at the high quartile of conditional variance and conditional kurtosis ($\tau = 95\%$) is 37.76% and 85.93%, respectively, which plays the role of a net spillover of risk and the spillover effect is very dramatic. However, the spillover effect of carbon trading market is very small in other cases. The possible reason is that the carbon trading market is still in the initial stage in China, and the degree of marketization of the carbon trading market with the implementation of the quota system is not enough, so when subjected to normal shocks, the net spillover effect of the carbon market is very low, but if subjected to extreme positive shocks, the carbon trading market will produce strong spillover effects, which indicates that carbon trading in the normal operation of the market can't produce a big impact on the energy structure of China [36], but when the market is subject to extreme shocks, carbon trading will stimulate the transformation of China's energy structure.

This difference in the role played in market risk under different conditions illustrates the defects of the approach to exploring risk from low-order moments and medians alone, and suggests that when exploring risk spillovers between new energy, crude oil, precious metals and carbon markets it is important not only to capture asymmetric information from the market's conditional skewness and conditional kurtosis, as well as the impact of extreme shock events, but also to recognize the time-varying volatility characteristics of the higher-order moments attribute, which is the only way to increase the precision of the market's risk characterizations, help investors and policymakers to better understand the market, and help them to formulate more accurate strategies.

4.2.2 Analysis of Risk Spillover Dynamics

Short-term and long-term risk spillover dynamics must be analyzed separately, as short-term risk spillover dynamics are more unstable compared to long-term risk spillover dynamics and are the main factor influencing risk volatility between markets[37]; decomposing the level of market risk spills into different frequency bands, where $d = \left(\frac{\pi}{22}, \pi\right)$ is the high-frequency band, the cycle length represents from 1 to 22 days, and $d = \left(0, \frac{\pi}{22}\right)$ is the low-frequency band, the cycle length is more than 22 days. The article obtains continuous spillover indexes through a fixed rolling window, decomposes the total spillover level into short-term spillover effects and long-term spillover effects, and utilizes dynamic spillover indexes to describe the dynamic characteristics of the spillover effects of different orders of moments among industries, where the median ($\tau = 50\%$) is utilized to characterize the dynamic average spillover effect, and the low quartile ($\tau = 5\%$) and the high quartile ($\tau = 95\%$) are utilized to characterize the risky spillover extent of the left and right tails of the effect. As can be observed in Figures 2, the total and short-term spillover levels of conditional returns(Due to space limitations, the continuous overflow index plots for the total overflow level and short-term overflow level of conditional variance, conditional skewness, and conditional kurtosis have been omitted here. If necessary, please contact the author) are more synergistic, and the short-term spillover level is generally higher than the long-term spillover level throughout the period under study, which illustrates that the risk spillover between the markets is mainly dominated by short-term risk spillover. Meanwhile, there are significant differences in the volatility between markets at different order moments and different quartiles, and the average spillover level of conditional returns is at 65% at the low and high quartiles, and this result shows that the risk spillover between new energy, crude oil, precious metals, and carbon trading markets is more severe in the left and right tails. Conditional variance and conditional skewness have sharp fluctuations in market spillovers at the high quartile ($\tau = 95\%$), which indicates that they are more affected by positive shocks; conditional kurtosis also has sharp fluctuations at the low quartile ($\tau = 5\%$), which indicates that they are more seriously affected by extreme negative event shocks.

The sensitivity of the net spillover index for each market at different time-frequency quartiles is explored. Figures 3 show heat maps of the sensitivity of the time-frequency quartiles between the new energy, crude oil, precious metals, and carbon markets, respectively. Red color indicates that the market is a contributor to the net spillover and blue color indicates that the market is a recipient of the net spillover.

Based on Table 2, we can draw the following conclusions:First, the net spillover effects of new energy and precious metals are consistent with each other, with the net spillover effect of expected returns acting mainly as a contributor, and the net spillover effect of conditional variance acting as a major recipient of the net spillover effect. At the low quartile of conditional skewness ($\tau < 20\%$) and at the high quartile ($\tau > 80\%$) they are both recipients and contributors of net market spillovers, while under the high quartile of conditional skewness, they act mainly as recipients of net spillovers. Playing different roles in quartiles of different order moments indicates that there

