



Spillovers among China's precious and industrial metals markets: Evidence from higher moments and jumps

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Abstract: This study reveals the time-varying spillover effects of higher moments (realized volatility, realized skewness and realized kurtosis) and jumps between China's precious metals and industrial metals markets. Using 5-min high-frequency data from May 10, 2012 to October 21, 2021, the dynamic effects of spillovers are uncovered using the time–frequency domain spillover index framework. The results show that the system connectedness weakens as the moment order gets higher whereas the total jumps connectedness is the smallest, and the spillovers of all estimators are more evident in the short term. The overall information spillovers are time-varying and influenced by major market events. Specifically, for realized volatility, copper is the largest net transmitter and silver is always a net transmitter, while zinc is the largest net receiver. For realized skewness, copper is the largest net transmitter and silver is always a net transmitter, while lead is the largest net receiver. For realized kurtosis and jumps, copper is the largest net transmitter, while aluminum is the largest net receiver. Overall, copper and silver play dominant roles in China's precious and industrial metals markets system.

Key words: spillovers; precious metals; industrial metals; time–frequency domain analysis; higher moments; jumps

1 Introduction

The issue of commodity financialization has been more and more considered by many researchers [1–4], and the financialization of metals is an important part of it [5–9]. Precious metals are usually included in portfolio, such as gold, which is widely recognized by its role as a safe haven for investors in financial and commodity markets. Same as precious metals, industrial metals may arouse investors' interest in portfolio allocation and diversified returns. Understanding spillovers between precious metals markets and industrial metals markets can serve as a useful analytical tool for portfolio allocation and risk management.

Spillovers among metals markets have been

analyzed by a series of academic literature. AL-YAHYAEE et al [10] examine the volatility spillover among precious metals and non-ferrous metals, showing that aluminum is the highest transmitter to shocks in the LME (London Metal Exchange) metal markets. CINER et al [11] employ the spillover index method to study the risk spillovers among global base metals, and find strong return and volatility transmission among these markets. REHMAN and VO [12] investigate the presence of returns integration between energy commodities, precious metal commodities, and industrial metal commodities. A common limitation of those studies is that they only discuss spillover effects based on the first and the second moments of the asset return distribution, namely return and volatility. However, given that assets return

distributions are generally non-normal, skewed, and fat-tails, the studies on spillovers which neglect higher moments, such as skewness and kurtosis, are in fact incomplete in terms of empirical inferences on cross-assets or cross-markets linkages [13]. DAI et al [14] show that the three-order moment of oil price returns can predict the aggregate stock market returns. Additionally, the jump risk can capture the discontinuous and large volatile characterization of assets, and contains more unique pricing information compared to the volatility risk [15]. Therefore, it is deserved to examine cross-markets transmission of higher moments and jumps risk. Motivated by the above discussion and the related research gap, we carry out academic debate especially from the aspect of China's precious metals and industrial metals markets. Specifically, we choose two precious metals including gold and silver, and four industrial metals including copper, aluminum, lead and zinc.

There are few studies paying attention to spillovers of higher moments. Earlier studies on risk spillovers of higher moments mainly focus on the stock and currency market [16–19]. As the research progresses, spillovers on higher moments among commodity markets have attracted more attention [20–23]. However, these studies mainly focus on spillovers in the time domain. To reveal potential heterogeneity of spillovers across various frequencies, we extend the debate by investigating spillovers in higher moments and jumps not only in time domain but also in frequency domain.

DIEBOLD and YILMAZ [20,23] propose a spillover framework based on the generalized forecast error variance decompositions (GFEVD) associated with a VAR system (DY method, hereafter). This approach provides the measures of the magnitude and direction of the spillovers, allowing measuring the level of systemic risk, and several studies emphasize its empirical advantages [24–26]. More recently, BARUŇÍK and KŘEHLÍK [27] have expanded the DY approach by combining the Fourier transform technique, which allows computing the forecast error variance decompositions in different frequency domains (BK method, hereafter). Hence, the BK method provides a new perspective to further understand system spillover from frequency domain aspect. Recent studies combine DY and BK methods to explore the pattern of connectedness across different markets.

MENSI et al [28] investigate the volatility spillover among 28 commodity futures markets in both time and frequency domains, showing that the total spillover is higher in the short term. WANG et al [29] examine return spillovers among gold, wheat, crude oil and copper via DY and BK methods, finding that copper is information transmitter to other commodity futures. Using daily data from November 2018 to June 2020, LE et al [30] use both DY and BK method to examine the volatility connectedness of returns series. In this work, we follow DY and BK frameworks to examine the magnitude and direction of spillovers in time domain and different frequency domains, enabling a more comprehensive investigation of spillovers in higher moments and jumps across precious metals and industrial metals markets.

Scholars have conducted a series of studies on the risk spillover between precious metals markets and industrial metals markets. Some progress has been achieved, while some deficiencies remain. Most of the studies on this topic limit to focus on return spillover or volatility spillover only, and there are few studies on higher moments or jumps risk spillover. Regarding the research perspective, most relevant studies are based on the time domain, and the relationship between precious metals and industrial metals under different frequency domains has rarely been investigated. However, under various time scales, market responses are heterogenous, leading to different mutual spillover effects among markets. Thus, it is necessary to explore the spillovers among precious metals and industrial metals in both time and frequency domains. This study pays special attention to risk spillovers based on higher moments and jumps among China's precious and industrial metals markets.

2 Methodology

2.1 High frequency data and daily realized estimators

We employ 5-min high-frequency data for gold, silver, copper, aluminum, lead and zinc. The data are derived from Wind database. The data period is from May 10, 2012 to October 21, 2021, according to its availability. For each trading day t , the i th 5-min intraday return is defined as the logarithmic difference between two consecutive

observed prices within a day, namely $p_{t,i-1}$ and $p_{t,i}$, shown as follows:

$$r_{t,i} = \lg p_{t,i} - \lg p_{t,i-1}, \quad i = 1, \dots, T \quad (1)$$

where $r_{t,i}$ denotes the i th intraday return, $p_{t,i}$ is the i th intraday price for the day t , and T is the total number of intraday returns during the trading day t .

For each trading day t , the realized volatility RV_t , which is referred to the estimator of the second realized moment and represents the dispersion risk of the price process, is calculated by the following expression:

$$RV_t = \sum_{i=1}^T r_{t,i}^2 \quad (2)$$

Subsequently, detection scheme proposed by DUONG and SWANSON [31] is applied to detecting jumps, which depend on the selection of the jump-robust realized volatility estimator. Using the threshold bi-power variation as a jump-robust realized volatility estimator [32], the jump statistic is defined as

$$ZJ_t^{(TBPV)} = \sqrt{T} \frac{(RV_t - TBPV_t)RV_t^{-1}}{[(\xi_1^{-4} + 2\xi_1^{-2} - 5)\max\{1, TQ_t / TBPV_t^{-2}\}]^{1/2}} \quad (3)$$

where $TQ_t = T\xi_{4/3}^{-3} \sum_{i=1}^T |r_{t,i}|^{4/3} |r_{t,i+1}|^{4/3} |r_{t,i+2}|^{4/3}$ stands

for the realized tri-power quarticity and converges in probability to integrated quarticity. The threshold bi-power variation ($TBPV_t$) as a jump-free volatility estimator is calculated as

$$TBPV_t = \sum_{i=2}^T \left(|r_{t,i-1}| \cdot |r_{t,i}| I_{\{|r_{t,i-1}|^2 \leq \theta_{i-1}\}} I_{\{|r_{t,i}|^2 \leq \theta_i\}} \right) \quad (4)$$

where $I_{\{\cdot\}}$ stands for an indicator function.

A jump is statistically significantly different from zero if $ZJ_t^{(TBPV)}$ exceeds the appropriate critical value of the standard gaussian distribution. Further, the jump component of realized volatility is constructed as

$$J_t = |RV_t - TBPV_t| I_{\{ZJ_t^{(TBPV)} < \Phi_\alpha\}} \quad (5)$$

where $I_{\{\cdot\}}$ is an indicator function of $ZJ_t^{(TBPV)}$ exceeding a given critical value of a Gaussian distribution denoted by Φ_α , at significant level α .

The skewness, which is the third moment and measures the asymmetry of the conditional asset return distribution, can be used as a proxy for jump

risk or crash risk [3,4]. For assets with fatter left tails, the skewness has a negative value, and for assets with fatter right tails, the skewness has a positive value. The realized skewness can be constructed using high-frequency data as follows:

$$RSK_t = \frac{\sqrt{T} \sum_{i=1}^T r_{t,i}^3}{RV_t^{3/2}} \quad (6)$$

The kurtosis, which is the fourth moment and used as a measure of “tailedness” of the conditional asset return distribution, corresponds to the extremity of deviations [33]. Kurtosis captures the discontinuous component of quadratic variation. The realized kurtosis is constructed as follows:

$$RKU_t = \frac{T \sum_{i=1}^T r_{t,i}^4}{RV_t^2} \quad (7)$$

Table 1 presents the descriptive statistics of the four estimators, namely realized volatility, realized skewness, realized kurtosis, and jumps over the entire sample period. The mean values of the realized volatility and realized kurtosis are greater than those of the realized skewness and jumps. The skewness values of most of series are positive, suggesting that most of series are right-skewed. Except for volatility series, the kurtosis values of the other series are greater than 3, suggesting that most of series have heavy tails. The Jarque–Bera test results show that all series depart from a normal distribution at the 1% significance level. ADF test results show that all series are stationary at 1% significance level.

2.2 Spillover index framework in time domain

Under the time-domain framework of DIEBOLD and YILMAZ [23], the DY spillover index and additional spillover measures are based on a vector autoregression (VAR) model and generalized forecast error variance decomposition (GFEVD).

