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Xuewei Zhou
Shanghai University of Finance and Economics
Zisheng Ouyangb
Hunan Normal University
Rangan Gupta
University of Pretoria
Qiang Ji
Chinese Academy of Sciences
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

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Xuewei Zhou[a], Zisheng Ouyang[b,*] Rangan Gupta[c], Qiang Ji[d,e]

[a] *School of Finance, Shanghai University of Finance and Economics, and Shanghai Institute of International Finance and Economics, Shanghai 200433, China*

[b] *Business School, Hunan Normal University, and Hunan Key Laboratory of Macroeconomic Big Data Mining and its Application, Changsha, Hunan 410081, China*

[c] *Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa*

[d] *Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China*

[e] *School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China*

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* Corresponding author.
E-mail addresses: xueweizhou@hunnu.edu.cn (X.-W. Zhou), ouyang_zs@hunnu.edu.cn (Z.-S. Ouyang), rangan.gupta@up.ac.za (R. Gupta), jqwxnjq@163.com (Q. Ji).

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Abstract

This paper constructs multilayer frequency networks containing short-, medium-, and long-term layers to examine the frequency connectedness among commodity futures markets. We examine the frequency heterogeneity of commodity volatility connectedness at the average, dynamic, and crisis levels. We also investigate the determinants of frequency connectedness among commodity futures markets. The results show that there are strong short-term volatility spillovers between commodity futures markets, while connectedness during crises is dominated by long-term factors. We find that there is heterogeneity in the edge structure of short- and long-term networks during the crisis. In addition, we note that cocoa futures can hedge frequency risk in commodity markets. Determinants analysis suggests that inflation risk is the key driver of frequency connectedness in commodity futures. Moreover, the drivers of connectedness differ between short-, medium-, and long-term. Our work provides new insights for studying the risk contagion of commodity markets and informs the decisions of investors and regulators.

Keywords: Frequency connectedness; Multilayer networks; Commodity futures markets; Systemic risk.

JEL code: G14, G15, G32

1. Introduction and literature review

Since 2020, the commodity markets have experienced lots of black swan events, including the COVID-19 pandemic in 2020, the Brexit in 2020, and the Russia-Ukraine conflict in 2022 (Kyriazis et al., 2023). These major crises have brought unprecedented challenges to the global economy and commodity futures markets (Boubaker et al., 2022; Mensi et al., 2024b). The Russia-Ukraine conflict led the US and its allies to impose strict sanctions and trade embargoes on Russia (Mahlstein et al., 2022). These sanctions and embargoes led to significant turbulence in global commodity markets. Moreover, loose monetary policies, speculative hot money, and individual investment demand in recent years have increased the financial liberalization of commodities (Gong and Xu, 2022). Under the above scenario, the volatility spillover and information transmission mechanisms between commodity markets become more complex.

In fact, volatility connectedness among commodity markets has implications for many aspects of empirical finance, such as asset pricing, derivatives pricing, portfolio allocation, and risk management (Gardebroek et al., 2015). For example, if the cross-commodity volatility connectedness is higher than the volatility of the commodity itself, we can consider that the cross-commodity connectedness contains incremental information that can be used to determine the future price of the commodity (Bouri et al., 2021b). In addition, commodity markets also have volatility spillovers to other financial markets, e.g., stock, forex, and currency markets. Some papers pointed out the existence of strong spillover effects between commodity markets and stock markets (Wen et al., 2022; Mensi et al., 2024a). In summary, understanding volatility spillovers across commodity markets has important implications for market participants, policy designers, and international risk management (Suleman et al., 2021).

Financial assets are usually characterized by thick tails and volatility clustering. Hence, many studies used the GARCH model to explore volatility connectedness among commodity markets. For example, Ji et al. (2018) applied the GARCH-Copula model to investigate the dependence between commodity markets, and they found that there was significant linkage between commodity markets during the downturn. Sun et al. (2020) used the GARCH-Copula-CoVaR approach to measure extreme risk spillovers among international commodity markets. Ahmed and Huo (2021) examined the volatility spillovers between Chinese stock market, commodity market, and global crude oil market through the VAR-BEKK-GARCH model. They observed that the Chinese stock market has a strong dependence on the oil market. Ma et al. (2021) applied the DCC-GARCH model to measure the connectedness between energy, agriculture, and financial commodity markets. Recent research shows that the COVID-19 pandemic has significantly increased volatility spillovers in metal commodities and energy commodities (Qiao and Han, 2023). However, it is worth noting that the volatility connectedness approach based on the GARCH model fails to identify risk contagion paths among commodity markets.