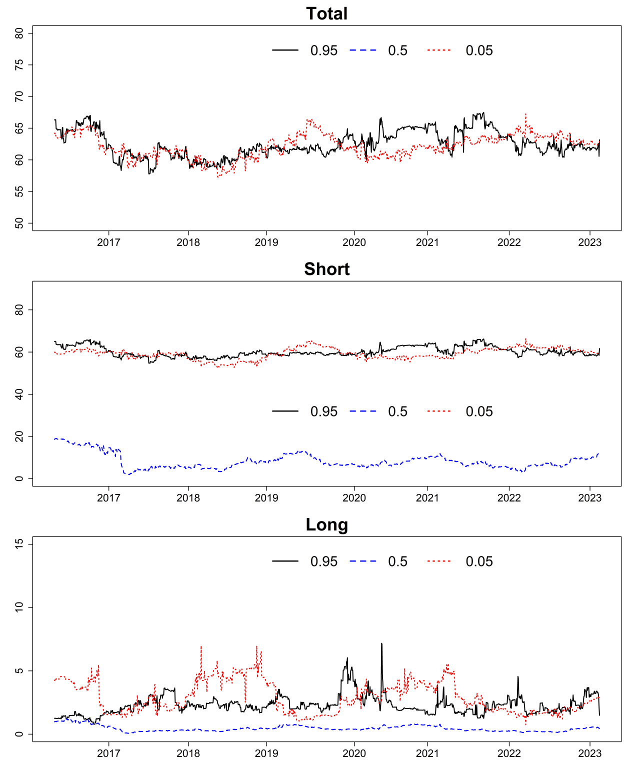

Figure 2. Plot of Total Spillovers from a Rolling Window of Conditional Yields

are obvious differences in risk spillovers across different dimensions, therefore, the study of multidimensional risk spillovers is very important for us to recognize and manage risks. Second, the carbon market is a contributor to the net spillovers from other markets in the $(30\%\tau < 70\%)$ quartile of conditional returns, and a recipient of the net spillovers from other markets in the $(\tau < 20\%, \tau > 70\%)$ quartile, which suggests that the structure of the net spillovers of the carbon market transforms from a contributor to an absorber when the market situation changes from a normal to an extreme state. This kind of information can help investors when making decisions. Third, according to Figuer 3 the heat map of the net spillover effect (Due to space limitations, the results of net overflow of conditional variance at different quantiles, net overflow of conditional skewness at different quantiles, and net overflow of conditional kurtosis at different quantiles have been omitted here. If necessary, please contact the author), it can be seen that the crude oil market plays the roles of both spillover and receiver in different order moments throughout the study period, which indicates that the crude oil market plays the role of risk transmitter, which may be due to the close connection between the other three markets of crude oil. Fourth, risk spillovers in conditional variance, conditional skewness, and conditional kurtosis are concentrated in the high and low quartiles (the extreme quartiles), which suggests that risk spillovers between markets are more severely affected by shocks from extreme events. Fifth, risk spillovers from conditional returns are more sensitive to risk spillover effects than higher-order moments at different quartiles.

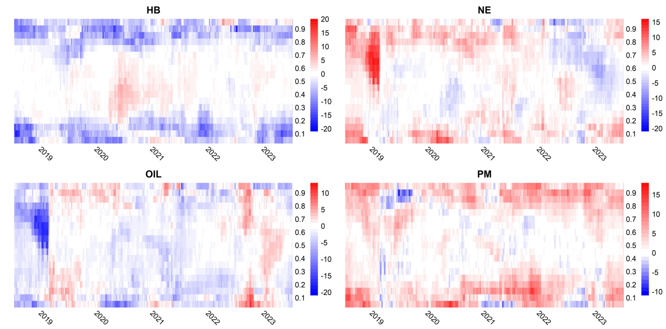

Figure 3. Net Spillover of Conditional Yields Across Quartile

In order to present more clearly the structural differences between short and long-term risk spillovers, the article draws short and long-term risk spillover network diagrams based on the risk spillover relationship between two-by-two markets under different frequency bands, which are shown in Figure 4 (Due to space limitations, the net spillover network diagrams of conditional variance between markets, conditional skewness between markets, and conditional kurtosis between markets have been omitted here. If necessary, please contact the author).Specifically, the nodes in the network connectivity denote each market, the line segments connecting the nodes denote the risk spillover paths between the markets, the thickness of the paths denotes the intensity of the risk spillover, and the arrows denote the net spillover from market i to market j, i.e., market i's contribution to the market is greater than market j's contribution to the market. From the net spillover network connectivity diagram, the following conclusions can be drawn:

First, the thickness of the paths in the short-term spillover network diagram is higher than that of the long-term spillover network diagram paths, indicating that short-term spillovers between markets are the main influence on net market spillovers, it also suggests that risk spillovers between markets are mainly caused by shocks to short-term events, which is consistent with the results of the previous analysis.