The DY framework starts by building a VAR(p) model as follows:

$$X_t = \Phi(L)X_t + \epsilon_t \quad (8)$$

where X_t represents the $n \times 1$ vector of endogenous variables at time t , $\Phi(L) = \sum_{h=1}^p \Phi_h L^h$ is an $n \times n$ autoregressive coefficient matrix with the p th lag

Table 1 Descriptive statistics of four estimators

Estimator	Metal	Parameter							
		Mean	Std.dev.	Min	Max	Skew	Kurt	Jarque–Bera	ADF
RV (Panel A)	Gold	0.454	0.718	0.000	11.746	5.979	56.271	361434.091***	−7.708***
	Silver	1.288	2.123	0.000	31.476	4.836	37.232	161608.993***	−4.908***
	Copper	0.771	1.18	0.000	25.157	7.888	114.908	1469171.05***	−8.017***
	Aluminum	0.63	1.135	0.001	25.144	7.991	120.883	1623745.27***	−5.533***
	Lead	0.887	1.371	0.000	22.521	5.739	54.684	340972.596***	−5.064***
	Zinc	1.071	1.822	0.001	59.509	14.833	416.587	19048792.8 ***	−4.918***
Estimator	Metal	Parameter							
		Mean	Std.dev.	Min	Max	Skew	Kurt	Jarque–Bera	ADF
RSK (Panel B)	Gold	0.037	2.376	−8.515	9.578	−0.081	1.951	417.454***	−53.079***
	Silver	0.088	2.192	−9.472	8.645	−0.039	2.496	679.996***	−53.386***
	Copper	−0.010	1.850	−8.303	7.98	−0.247	2.883	933.046***	−24.882***
	Aluminum	0.021	1.494	−8.142	8.014	0.151	2.064	474.245***	−26.946***
	Lead	−0.048	1.754	−7.208	6.734	0.108	1.170	154.165***	−52.108***
	Zinc	0.050	1.570	−6.675	8.188	0.095	2.357	609.258***	−38.029***
Estimator	Metal	Parameter							
		Mean	Std.dev.	Min	Max	Skew	Kurt	Jarque–Bera	ADF
RKU (Panel C)	Gold	13.191	14.239	1.689	97.574	2.394	6.223	6735.680***	−6.277***
	Silver	12.038	12.971	1.923	95.848	2.707	8.352	10823.773***	−8.148***
	Copper	9.168	9.654	1.47	76.018	3.257	12.821	22591.397***	−11.177***
	Aluminum	7.567	6.68	1.366	73.539	3.482	17.852	40106.226***	−7.962***
	Lead	9.078	7.586	1.506	63.486	2.547	8.367	10482.721***	−11.133***
	Zinc	7.789	7.27	1.521	74.927	3.492	16.250	34168.571***	−9.788***
Estimator	Metal	Parameter							
		Mean	Std.dev.	Min	Max	Skew	Kurt	Jarque–Bera	ADF
JUMPS (Panel D)	Gold	0.177	0.478	0.000	8.564	7.503	80.954	740319.02***	−5.801***
	Silver	0.442	1.207	0.000	19.623	6.135	54.661	342760.01***	−4.800***
	Copper	0.188	0.553	0.000	10.713	8.248	109.236	1332879.9***	−11.514***
	Aluminum	0.093	0.527	0.000	23.174	32.859	1400.826	214774310***	−16.959***
	Lead	0.181	0.553	0.000	12.126	9.396	141.210	2216253.9***	−5.566***
	Zinc	0.224	1.200	0.000	51.890	31.818	1317.261	189939567***	−22.667***

This table presents the descriptive statistics of realized volatility, realized skewness, realized kurtosis and jumps over the sample period, May 10, 2012 to October 21, 2021. The number of daily observations is 2631. The Jarque–Bera statistic tests are for the null hypothesis of normality for the distribution of the series. The ADF statistics are for the null hypothesis that the series has a unit root. *** denotes rejection of the null hypothesis at the 1% significance level

order, L is the lag operator, ε_t represents a white noise vector with zero mean, and its covariance matrix is Σ .

Let us suppose that the covariance in this VAR model is stable; hence, the moving average form

can be shown as

$$X_t = \Psi(L)\varepsilon_t = \sum_{i=1}^{\infty} \Psi_i \varepsilon_{t-i} + \varepsilon_t \quad (9)$$

where $\Psi(L)$ is an $n \times n$ moving average coefficient

matrix with an infinite lag order.

In the DY framework, the GFEVD of H -step-ahead forecast is presented as

$$\theta_{jk}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^H \left[(\Psi_h \Sigma)_{jk} \right]^2}{\sum_{h=0}^H (\Psi_h \Sigma \Psi_h')_{jj}} \quad (10)$$

where Ψ_h is an $n \times n$ moving average coefficient matrix with the p th lag order, and $\sigma_{kk} = \Sigma_{kk}$. We normalize $\theta_{jk}(H)$ as

$$\tilde{\theta}_{jk}(H) = \frac{\theta_{jk}(H)}{\sum_{k=1}^n \theta_{jk}(H)} \quad (11)$$

where $\tilde{\theta}_{jk}(H)$ signifies the contribution of the variable k to the variance of H -step-ahead forecast error of variable j . This is representative of the standard directional spillover effect.

The total spillover measures the forecasting variance caused by other variables in the system and is defined as follows:

$$C_H = 100 \times \frac{\sum_{j,k=1, j \neq k}^n \tilde{\theta}_{jk}(H)}{\sum_{j,k=1}^n \tilde{\theta}_{jk}(H)} \quad (12)$$

The TO spillover transmitted from variable j to all other variables is

$$(C_H)_{\leftarrow j} = 100 \times \frac{\sum_{k=1, k \neq j}^n \tilde{\theta}_{kj}(H)}{\sum_{j,k=1}^n \tilde{\theta}_{kj}(H)} \quad (13)$$

The FROM spillover received from all other variables to variable j is

$$(C_H)_{j \leftarrow \cdot} = 100 \times \frac{\sum_{k=1, k \neq j}^n \tilde{\theta}_{jk}(H)}{\sum_{j,k=1}^n \tilde{\theta}_{jk}(H)} \quad (14)$$

The net spillover of variable j is the difference between TO and FROM spillovers:

$$(C_H)_j = (C_H)_{\leftarrow j} - (C_H)_{j \leftarrow \cdot} \quad (15)$$

The net pairwise spillover between variable j and k is

$$(C_H)_{jk} = 100 \times \frac{\tilde{\theta}_{kj}(H) - \tilde{\theta}_{jk}(H)}{n} \quad (16)$$

2.3 Spillover index framework in frequency domain

Extending the DY framework, BARUNÍK and KŘEHLÍK [27] develop a new measure of connectedness in the frequency domain based on the spectral representation of the GFEVD. A frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h$

is obtained from a Fourier transform, where $i = \sqrt{-1}$, and ω is the frequency. The share of a shock to variable k in the fluctuations of variable j at the frequency $\omega \in (-\pi, \pi)$ is expressed as

$$(f(\omega))_{jk} = \frac{\sigma_{kk}^{-1} \left| (\Psi(e^{-i\omega}) \Sigma)_{jk} \right|^2}{\sum_{h=1}^H (\Psi(e^{-i\omega}) \Sigma \Psi^{-1}(e^{i\omega}))_{jj}} \quad (17)$$

To obtain the GFEVD at different frequencies, BARUNÍK and KŘEHLÍK [27] weight the $(f(\omega))_{jk}$ by the frequency share of variance of the variable j . The weighting function is

$$\Gamma_j(\omega) = \frac{(\Psi(e^{-i\omega}) \Sigma \Psi^{-1}(e^{i\omega}))_{jj}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} (\Psi(e^{-i\varphi}) \Sigma \Psi^{-1}(e^{i\varphi}))_{jj} d\varphi} \quad (18)$$

Given a frequency band $d = (a, b)$, $a, b \in (-\pi, \pi)$, the GFEVD at frequency band d is

$$\theta_{jk}(d) = \frac{1}{2\pi} \int_a^b \Gamma_j(\omega) (f(\omega))_{jk} d\omega \quad (19)$$

The normalized $\theta_{jk}(d)$ is calculated by

$$\tilde{\theta}_{jk}(d) = \frac{\theta_{jk}(d)}{\sum_{k=1}^n \theta_{jk}(\infty)} \quad (20)$$

where $\tilde{\theta}_{jk}(d)$ represents the directional spillover from variable k to variable j at frequency band d . It should be noted that the forecast horizon is unrelated to this framework.

Using the above-mentioned directional connectedness at frequency band d , the frequency overall connectedness (spillovers) can be calculated as

$$C_d^F = 100 \times \left(\frac{\sum_{j,k=1, j \neq k}^n \tilde{\theta}_{jk}(d) - \text{Tr}(\tilde{\theta}_d)}{\sum_{j,k=1}^n \tilde{\theta}_{jk}(\infty)} \right) \quad (21)$$

Similarly, the TO connectedness is

$$(C_d^F)_{\leftarrow j} = 100 \times \left(\sum_{k=1, j \neq k}^n \tilde{\theta}_{kj}(d) \right) \frac{\sum_{j,k=1}^n \tilde{\theta}_{kj}(d)}{\sum_{j,k=1}^n \tilde{\theta}_{kj}(\infty)} \quad (22)$$

The FROM connectedness is

$$(C_d^F)_{j \leftarrow} = 100 \times \left(\sum_{k=1, j \neq k}^n \tilde{\theta}_{jk}(d) \right) \frac{\sum_{j,k=1}^n \tilde{\theta}_{jk}(d)}{\sum_{j,k=1}^n \tilde{\theta}_{jk}(\infty)} \quad (23)$$

The net connectedness of variable j is

$$(C_d^F)_j = (C_d^F)_{\leftarrow j} - (C_d^F)_{j \leftarrow} \quad (24)$$

3 Empirical analysis

Firstly, we study the static time–frequency connectedness of realized higher moments (volatility, skewness, and kurtosis) and jumps among the six metals markets. Secondly, we turn to the time–frequency dynamics of connectedness to investigate time-varying movements adopting a rolling-window method. Lastly, we construct the time–frequency connectedness networks to reveal net spillovers of all pairs of markets.

Under the time-domain DY framework, forecast horizon is kept in 100 d. Under the frequency-domain BK framework, two types of time scales are considered, corresponding to high frequency (1–22 d) and low frequency (more than 22 d). The window size is kept in 250 d.