Second, distinct markets may have distinct roles to play in the short and long-term connection, and they may diverge, resulting in divergent short- and long-term market reactions to an economic shock event. In the short-term market under the $(\tau = 50\%)$ quantile of conditional variance, the new energy market is a net spillover contributor to the carbon trading market, while in the long-term market, the new energy market is a net spillover recipient from the carbon trading market. It may be because in the short term China's energy structure dominated by coal, oil, etc. cannot be changed in the short term, and the development of new energy is still immature, which cannot fully meet China's energy demand, combine with the country's strategic goal of carbon peaking and carbon neutrality, which pushes up the price of new energy market, and the price of new energy causes the price of carbon trading market to rise.

Third, the direction and thickness of the net spillover connectivity paths between markets change under different quartiles. In the net spillover network diagram of conditional yields, at the median ($\tau = 50\%$), the fact that the crude oil market is a net spillover recipient from the other three markets illustrates that China's energy structure, which is dominated by traditional fossil energy sources, has not changed, and that when there is a normal price shock in the market, the resulting risk spills over to the crude oil market. However, in the low quartile ($\tau = 5\%$) and high quartile ($\tau = 95\%$), the crude oil market has a net risk spillover effect on the carbon trading market and the degree of risk spillover is significantly enhanced, which indicates that the median is not able to completely portray the risk spillover effect between markets. Fourth, in different order moments, the direction and degree of risk spillover between markets are also differentiated. In the connectivity network diagram of conditional expectation and conditional skewness, the crude oil market is a net recipient of market risk, but in the connectivity network diagram of conditional variance and conditional kurtosis, the crude oil market has a net spillover effect on the precious metal market. Through the net spillover index network diagram can be more accurate to recognize the source and size of the impact of each market, conducive to investors to build investment portfolios and hedging, conducive to reducing risk, to help investors to obtain higher returns, but also to help regulatory agencies for different markets to develop appropriate risk prevention measures to enhance market stability.

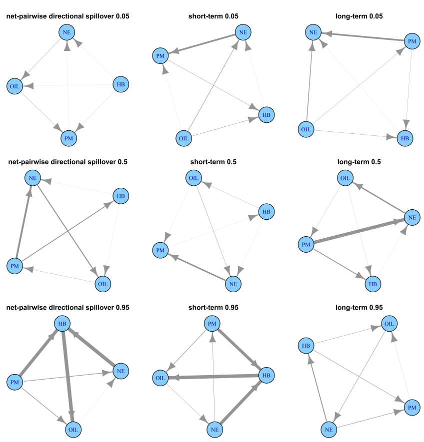

Figure 4. Network Diagram of Net Spillovers in Conditional Yields Between Markets

4.3 Further Analysis of Research Results

The empirical analysis in this section provides evidence of high-order moment risk spillover between four commodity markets. Previous studies have only examined the risk spillover effects between commodity markets from the perspective of returns or volatility spillover effects, while focusing on skewness and kurtosis spillover to reflect the asymmetric risk distribution or tail risk connections, as well as how extreme events propagate throughout the market and produce chain effects. In the context of economic integration, markets will be interconnected through commodity channels or financial channels. Under the impact of risks, market connectivity is enhanced and spillover is intensified. For example, during the COVID-19 pandemic, crude oil prices plummeted, even exceeding the spillover level during the 2008 global financial crisis. During the market downturn and the outbreak of COVID-19, the spillover effects of the three high-order moment indicators have increased, reflecting the rapid spread of market risk. Monitoring market risk solely through the measurement of volatility spillover is not enough. However, as the moment order increases, the connectivity of the system weakens. This may be because systemic volatility risk still plays a major role, with weaker skewness and kurtosis risks. The long-term effects between markets can be explained from two perspectives: first, the persistence and long-term nature of some market shocks, such as the impact of the shale revolution and the COVID-19 [38]; Secondly, the market often takes a long time to respond to shocks. The longer response time to market shocks may be due to the larger spillover effects between different markets in the precious metals and energy systems compared to similar markets. The research results of this section indicate that there is a strong spillover effect between the gold and carbon markets, while the connection between the crude oil and natural gas markets is not very close, which may be due to the decoupling of oil and natural gas [39], [40]. Different types of markets interact through commodity channels, including cost-effectiveness and inflation mechanisms, resulting in slow information transmission [41].

5. Conclusions and Recommendations

Based on a new quartile time-frequency linkage method, the article combines the GJRSK model to comprehensively analyze the static spillover effect, dynamic spillover effect ,and net spillover effect of different quartiles among crude oil, new energy, carbon ,and precious metal markets, also investigates the quartile-extreme risk spillover effect among the four markets, and at the same time combines the network analysis to reveal the risk spillover among oil, new energy, carbon and precious metal markets transmission paths and network structure to determine the relative importance of each market. The main conclusions are summarized below: First, this new measure better captures multidimensional risk spillovers between markets, with differences in risk spillovers between oil, new energy, carbon, and precious metals markets under different market conditions, as well as greater risk spillovers between markets under extreme upward and extreme downward market conditions; second, the different market conditions in which oil, new energy, carbon, and precious metals markets are linkages are time-varying and vulnerable to extreme events. At the same time, there is a strong relative tail dependence between markets and tail risks are characterized by asymmetry.

Based on the above findings, the following recommendations are made: First, the market structure between oil, new energy, carbon and precious metals is complex and varies across distinct market situations and temporal contexts, investors need to pay close attention to the changes in the economic environment and the sense of volatility of the market in real time, to adjust their portfolio ratios in a timely manner in order to achieve the goal of risk-return maximization. Second, in extreme market conditions, the risk spillover effect between markets is significantly enhanced and different dimensions of risk exhibit different characteristics, so market regulators should pay attention not only to the return and volatility risks between markets, but also to their skewness and kurtosis risks, as well as to the multidimensional risk transfer between financial markets, especially the extreme risk transfer under the influence of extreme events. Therefore, policymakers should establish a system of early warning of risks as well as timely and appropriate macroeconomic regulation after extreme events to reduce the impact of economic uncertainty on risk spillovers and to strengthen the emergency response mechanism for major emergencies, thereby helping investment managers and investors drop risk.

This article analyzes the high-order moment risk spillover effects between precious metals and energy markets based on a time-frequency domain spillover model, and explores the time-frequency spillover effects between carbon markets, oil, new energy, and precious metals through the connection of the GIRSK model and quantile VAR network. Suggestions are provided for investors and policy makers. However, this article still has shortcomings and needs to be expanded in future research. Firstly, due to the limitations of the types of samples obtained, this study mainly selected gold as the representative of the precious metal market, and crude oil, carbon market, and new energy market as the representatives of the energy market. However, there are far more varieties of precious metals and energy markets than these four. In the future, more precious metals and energy markets will be considered for research. Furthermore, this article only provides theoretical suggestions for constructing relevant investment portfolios based on the empirical results of the risk linkage between precious metals and energy markets. When constructing investment portfolios containing precious metals and energy commodities, further empirical research is needed to consider whether the spillover effects of high-order moments will significantly improve the performance and efficiency of the investment portfolio. In addition, there are varying degrees of cross moment spillovers in the commodity market at both low and high frequencies, indicating that it is necessary to study this issue in the context of portfolio management and asset allocation in the future. Consider optimizing investment portfolios into differentiated strategies that include different high-order moments and frequencies to serve short-term and long-term investment needs.

In future work, we will introduce macroeconomic and policy factors to more comprehensively assess their impact on risk spillovers; refine the analysis of market development stages and introduce market maturity indicators; employ nonlinear models and multi-frequency band analysis methods to more accurately capture the dynamic characteristics of risk spillovers; construct dynamic models that include feedback mechanisms to deeply explore the bidirectional causal relationships between variables; and validate the robustness of the models through out-of-sample forecasting. In addition, we will expand the scope of our research to conduct comparative analyses between China's carbon market and international mature markets, as well as emerging economies, to reveal broader global characteristics. These improvements will make our research more in-depth and extensive, providing stronger support for research and practice in related fields.

References

[1] P. Liu, D. Vedenov, and G. J. Power, "Commodity financialization and sector etfs: Evidence from crude oil futures," *Research in International Business and Finance*, vol. 51, p. 101109, 2020.

[2] Z. Yang and Y. Zhou, "Global systemic financial risk spillover and external shocks," *Chinese Social Sciences*, no. 12, pp. 69–90, 2018.