3.1 Static information spillover effect

The results of volatility spillovers among the six metals markets are shown in Table 2, using the DY and BK models in Panels A and B, respectively. Panel A shows that the total volatility spillover index for the system is 45.67%. Copper is the largest volatility spillover transmitter, contributing to others at 10.64%; zinc is the largest receiver, receiving 8.85% from others. The highest spillover occurs from silver to gold (29.34%), and the second highest spillover occurs from gold to silver (25.35%). Panel B shows the total volatility spillover indices at high- and low-frequency bands are 30.44% and 15.23%, respectively. Evidently, the level of volatility spillover in the short term (at high frequency) is higher than that in the long term (at low frequency). This finding suggests that the

volatility connectedness across these markets is driven by the short-term effect, which is consistent with MENSİ et al [28]. In the short term, copper is the largest volatility transmitter and receiver. In the long term, copper is the largest volatility transmitter whereas zinc is the largest volatility receiver. These findings indicate that copper is a strong transmitter in the system, which accords with CINER et al [11]. Besides, both in short and long terms, the highest directional spillover between two markets occurs between gold and silver. Such finding suggests that close volatility transmission happens between gold and silver markets, which confirms the result reported by previous study [34].

Table 3 shows the skewness spillover results of the DY and BK models among the six metals markets. It is seen that the total skewness spillover index for the system is 35.91% from Panel A, revealing a rather strong degree of skewness interdependence among these markets. Silver and zinc are the two largest transmitters of skewness spillovers, whereas silver is the largest receiver of skewness spillovers. The two highest spillovers from one market to another are reported between gold and silver markets: The share of volatility transmitted from silver to gold is 34.74% and that transmitted from gold to silver is 32.89%. Panel B indicates that the total skewness spillover indices at high- and low-frequency bands are 34.37% and 1.54%, respectively. The level of skewness spillover at high frequency is higher than that at low frequency. Similar to the results in the time domain, we find both at two frequency bands that silver and zinc are the two largest transmitters, whereas silver is the largest receiver. Besides, the highest directional spillover is from silver to gold and the second highest directional spillover is from gold to silver. These results are quite regular. They indicate that silver is the largest skewness transmitter and receiver, as well as a close transmission between gold and silver markets and the skewness shocks mainly spill over from silver to gold.

The kurtosis spillover results of the DY and BK models are shown in Table 4. From Panel A, we see that the total kurtosis spillover index for the system is 31.58%. Silver and copper are the two largest transmitters of kurtosis spillover, and silver and gold are the two largest receivers. Of these, silver is the largest kurtosis spillover transmitter and receiver. The highest kurtosis spillover occurs

Table 2 Volatility spillover results (%)

Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel A: DY (2012)	Gold	60.77	29.34	4.86	1.48	1.56	1.99	6.54
	Silver	25.35	63.44	5.04	2.09	2.14	1.93	6.09
	Copper	3.56	3.9	48.97	14.58	14.91	14.08	8.5
	Aluminum	1.12	2.51	18.06	54.1	12.48	11.74	7.65
	Lead	1.03	1.89	18.28	11.58	51.79	15.43	8.03
	Zinc	1.34	1.8	17.59	12.7	19.65	46.91	8.85
	TO	5.4	6.57	10.64	7.07	8.46	7.53	45.67
	NET	−1.14	0.48	2.13	−0.58	0.42	−1.32	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018) Frequency 1 (High frequency): 1 month	Gold	52.61	23.42	4.12	1.36	1.45	1.84	5.37
	Silver	19.1	43.83	3.92	1.78	1.87	1.65	4.72
	Copper	2.68	3.07	36.41	10.05	10.51	9.78	6.01
	Aluminum	0.93	1.62	11.3	37.56	6.95	6.55	4.56
	Lead	0.86	1.53	10.25	5.82	31.41	9.05	4.58
	Zinc	1.2	1.51	10.8	6.44	11.23	36.11	5.2
	TO_ABS	4.13	5.19	6.73	4.24	5.33	4.81	30.44
	NET	−1.24	0.48	0.72	−0.32	0.75	−0.39	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018) Frequency 2 (Low frequency): more than 1 month	Gold	8.17	5.92	0.74	0.11	0.11	0.15	1.17
	Silver	6.26	19.61	1.12	0.31	0.27	0.29	1.37
	Copper	0.88	0.83	12.56	4.54	4.4	4.29	2.49
	Aluminum	0.19	0.88	6.75	16.54	5.53	5.19	3.09
	Lead	0.16	0.35	8.04	5.77	20.38	6.38	3.45
	Zinc	0.14	0.29	6.79	6.26	8.43	10.8	3.65
	TO_ABS	1.27	1.38	3.91	2.83	3.12	2.72	15.23
	NET	0.1	0.01	1.42	−0.26	−0.33	−0.93	

The “FROM” column, “TO” row (or “TO_ABS” row), and “NET” row refer to the FROM connectedness, TO connectedness, and NET connectedness, respectively. The j kth value is the directional connectedness from k to j

from silver to gold, and the second highest spillover occurs from gold to silver, which are 30.1% and 29.25%, respectively. As shown in Panel B, the total kurtosis spillover indices at high- and low-frequency bands are 29.46% and 2.13%, respectively. The level of kurtosis spillover at high frequency is higher than that at low frequency, which is similar to the results for volatility and skewness spillovers. At two frequency bands, the

results are exactly consistent with those in the time domain, whether in the case of the largest transmitters, the largest receivers, or the markets where the highest directional spillover occurs. These findings indicate silver and copper are the two largest kurtosis transmitters. Moreover, a close transmission between gold and silver markets is verified again. The kurtosis shocks mainly spill over from silver to gold.

Table 3 Skewness spillover results (%)

Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel A: DY (2012)	Gold	63.2	34.74	0.7	0.49	0.43	0.45	6.13
	Silver	32.89	59.73	3.31	1.68	0.87	1.52	6.71
	Copper	0.67	3.41	60.52	10.55	7.85	17	6.58
	Aluminum	0.52	2	12.27	69.76	4.82	10.62	5.04
	Lead	0.49	1.04	9.21	4.87	71.12	13.26	4.81
	Zinc	0.53	1.74	17.07	9.14	11.34	60.18	6.64
	TO	5.85	7.15	7.09	4.45	4.22	7.14	35.91
	NET	−0.28	0.44	0.51	−0.59	−0.6	0.51	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 1 (High frequency): 1 month	Gold	60.28	33.08	0.68	0.47	0.41	0.43	5.85
	Silver	31.42	57	3.17	1.59	0.83	1.45	6.41
	Copper	0.65	3.29	57.67	10.06	7.54	16.25	6.3
	Aluminum	0.5	1.93	11.77	66.29	4.63	10.19	4.84
	Lead	0.47	1	8.85	4.63	67.7	12.63	4.6
	Zinc	0.53	1.71	16.42	8.76	10.89	57.43	6.38
	TO_ABS	5.59	6.83	6.81	4.25	4.05	6.83	34.37
	NET	−0.25	0.42	0.52	−0.58	−0.55	0.44	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 2 (Low frequency): more than 1 month	Gold	2.92	1.65	0.02	0.02	0.02	0.02	0.29
	Silver	1.47	2.73	0.14	0.09	0.04	0.07	0.3
	Copper	0.02	0.12	2.85	0.49	0.31	0.75	0.28
	Aluminum	0.02	0.07	0.5	3.47	0.19	0.43	0.2
	Lead	0.02	0.04	0.36	0.24	3.42	0.63	0.22
	Zinc	0.01	0.03	0.66	0.38	0.45	2.75	0.25
	TO_ABS	0.26	0.32	0.28	0.2	0.17	0.32	1.54
	NET	−0.03	0.02	−0.00	−0.00	−0.05	0.06	

The jumps spillover results of the DY and BK models are reported in Table 5. Panel A shows that the total jumps spillover index for the system is 18.00%. Silver is the largest jumps spillover transmitter contributing to others at 4.55%; gold is the largest receiver, receiving 4.41% from others. The highest jumps spillover occurs from gold to silver, and the second highest spillover occurs from silver to gold, which are 24.76% and 23.62%, respectively. Panel B shows that the total jumps spillover indices at high- and low-frequency bands

are 16.01% and 1.99%, respectively. The jumps connectedness weakens as the frequency band increases, which is similar to the spillover results of above three estimators. In the short term, silver acts mainly as a jumps spillover transmitter, whereas gold acts as a jumps spillover receiver. In the long term, copper is the largest transmitter, whereas silver is the largest receiver. Additionally, both in short and long terms, the largest directional spillover between two markets occurs between gold and silver. These findings indicate silver and copper

Table 4 Kurtosis spillover results (%)

Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel A: DY (2012)	Gold	62.76	30.1	2.56	1.09	1.53	1.96	6.21
	Silver	29.25	61.23	3.91	1.76	1.54	2.32	6.46
	Copper	2.6	4.02	66.09	7.4	5.75	14.14	5.65
	Aluminum	1.18	2.1	8.48	77	4.23	7.01	3.83
	Lead	1.73	1.69	6.78	4.07	76.45	9.28	3.92
	Zinc	2.03	2.5	14.16	6.07	8.25	67	5.5
	TO	6.13	6.73	5.98	3.4	3.55	5.78	31.58
	NET	−0.08	0.27	0.33	−0.43	−0.38	0.28	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 1 (High frequency): 1 month	Gold	58.59	27.89	2.3	1.01	1.37	1.78	5.73
	Silver	27.21	57.18	3.55	1.63	1.38	2.11	5.98
	Copper	2.43	3.77	62.24	6.78	5.53	13.18	5.28
	Aluminum	1.1	2.06	7.85	71.85	3.91	6.5	3.57
	Lead	1.62	1.62	6.6	3.77	71.23	8.78	3.73
	Zinc	1.9	2.39	13.23	5.66	7.8	62.9	5.16
	TO_ABS	5.71	6.29	5.59	3.14	3.33	5.39	29.46
	NET	−0.01	0.31	0.31	−0.43	−0.4	0.23	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 2 (Low frequency): more than 1 month	Gold	4.17	2.21	0.26	0.09	0.16	0.18	0.48
	Silver	2.03	4.05	0.35	0.13	0.16	0.21	0.48
	Copper	0.17	0.25	3.85	0.61	0.22	0.96	0.37
	Aluminum	0.08	0.05	0.63	5.15	0.32	0.51	0.26
	Lead	0.11	0.07	0.18	0.3	5.22	0.5	0.19
	Zinc	0.13	0.1	0.93	0.41	0.45	4.1	0.34
	TO_ABS	0.42	0.45	0.39	0.26	0.22	0.39	2.13
	NET	−0.06	−0.03	0.02	−0.01	0.02	0.06	

are the two largest jumps transmitters as well as a close transmission between gold and silver markets.