[3] X. Gong and X. Xiong, "Research on financial risk transmission from the perspective of volatility spillover networks," *Financial Research*, no. 05, pp. 39–58, 2020.

[4] R. Wan and J. Lu, "Research on the contagion of exchange rate risk during financial crises," *Journal of Management Science*, vol. 21, no. 06, pp. 12–28, 2018.

[5] D. Zhang, "Oil shocks and stock markets revisited: Measuring connectedness from a global perspective," *Energy Economics*, vol. 62, pp. 323–333, 2017.

[6] I. H. Cheng and W. Xiong, "Financialization of commodity markets," *Annual Review of Financial Economics*, vol. 6, pp. 419–441, 2014.

[7] J. B. Geng, Q. Ji, and Y. Fan, "The relationship between regional natural gas markets and crude oil markets from a multi-scale nonlinear granger causality perspective," *Energy Economics*, vol. 67, pp. 98–110, 2017.

[8] X. Shi and H. M. P. Variam, "East asia's gas-market failure and distinctive economics—a case study of low oil prices," *Applied Energy*, vol. 195, pp. 800–809, 2017.

[9] Q. Ji, J. B. Geng, and A. K. Tiwari, "Information spillovers and connectedness networks in the oil and gas markets," *Energy Economics*, vol. 75, pp. 71–84, 2018.

[10] A. Dutta, E. Bouri, and D. Roubaud, "Nonlinear relationships amongst the implied volatilities of crude oil and precious metals," *Resources Policy*, vol. 61, pp. 473–478, 2019.

[11] D. Ç. Yıldırım, E. I. Cevik, and Ö. Esen, "Time-varying volatility spillovers between oil prices and precious metal prices," *Resources Policy*, vol. 68, p. 101783, 2020.

[12] G. Bakshi, N. Kapadia, and D. Madan, "Stock return characteristics, skew laws, and the differential pricing of individual equity options," *Review of Financial Studies*, vol. 16, no. 1, pp. 101–143, 2003.

[13] H. X. Do, R. Brooks, S. Treepongkaruna, *et al.*, "Stock and currency market linkages: New evidence from realized spillovers in higher moments," *International Review of Economics and Finance*, vol. 42, pp. 167–185, 2016.

[14] F. X. Diebold and K. Yilmaz, "Better to give than to receive: Predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.

[15] J. Baruník and T. Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk," *Journal of Financial Econometrics*, vol. 16, no. 2, pp. 271–296, 2018.

[16] L. Morales and B. Andreosso-O'Callaghan, "The global financial crisis: World market or regional contagion effects?," *International Review of Economics and Finance*, vol. 29, pp. 108–131, 2014.

[17] K. Zhou, H. Yang, and Y. Wu, "Spillover effects and return guidance role of the hong kong stock market in china: an analysis based on the stock markets in the asia pacific region," *Journal of Management Science*, vol. 21, no. 05, pp. 22–43, 2018.

[18] C. Liu, F. Gao, M. Zhang, and Q. Xie, "Research on risk spillover effect, impact effect, and risk warning in china's financial market," *China Management Science*, pp. 1–14, 2021.

[19] S. H. Kang, R. McIver, and S. M. Yoon, "Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets," *Energy Economics*, vol. 62, pp. 19–32, 2017.

[20] Z. Liu, H. K. Tseng, J. S. Wu, *et al.*, "Implied volatility relationships between crude oil and the u.s. stock markets: Dynamic correlation and spillover effects," *Resources Policy*, vol. 66, p. 101637, 2020.

[21] S. M. Yoon, M. Al Mamun, G. S. Uddin, *et al.*, "Network connectedness and net spillover between financial and commodity markets," *North American Journal of Economics and Finance*, vol. 48, pp. 801–818, 2019.

[22] D. Amaya, P. Christoffersen, K. Jacobs, *et al.*, "Does realized skewness predict the cross-section of equity returns?," *Journal of Financial Economics*, vol. 118, no. 1, pp. 135–167, 2015.

[23] X. Tan, J. Zhang, and X. Zheng, "The bidirectional spillover effects between international commodity markets and financial markets: An empirical study based on the bekk-garch model and spillover index method," *China Soft Science*, no. 08, pp. 31–48, 2018.

[24] H. Langlois, "Measuring skewness premia," *Journal of Financial Economics*, vol. 135, no. 2, pp. 399–424, 2020.