To sum up, the total volatility, skewness, kurtosis and jumps spillover indices in the time domain are 45.67%, 35.91%, 31.58% and 18.00%, respectively. We notice that the system connectedness weakens as the moment order gets higher whereas the total jumps connectedness is the smallest among the results of four risk estimators. These results are confirmed by BOURI et al [22], which claims that spillovers of volatility are more dominant than spillovers of the other realized

estimators in terms of the linkages' strength. From the perspective of frequency domain, the connectedness of all realized estimators on high-frequency band contributes most to their respective total one, indicating that information transmission is relatively quick across metals markets. The results of the four estimators highlight the significance of silver and copper market in the system. It is understandable given that silver and copper play important roles in China's metal futures markets. Silver, which has industrial and hedging attribute is the most important metal in terms of

Table 5 Jumps spillover results (%)

Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel A: DY (2012)	Gold	73.56	24.76	1.01	0.11	0.19	0.37	4.41
	Silver	23.62	74.24	1.36	0.19	0.27	0.32	4.29
	Copper	1.21	1.45	80.02	3.46	6.25	7.61	3.33
	Aluminum	0.11	0.32	6.29	91.03	0.83	1.42	1.49
	Lead	0.46	0.37	7.66	0.41	87.37	3.73	2.11
	Zinc	0.45	0.39	7.81	0.58	5.00	85.76	2.37
	TO	4.31	4.55	4.02	0.79	2.09	2.24	18.00
	NET	−0.1	0.25	0.69	−0.70	−0.01	−0.13	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 1 (High frequency): 1 month	Gold	68.02	22.70	0.96	0.11	0.19	0.37	4.05
	Silver	21.39	63.95	1.18	0.18	0.26	0.28	3.88
	Copper	1.18	1.37	73.16	3.07	5.66	6.70	3.00
	Aluminum	0.11	0.32	5.2	84.21	0.64	1.17	1.24
	Lead	0.46	0.35	6.53	0.36	79.54	3.44	1.86
	Zinc	0.45	0.37	6.72	0.54	3.79	78.41	1.98
	TO_ABS	3.93	4.18	3.43	0.71	1.76	1.99	16.01
	NET	−0.12	0.30	0.44	−0.53	−0.10	0.01	
Model	Receiver	Transmitter						FROM
		Gold	Silver	Copper	Aluminum	Lead	Zinc	
Panel B: BK (2018); Frequency 2 (Low frequency): more than 1 month	Gold	5.54	2.05	0.05	0.00	0.00	0.00	0.35
	Silver	2.23	10.29	0.18	0.00	0.01	0.04	0.41
	Copper	0.03	0.08	6.87	0.39	0.59	0.91	0.33
	Aluminum	0.00	0.01	1.09	6.82	0.19	0.25	0.26
	Lead	0.00	0.01	1.13	0.06	7.82	0.29	0.25
	Zinc	0.00	0.02	1.09	0.04	1.20	7.35	0.39
	TO_ABS	0.38	0.36	0.59	0.08	0.33	0.25	1.99
	NET	0.02	−0.05	0.26	−0.17	0.08	−0.15	

trading volume in the Shanghai Futures Exchange. Copper futures market is the most mature and stable market in China's industrial metal futures markets. Thus, silver and copper somewhat dominate spillovers in higher moment and jump risks among China's metal nexus. We conclude that shocks mainly spill over from silver to gold, which is different from the prevalent conclusion that silver is a spillover receiver of gold in the international metal futures market. This may be because silver has a higher trading status than gold in China's

metal futures market (Authors collect and analyze the total annual trading volumes of metal futures in SHFE. Data are obtained from the Wind database). In addition, the dominators revealed via the four estimators are not the same, probably because information transmission of various higher moment and jumps follows different patterns [22].

3.2 Dynamic overall spillovers

Figure 1 shows that the total volatility connectedness index of the system varies over the

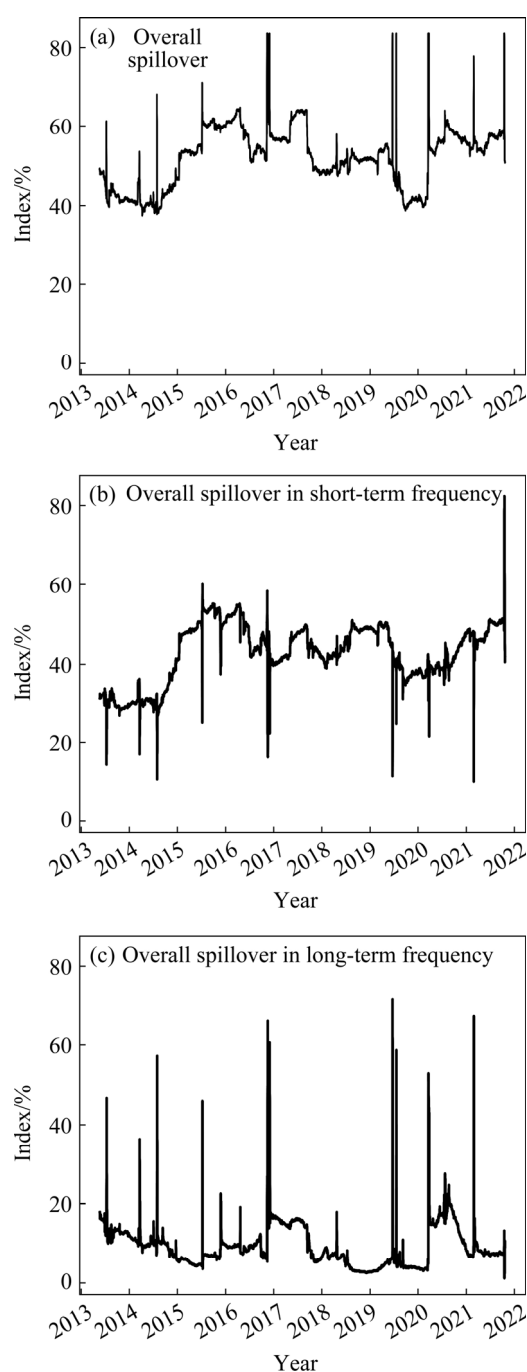


Fig. 1 Overall volatility spillover indices in time–frequency domain: (a) Dynamic overall spillover; (b, c) Dynamic frequency connectedness C_d^F with frequency band $d_1 \in [3.14, 0.14]$ and frequency band $d_2 \in [0.14, 0.00]$, respectively

sample period. The total volatility spillover is fluctuant generally ranging 35%–80% and reaches over 80% six times. In November 2016, the total spillover reached two high points of over 80% with fluctuations in copper and lead markets. It is also clearly seen that the total volatility spillover

reached two high points of over 80% again in June and July 2019, when gold and silver markets were in a strong uptrend. In March 2020, affected by the COVID-19 outbreak, copper prices fluctuated and fell heavily, and the overall volatility spillover index rose to 80%. In October 2021, the spillover rose to 80% for the last time. At that time, Nyrstar, the world's largest zinc smelter, announced a large production cut, sparking a surge in global zinc prices and leading to a surge in industrial metals prices. In general, it is obviously seen that volatility spillover index is influenced by market risk events. In volatility frequency connectedness, as shown in Figs. 1(b, c), spillovers at high-frequency band are higher than those at low-frequency band, which indicates that total volatility spillover among precious metals and industrial metals markets is mostly driven by the transmission of shocks in the short term. This phenomenon means that markets reactions to shocks occur principally in the short term in the system. The spread of shocks in the short term means that contagion effects exist in metals markets, which is similar to traditional asset classes such as stocks [35]. It is notable that many spillover peaks show up at low-frequency band. This probably implies that market risk events not only brought short-term fluctuations to the markets, but also affect the markets for more than a month, leading to large spillovers in the short and long terms.

Figure 2 presents the overall skewness connectedness in the time–frequency domain. Overall, the total skewness spillover ranges from 25% to 50%, which is lower and more stable than the total volatility spillover in general. In the whole sample period, the peak of the total skewness index appeared around 2016. After the China's stock market crash in 2015, macro risk appetite of global markets boosted in 2016, commodity markets fundamentals improved in general, and base metal prices mostly rebounded from recent lows. Zinc, in particular, is the best performing metal. Improved metals markets conditions and close market linkage are reflected in the increase of skewness spillover. Spillovers at high-frequency band are higher than those at low-frequency band, indicated by Figs. 2(b, c). Additionally, the short-term spillover has similar features to the overall skewness spillover, which reflects that the market interaction is more significant in the short term.

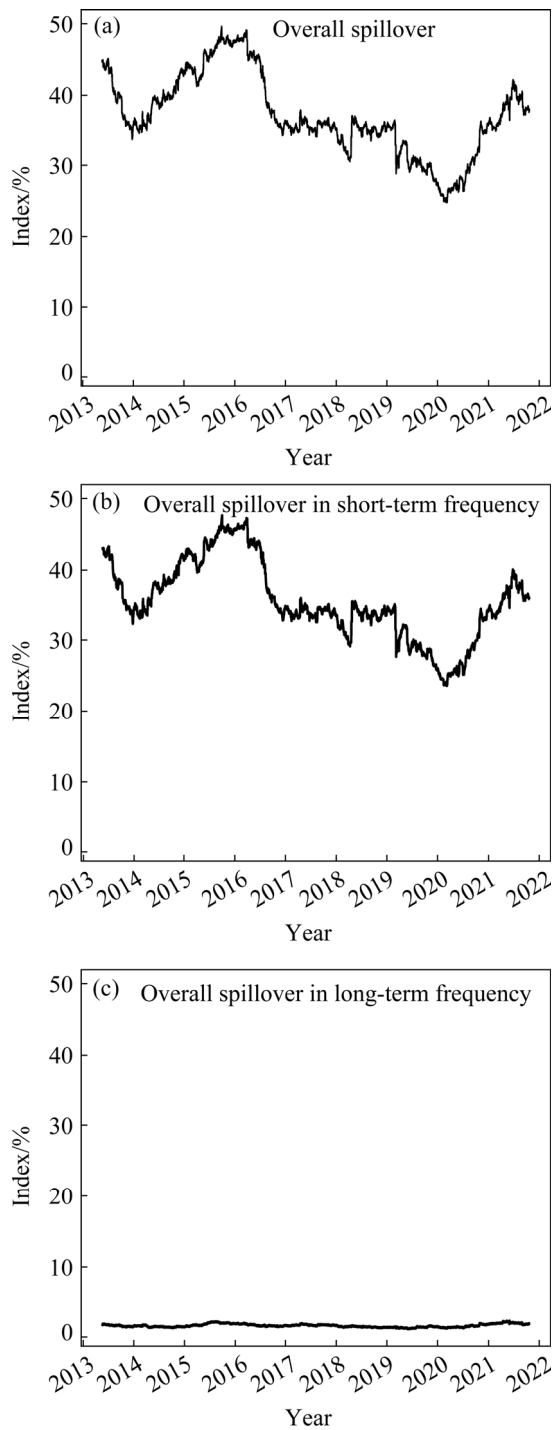


Fig. 2 Overall skewness spillover indices in time-frequency domain: (a) Dynamic overall spillover; (b, c) Dynamic frequency connectedness C_d^F with $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$, respectively