[25] M. Bevilacqua and R. Tunaru, "The skew index: Extracting what has been left," *Journal of Financial Stability*, vol. 53, p. 100816, 2021.

[26] H. X. Do, R. Brooks, and S. Treepongkaruna, "Realized spillover effects between stock and foreign exchange market: Evidence from regional analysis," *Global Finance Journal*, vol. 28, pp. 24–37, 2015.

[27] M. Greenwood-Nimmo, V. H. Nguyen, and B. Rafferty, "Risk and return spillovers among the g10 currencies," *Journal of Financial Markets*, vol. 31, pp. 43–62, 2016.

[28] F. X. Diebold and K. Yilmaz, "On the network topology of variance decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, vol. 182, no. 1, pp. 119–134, 2014.

[29] J. Cui, A. Maghyereh, M. Goh, *et al.*, "Risk spillovers and time-varying links between international oil and china's commodity futures markets: Fresh evidence from the higher-order moments," *Energy*, vol. 238, p. 121751, 2022.

[30] A. I. Maghyereh, B. Awartani, and P. Tziogkidis, "Volatility spillovers and cross-hedging between gold, oil and equities: Evidence from the gulf cooperation council countries," *Energy Economics*, vol. 68, pp. 440–453, 2017.

[31] A. D. Ahmed and R. Huo, "Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from china," *Energy Economics*, vol. 93, p. 104741, 2021.

[32] X. Sun, C. Liu, J. Wang, *et al.*, "Assessing the extreme risk spillovers of international commodities on maritime markets: A garch-copula-covar approach," *International Review of Financial Analysis*, vol. 68, no. 15, p. 101453, 2020.

[33] Á. León, G. Rubio, and G. Serna, "Autoregressive conditional volatility, skewness and kurtosis," *The Quarterly Review of Economics and Finance*, vol. 45, no. 4–5, pp. 599–618, 2005.

[34] T. Ando, M. Greenwood-Nimmo, and Y. Shin, "Quantile connectedness: Modelling tail behaviour in the topology of financial network," *Management Science*, vol. 68, no. 4, pp. 2401–2431, 2022.

[35] B. Lin and Y. Chen, "Dynamic linkages and spillover effects between cet market, coal market and stock market of new energy companies: A case of beijing cet market in china," *Energy*, 2019.

[36] D. Nie, Y. Li, and X. Li, "Dynamic spillovers and asymmetric spillover effect between the carbon emission trading market, fossil energy market, and new energy stock market in china," *Energies*, vol. 14, 2021.

[37] I. Chatziantoniou, E. Abakah, D. Gabauer, *et al.*, "Quantile time-frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets," *Journal of Cleaner Production*, vol. 361, 2022.

[38] Y. Wei, Z. Wang, D. Li, *et al.*, "Can infectious disease pandemic impact the long-term volatility and correlation of gold and crude oil markets?," *Finance Research Letters*, vol. 47, p. 102648, 2022.

[39] J. A. Batten, C. Ciner, and B. M. Lucey, "The dynamic linkages between crude oil and natural gas markets," *Energy Economics*, vol. 62, pp. 155–170, 2017.

[40] D. Zhang and Q. Ji, "Further evidence on the debate of oil-gas price decoupling: A long memory approach," *Energy Policy*, vol. 113, pp. 68–75, 2018.

[41] A. K. Tiwari and I. Sahadudheen, "Understanding the nexus between oil and gold," *Resources Policy*, vol. 46, pp. 85–91, 2015.

Biographies

Baoshuai Zhang is currently a teacher at the School of Economics and Management, Chongqing Normal University. He teaches courses in Investment and Finance. His research interests include Financial Engineering and Risk Management. He has published more than 30 papers in journals such as the Journal of Management Science and the Journal of Management Engineering, and has participated in or led over 10 provincial- and ministerial-level research projects, including projects funded by the National Social Science Fund, Chongqing Social Science Planning Project, and Chongqing Statistics Bureau. He has also published one monograph.

Jia You is currently a teacher at the School of Economics and Management, Chongqing University of Mechanical and Electrical Technology. She teaches courses in Accounting and Advanced Financial Management. Her research interests include corporate finance and risk management. She has published more than 10 papers in journals such as China Market, and has participated in or led six provincial- and ministerial-level research projects, including the Chongqing Social Science Planning Project and the Chongqing Statistics Bureau Project.