Figure 3 presents the overall kurtosis connectedness in the time-frequency domain over time. As shown in Fig. 3(a), the total kurtosis spillover ranges from 20% to 50%, which is lower than the total volatility spillover in general, and

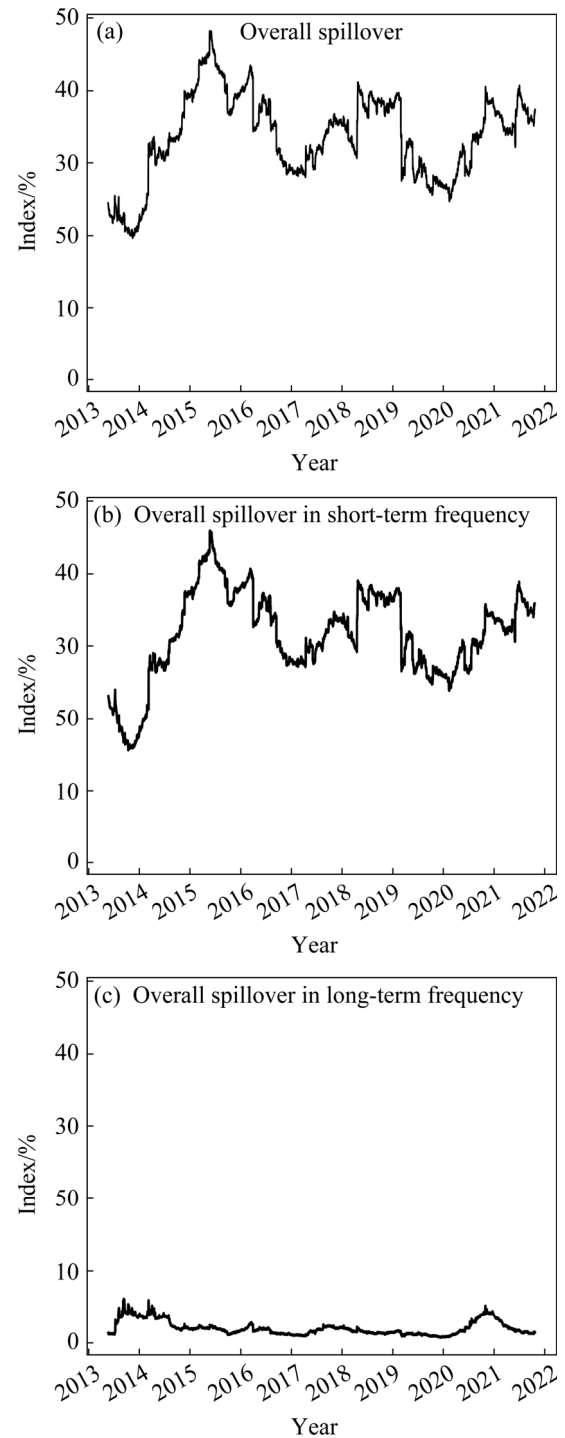


Fig. 3 Overall kurtosis spillover indices in time-frequency domain: (a) Dynamic overall spillover; (b, c) Dynamic frequency connectedness C_d^F with $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$, respectively

similar to the total skewness spillover. The highest kurtosis spillovers showed up during 2015 with Chinese economic slowdown, weak demand and low base metal prices. Market risk conditions enhance kurtosis spillover. Focusing on the

dynamics of kurtosis frequency connectedness in Figs. 3(b, c), the largest portion of total connectedness occurs at the high-frequency band. The maximum total spillover reaches close to 50% in the short term compared to the value less than 10% in the long term, which implies that short-term effect plays a leading role in the transmission of kurtosis shocks. This phenomenon is the same as that of volatility and skewness frequency connectedness.

Figure 4 presents the overall jumps connectedness in the time–frequency domain over time. Similar to the total volatility spillover, the total jumps spillover ranges from 20% to 80% with several distinct peaks. In mid-July 2013, the total spillover reached the first peak of over 80% with China's gold and silver futures launching night trading and trading volumes increasing. The overall jumps spillover index rose to 80% at the second time in March 2014 as aluminum prices plumped. The total volatility spillover reached over 80% again in late November 2016, when lead markets were in an uptrend. The total spillover reached the fourth peak of over 80% in April 2018, at that time, the United States announced the implementation of sanctions on Russian aluminum enterprises, which triggered a sharp shock in international aluminum prices. China's aluminum prices rose rapidly driven by the strong international market. At the end of the month, with the easing of sanctions, aluminum prices gradually declined. In October 2021, the jumps spillover rose to 80% for the last time with a surge in industrial metals prices. Market risk events evidently enhance jumps spillover. In jumps frequency connectedness, as shown in Figs. 4(b, c), similar to the frequency connectedness results of the above three estimators, the magnitude of the short-term spillover is larger than that of the long-term spillover. It is notable that high spillovers showed up at both two frequency bands in mid-July 2013, during China's gold and silver futures launching night trading. This probably indicates that the night trading of gold and silver not only brought short-term fluctuations to the markets, but also influenced the markets more than 1 month, leading to large spillovers in the short and long terms.

Overall, spillovers of higher moment and jumps among precious metals and industrial metals markets are time-varying and influenced by major

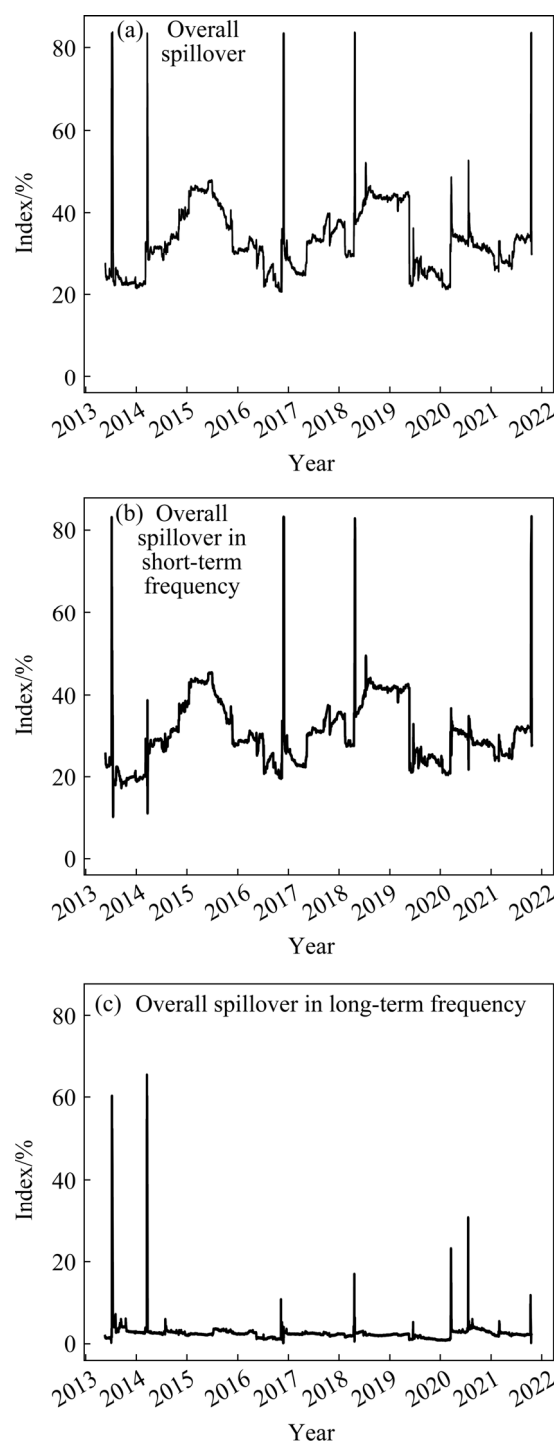


Fig. 4 Overall jumps spillover indices in time–frequency domain: (a) Dynamic overall spillover; (b, c) Dynamic frequency connectedness C_d^F with $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$, respectively

market events, which are revealed in the dynamic overall spillover indices. This finding confirms the results reported by BOURI et al [22], which states that dynamic risk spillovers under different realized moments are sensitive to major market events. In

addition, total spillovers of volatility and jumps have many distinct high peaks compared to those of skewness and kurtosis, which implies that the dynamic links in volatility and jumps are more volatile. The spillovers are more evident at higher frequency, which suggests that market interaction is more significant in the short term.

To examine whether the results are sensitive to rolling-window size in spillover framework, we conduct the robustness test of the overall spillovers for all realized estimators in the time–frequency domain using two rolling-window sizes (i.e., 200 and 300 d). Our results are not influenced by the rolling-window size. For the sake of brevity, we present these results in Figs. A1–A4 in the Appendix.

3.3 Dynamic net directional spillovers

To further investigate the dynamic behavior of realized volatility, skewness, kurtosis and jumps spillover effects of each market, we study the net directional spillover of gold, silver, copper, aluminum, lead and zinc accordingly.

Figure 5 presents the net volatility spillover effects over time in the time–frequency domain. Shown by Figs. 5(a₁–a₆), the net directional spillover of copper is mainly positive and that of aluminum is mainly negative, which indicates that gold serves as a net transmitter while aluminum serves as a net receiver throughout the period. In June 2019, gold market exhibited net spillover of up to 60%. At that time, the Shanghai gold index hit a past six-year high in the midst of a bull market for gold. In July 2019, silver had more than 60% net volatility spillover, since China's and international silver markets were in a strong uptrend. At the above two time points, four industrial metals markets became receiver of volatility spillover, suggesting that volatility shocks spilled over from precious metals to industrial metals. In mid-November 2016, the net spillover of copper reached a distinct peak of over 20%. At that time, infrastructure plan boosted the price of base metals, copper led the price rise of base metals, but speculative forces sentiment and policy attitude swing causing copper prices fluctuated alternately. Similar copper price fluctuation occurred in the middle and late March of 2020, when the net spillover index reached 30%. Copper prices fell to the lowest point of that year due to the COVID-19

outbreak, and macro policy stimulus and fundamental news were mixed, leading copper market fluctuant. As for aluminum market, aluminum prices were sagging in March 2014, and the net spillover of aluminum reached a peak of over 20%. Lead had a net volatility spillover effect of about 40% in late November 2016. It was a peak demand season but supply contracted, and the entry of speculative capital led to an increase in lead prices. At the same time, aluminum exhibited a net spillover of –12.5%, indicating that volatility spillover occurred from lead market to aluminum market. In October 2021, it is clearly seen that the net spillover of zinc reached over 80% while the remaining five markets acted as spillover receivers. At that time, Nyrstar's plan to cut zinc production triggered a chain reaction of soaring industrial metal prices. A few days later, however, weak demand brought negative feedback, industrial metal prices fell back under pressure. The peaks of overall spillover and net spillover in the time domain are almost consistent, while the dynamics of net spillover reveals how the spillover effects are transmitted among these markets. Next, we consider Figs. 5(b₁–b₆) which represent the results of net spillovers at high and low frequencies. Net spillovers in the short term are more pronounced.

Figure 6 presents the net skewness spillover effects over time in the time–frequency domain. Compared to the range of net volatility spillover, the range of net skewness spillover is relatively narrow. During the period, silver, copper and zinc usually act as net information transmitters, while gold, aluminum and lead are net information receivers. Especially, the net spillovers of silver and copper are mostly positive while those of aluminum and lead are mostly negative throughout the sample period. This result signifies that silver and copper are powerful net skewness spillover transmitter in this system. Silver showed continuous high overflow during the silver market downturn in 2018. In contrast, copper exhibited continuous high spillovers during 2015 when copper market was in a large number of transactions. These results indicate that net skewness spillovers are affected by extreme market conditions. From Figs. 6(b₁–b₆), we clearly see that short-term net spillovers play an overwhelmingly dominant role.

Figure 7 presents the net kurtosis spillover effects over time in the time–frequency domain.

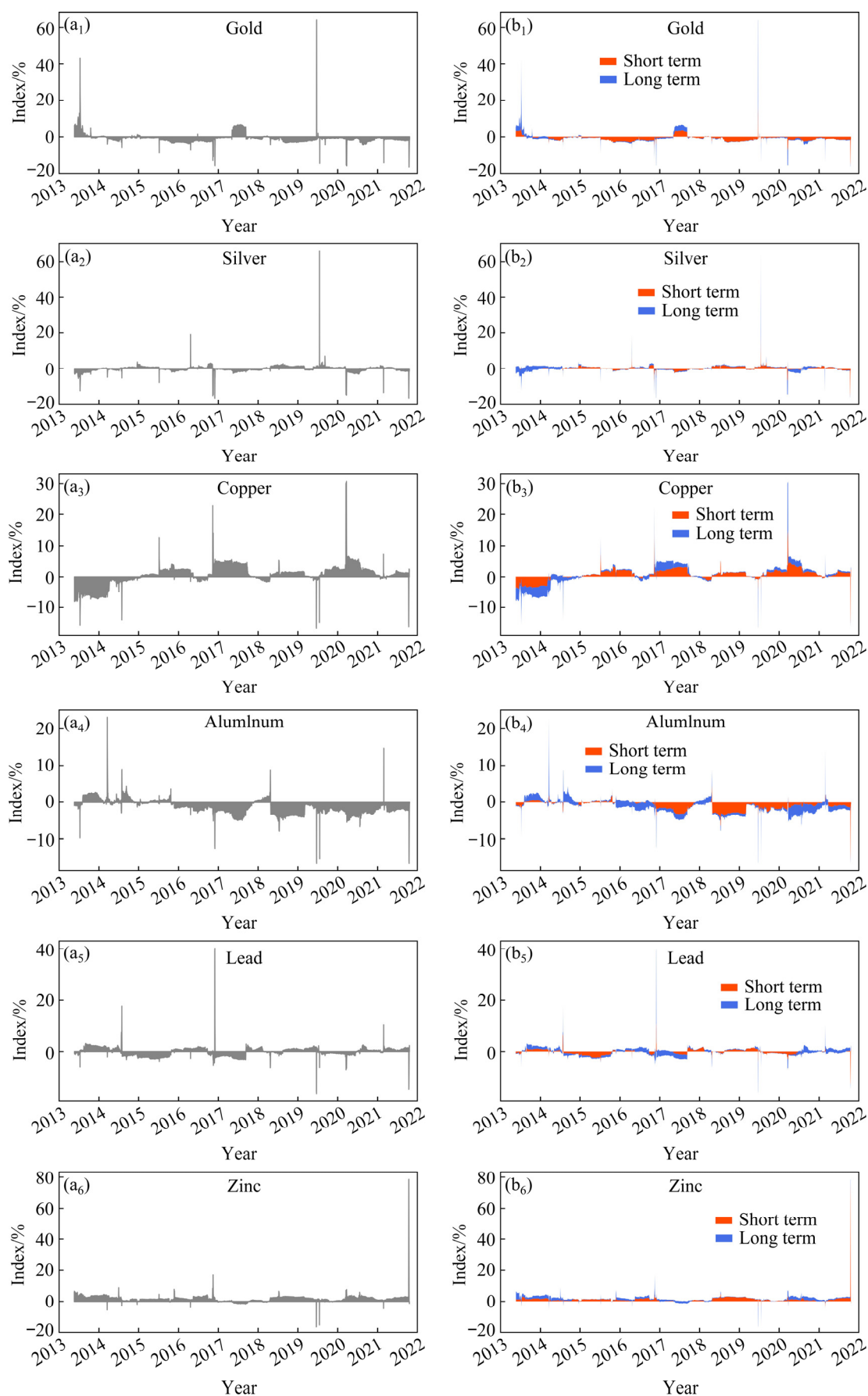


Fig. 5 Net directional volatility spillover indices in time–frequency domain: (a₁–a₆) Dynamic time domain net spillover; (b₁–b₆) Dynamic net spillover at two frequency bands, $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$

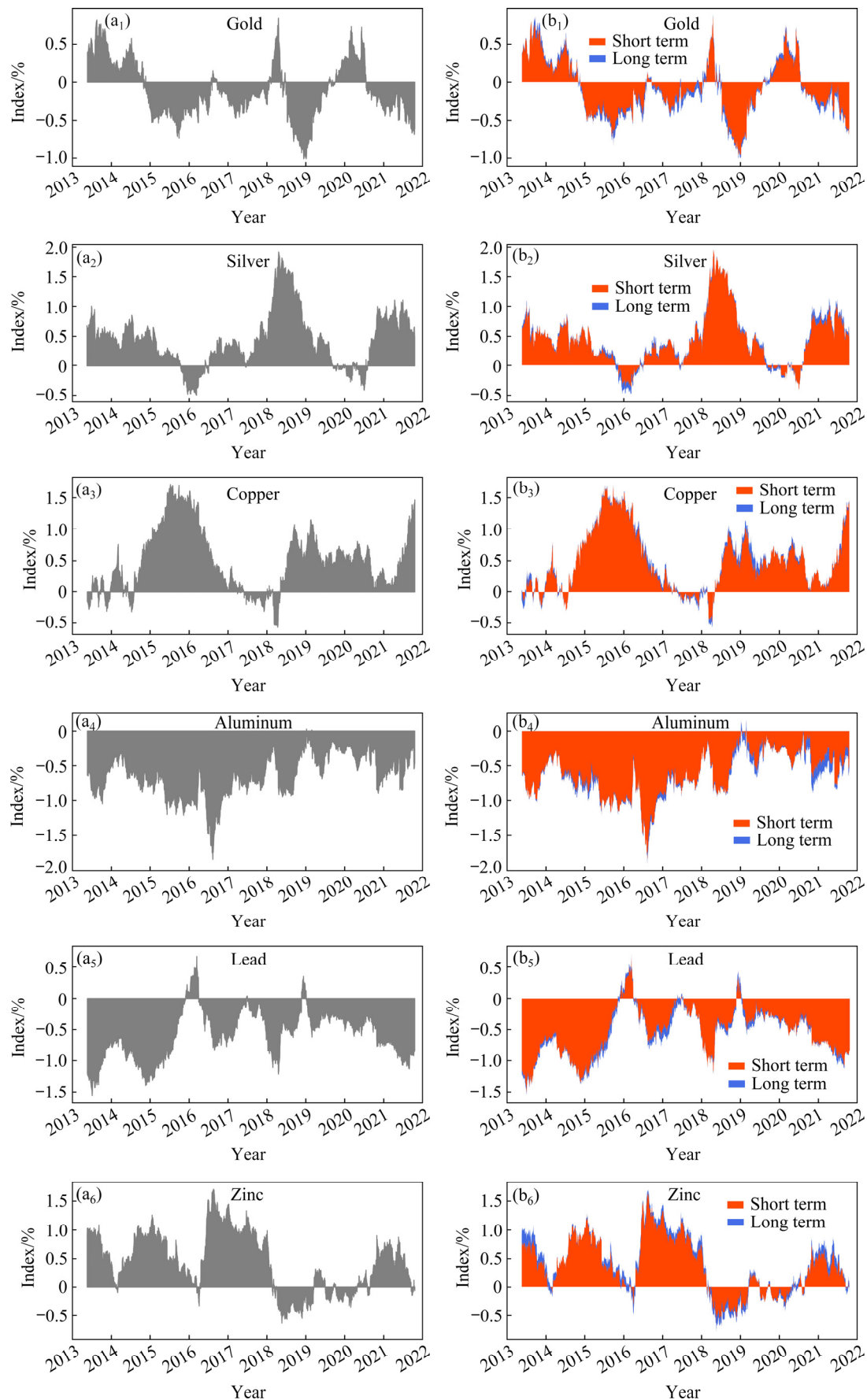


Fig. 6 Net directional skewness spillover indices in time–frequency domain: (a₁–a₆) Dynamic time domain net spillover; (b₁–b₆) Dynamic net spillover at two frequency bands, $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$

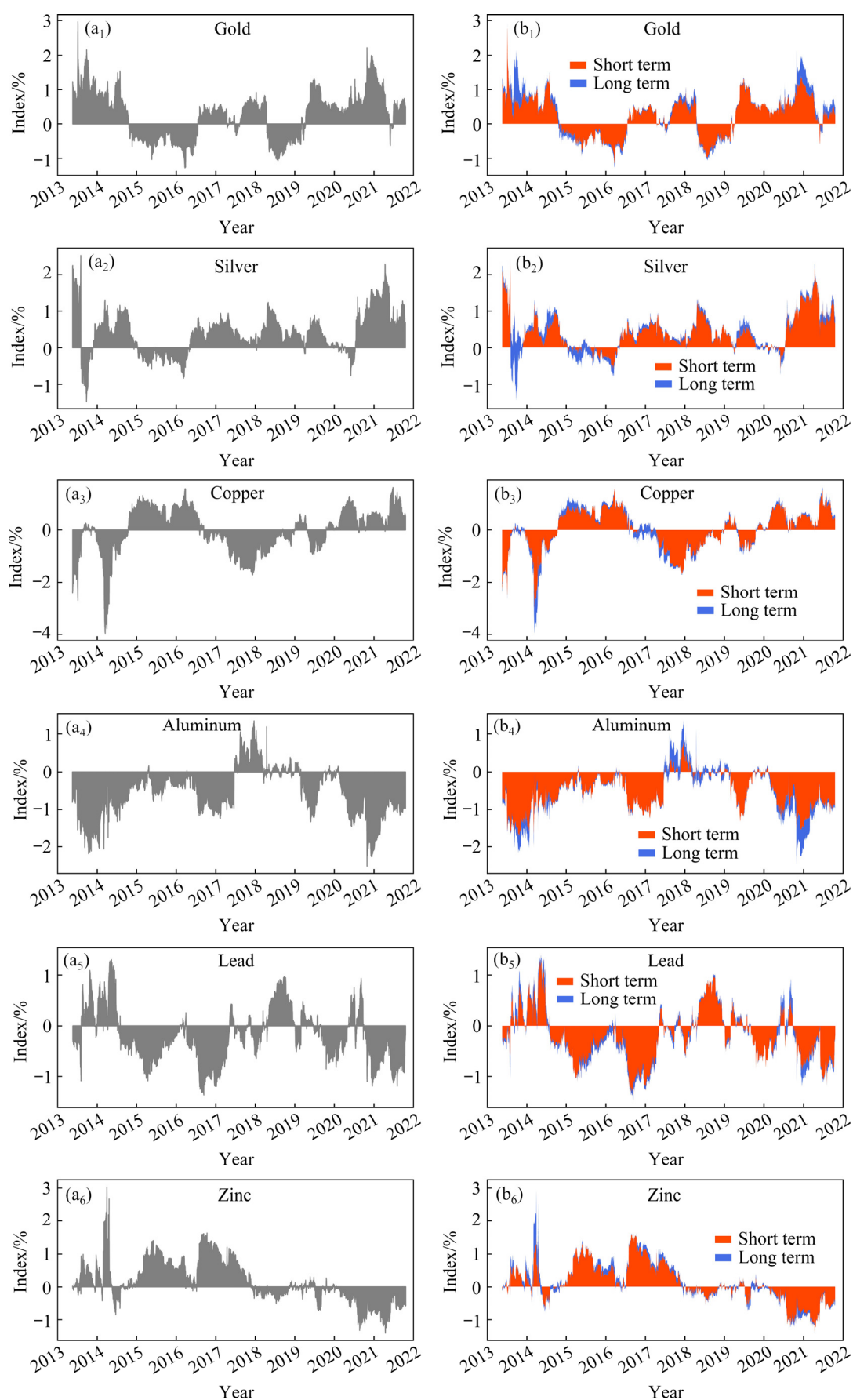


Fig. 7 Net directional kurtosis spillover indices in time–frequency domain: (a₁–a₆) Dynamic time domain net spillover; (b₁–b₆) Dynamic net spillover at two frequency bands, $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$

Similar to the range of results of net skewness spillover, the range of net kurtosis spillover is narrow. Silver mainly acts as net kurtosis transmitter, while aluminum mainly as net kurtosis receiver in the whole sample period. In particular, during 2015 Chinese stock market crash, copper and zinc exhibited continuous positive spillovers to other markets. Probably because copper and zinc are the most important industrial metals in terms of trading volume in the Shanghai Future Exchange in 2015, and the kurtosis spillover of them matters to that of the other markets. From Figs. 7(b₁–b₆), we see that the net spillovers are more evident in the short term relative to those in the long term.

Figure 8 presents the net jumps spillover effects over time in the time–frequency domain. The range of net jumps spillover is relatively wide with some distinct high peaks, similar to that of net volatility spillover. Shown by Fig. 8, silver and copper mainly serve as net transmitters while aluminum mainly serves as a net receiver throughout the period. In mid-July 2013, gold had more than 60% net volatility spillover with China's gold and silver futures launching night trading and trading volumes increasing, the remaining five markets became jumps spillover receivers at that point. In early June 2016, silver market exhibited net spillover about 10%. At that time, Britain's exit from the European Union increased economic uncertainty, risk aversion drove precious metals prices higher, and silver led the price rise of precious metals. Silver had about 15% net jumps spillover in late July 2020, when silver rose to its highest level since 2013 as tensions between the US and China spurred demand for safe-haven assets. In addition, European green recovery plan also boosted demand for silver, an important element of environmentally friendly industry. By the way, silver prices increased whether under the background of rising risk aversion or strong industrial demand, which reflects that silver with hedging and industrial attribute is favored in the metals markets. In mid-November 2016, the net jumps spillover of copper reached over 10% with copper prices fluctuating alternately. Affected by the COVID-19 outbreak, copper price fluctuation occurred again in the second half of March 2020, when the net jumps spillover index reached 10% again. As for aluminum, it had about 60% net volatility spillover twice in late March 2014 and

April 2018 with prices fluctuated falling. At the same time, the remaining five markets all acted as jumps spillover receivers. The net spillovers of lead reached peak of over 60% in late November 2016 with lead prices fluctuated strongly, and that of zinc reached peak of over 80% in mid-October 2021 as zinc market was volatile. During the above two periods, the remaining metals markets became receiver of jumps spillover. The net spillover indices of the six markets clearly figure out which markets dominate and when. Similar to the results of the above three estimators in frequency domain, net jumps spillovers are more significant in the short term.

On the whole, in terms of net spillovers of all realized higher moments and jumps over the whole rolling period, silver and copper markets are the main net transmitters, whereas aluminum market is the main net receiver. The results of net spillover clearly reflect how the spillover effects of the four estimators are shaped among precious and industrial metals markets. From the perspective of frequency domain, the short-term net spillovers of the four estimators are more evident than the long-term net spillovers, according with the previous conclusions in Sections 3.1 and 3.2.

3.4 Connectedness networks

We construct networks to analyze the pairwise net spillovers of all pairs in the time and frequency domains. The connectedness networks of volatility, skewness, kurtosis and jumps in the time–frequency domain are drawn in Figs. 9–12, respectively. The directions of the arrows represent a positive net directional connectedness among the markets. The thicker the arrow lines are, the stronger the connectedness between two pairwise nodes is.

In the volatility connectedness network (Fig. 9), it is clearly seen from the DY results that copper, silver and lead are net transmitters, while zinc, gold and aluminum are net receivers. Among them, copper is a main net transmitter, and zinc is a main net receiver. Besides, copper market is a net volatility transmitter of the other five markets, while gold market is a net receiver of volatility with respect to the other five markets. The BK results show that in the short term, lead plays a leading role in the volatility connectedness, and becomes a transmitter of the other five markets; whereas gold is a receiver of the other five markets. In the long

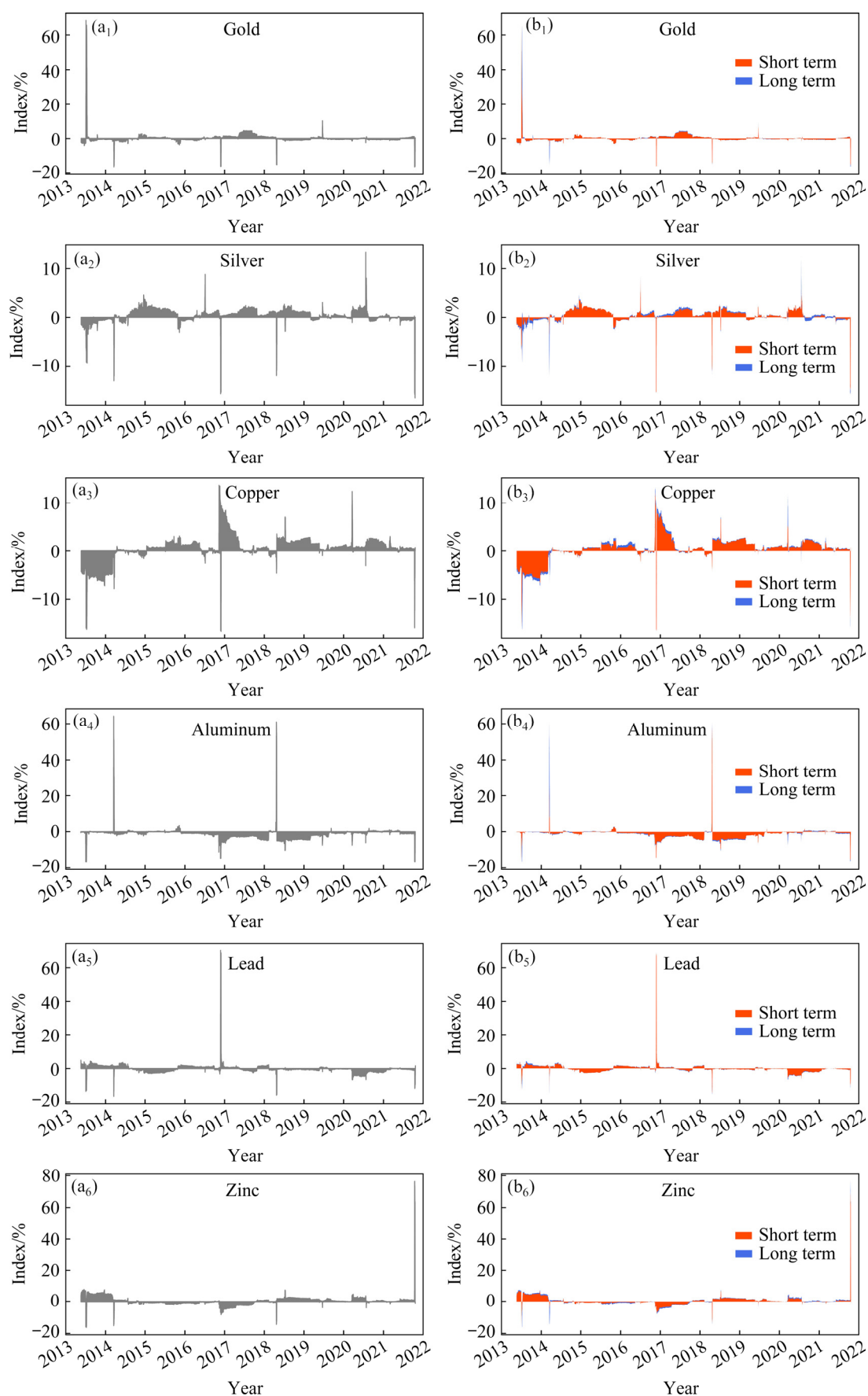


Fig. 8 Net directional jumps spillover indices in time–frequency domain: (a₁–a₆) Dynamic time domain net spillover; (b₁–b₆) Dynamic net spillover at two frequency bands, $d_1 \in [3.14, 0.14]$ and $d_2 \in [0.14, 0.00]$

term, copper exhibits stronger volatility spillover. In particular, copper and silver are always net volatility spillover transmitters and zinc and aluminum are always receivers in the time domain and two frequency domains.

In the skewness connectedness network (Fig. 10), the DY results show that copper, zinc and silver are net transmitters, and lead, aluminum and gold are net receivers. Silver is a transmitter of the other five markets, and lead is a receiver of the other five markets. From the BK results, in the high-frequency connectedness network, copper, zinc and silver are still transmitters; silver is a transmitter whereas lead is a receiver with respect to the other five markets. These findings are similar to the static time domain network, indicating that systematic skewness spillover is a short-term effect. In the low-frequency connectedness network, copper changes its role to a receiver, which indicates that copper transmits skewness shocks mainly in the short term. Zinc is a transmitter of the other five markets. Overall, silver and zinc are always net spillover transmitters, and lead, aluminum and gold are always receivers in the time domain and at the two frequencies considered.

In the network of kurtosis connectedness

(Fig. 11), the DY results show that copper, zinc and silver play as a net transmitter to other markets. Silver is a transmitter of the other five markets, and aluminum is a receiver of the other five markets. From the BK results, the connectedness network in the short term is similar to the static time domain network, whether in the case of transmitters or receivers, which suggests that systematic kurtosis spillover is a short-term effect. In the long term, zinc exhibits stronger kurtosis spillover and is a transmitter of the other five markets, while gold is a receiver of the others. Generally, copper and zinc are always a net kurtosis spillover transmitter, while aluminum and gold are always net receivers in the time domain and the two frequency domains.

In the jumps connectedness network (Fig. 12), it is clear from the DY results that copper and silver are net transmitters, the remaining metals are net receivers. Silver is a transmitter of the other five markets. The BK results show that in the high-frequency connectedness network, copper, silver and zinc are net transmitters, and silver is a transmitter of the other five market. In the low-frequency connectedness network, copper still remains strong jumps net spillovers and becomes a transmitter of the other five markets. In the time

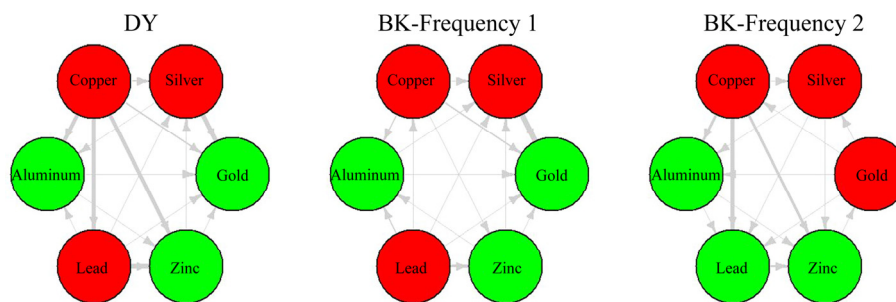


Fig. 9 Volatility connectedness network in time–frequency domain (Each node represents a metal market. Red nodes represent net information transmitters, while green nodes represent net information receivers. Frequencies 1 and 2 represent 1–22 d and more than 22 d, respectively)

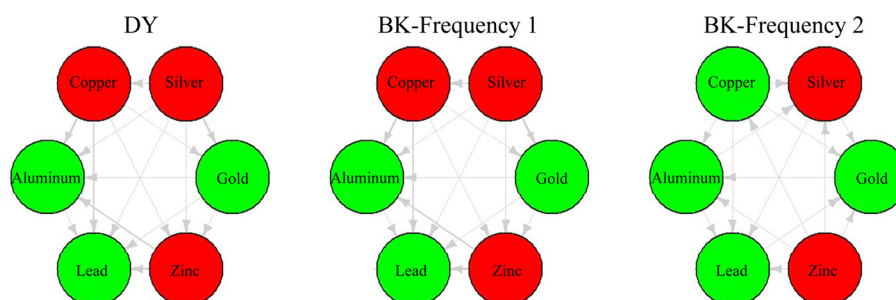


Fig. 10 Skewness connectedness network in time–frequency domain

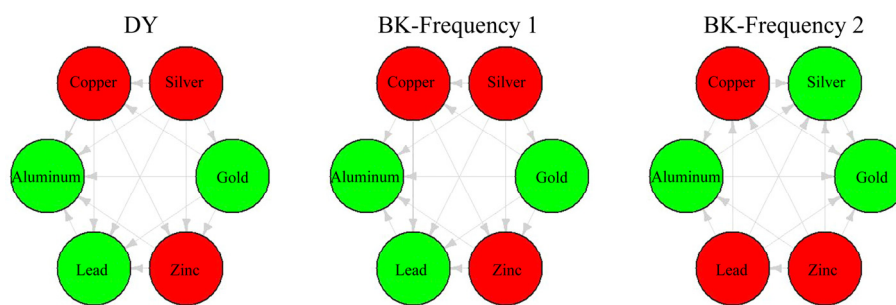


Fig. 11 Kurtosis connectedness network in time–frequency domain

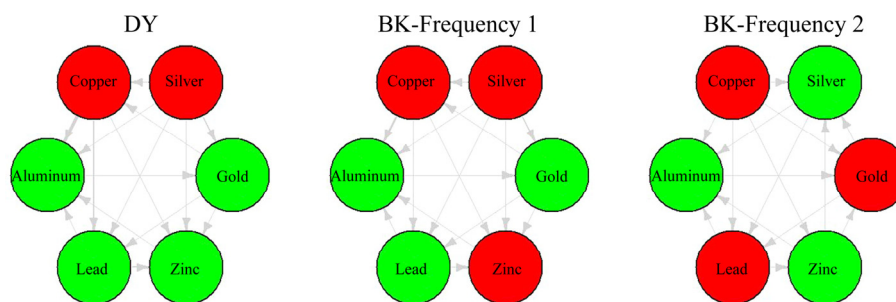


Fig. 12 Jumps connectedness network in time–frequency domain

domain and two frequency domains, copper is always net jumps spillover transmitter and aluminum is always receiver.

To sum up, we observe that in the volatility connectedness network, copper and silver have the core status and contribute the most to volatility spillover. Zinc is the largest net volatility spillover receiver. In the skewness connectedness network, copper is the largest net skewness spillover transmitter and silver is always a net transmitter in the time domain and both two frequency domains, while lead is the largest skewness receiver. In the kurtosis connectedness network, copper is the largest net kurtosis spillover transmitter and aluminum is the largest net kurtosis spillover receiver. In the jumps connectedness network, copper is the most influential jumps spillover sources, while aluminum is the largest receiver from the other markets. These findings demonstrate copper and silver play a dominant role in precious and industrial metals markets.

4 Conclusions

(1) In the static analysis, the total volatility, skewness, kurtosis and jumps spillover indices are 45.67%, 35.91%, 31.58% and 18%, respectively.

The system connectedness weakens as the moment order gets higher whereas the total jumps connectedness is the smallest. Additionally, the connectedness of all risk estimators at high-frequency band contributes most to their respective total one.

(2) The dynamic analysis shows that the overall information spillovers in the system of precious and industrial metals are time-varying and influenced by major market events. The net spillovers are more evident at higher frequency, suggesting that market interaction is more significant in the short term.

(3) For volatility, copper is the largest net transmitter and silver is always a net transmitter in the time and frequency domains, while zinc is the largest net receiver. For skewness, copper is the largest net transmitter and silver is always a net transmitter in the time and frequency domains, while lead is the largest net receiver. For kurtosis and jumps, copper is the largest net transmitter, while aluminum is the largest net receiver. Overall, copper and silver play a dominant role in the precious and industrial metals system.

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Appendix

Appendix in this paper can be found at: <http://www.yxsb.cn.com/download/26-TNMSC-2021-1594-appendix.pdf>.

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中国贵金属和工业金属市场的溢出效应： 来自高阶矩和跳的证据

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摘 要: 揭示中国贵金属和工业金属市场的高阶矩(已实现波动, 已实现偏度和已实现峰度)和跳跃的时变溢出效应。使用 2012 年 5 月 10 日至 2021 年 10 月 21 日的 5-min 高频数据, 并基于时频域溢出指数框架揭示溢出的动态效应。研究结果表明, 系统连通性随着高阶矩阶数的增加而减弱, 而总跳跃连通性最小, 且所有指标的溢出效应均在短期更加显著。系统总信息溢出随时间变化并受重大市场事件的影响。具体而言, 对于波动溢出, 铜是最大的净发出者, 银始终是时域和频域上的净发出者, 而锌是最大的净接收者; 对于偏度溢出, 铜是最大的净发出者, 银始终是时域和频域上的净发出者, 而铅是最大的净接收者; 对于峰度溢出和跳跃溢出, 铜是最大的净发出者, 而铝是最大的净接收者。总体上, 铜和银在中国贵金属和工业金属市场中占据主导地位。

关键词: 溢出; 贵金属; 工业金属; 时频域分析; 高阶矩; 跳跃

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