Network analysis has the potential to help monitor the connectedness paths of financial markets and asses system vulnerabilities Bianchi et al. (2019). Hence, some literature applies complex network theory to study risk connectedness among commodity markets. Diebold and Yilmaz (2014) constructed a spillover index model based on variance decomposition to examine connectedness among financial institutions. Subsequently, many papers used this approach to investigate the connectedness among commodity markets. Xiao et al. (2020) measured the risk correlation among 18 commodity futures and found that metal futures are risk transmitters. Zhang et al. (2023a) explored the high-order moment connectedness between Chinese commodity markets, and they noted that high-order moment spillovers contain more risk information. Furthermore, Rehman et al. (2023) further measured the tail connectedness between commodity futures markets from a quantile perspective. Hu et al. (2023) explored the dynamic connectedness between commodity futures markets during the oil crisis based on the TVP-VAR model. Representative papers also include Iqbal et al. (2023), Billah et al. (2023), Wu et al. (2023b), Mensi et al. (2024a), Long et al. (2024), Zhou et al. (2024), and Lin and Lan (2024).

In addition, the determinants of connectedness between commodity markets are also of interest to researchers. Bakas and Triantafyllou (2018) studied the impact of uncertainty shocks on commodity prices. Hu et al. (2020) analyzed the link between macro factors and realized volatility of commodity futures with the help of dynamic network approach. They observed that macro factors are more closely linked to crude oil. Bouri et al. (2021b) found that commodity connectedness is mainly driven by uncertainty. Saeed et al. (2021) argued that global macroeconomics is the determining factor driving extreme market correlations. Akyildirim et al. (2022) examined the impact of news sentiment on agricultural market connectedness and they believed significant spillover effects between news sentiment and agricultural product returns. Gong and Xu (2022) used geopolitical risks to explain the connections between commodity markets. There are also some papers believe that global financial stress (Billah et al., 2024), economic policy uncertainty (Mensi et al., 2024c; Elsayed et al., 2024), inflation (Kyriazis et al., 2024), and climate risks (Guo et al., 2023; Hoque et al., 2023; Khalfaoui et al., 2024) have an impact on commodity connectedness.

Although many papers have made efforts to explore the interconnectedness and its determinants among commodity futures markets. But, we believe that the existing literature has the following shortcomings: First, among the existing studies that use network analysis to examine risk contagion among commodity futures markets, we find that these papers mainly focus on single-layer network analysis. For example, return network (Zhang and Broadstock, 2020; Dai et al., 2022; Abricha et al., 2023), volatility network (Hu et al., 2020; Bouri et al., 2021b; Akyildirim et al., 2022; Gong and Xu, 2022), and extreme risk network (Iqbal et al., 2023; Zhang et al., 2024a). However, the connectedness mechanisms between financial assets are complex and diverse (Wang et al., 2021; Ouyang and Zhou, 2023), and single-layer networks may not fully reveal the mechanisms of volatility spillovers between commodity markets. In fact, focusing only on a single-layer network may also misunderstand the real connection mechanisms in the financial system (Aldasoro and Alves, 2018; Ouyang et al., 2024). Therefore, it is a valuable work to construct suitable multilayer networks and identify complex spillover mechanisms between commodity futures markets. Second, we find that existing paper mainly examine the determinants of connectedness between commodity markets in the time domain dimension, ignoring the impact of different determinants on commodity frequency connectedness. However, many studies show that connectedness and volatility spillovers between financial markets vary with frequency (Jian et al., 2023; Huang et al., 2023; Ouyang et al., 2023). Also, from a portfolio management perspective, short-term investors (speculators) are more interested in the high-frequency connectedness of the market (i.e., short-term connectedness), while long-term investors (fund managers and institutional investors) focus on lower frequencies relationship (i.e. long-term connectedness). At the same time, regulatory policies often have short-term and long-term goals, and understanding the frequency spillover mechanism of macroeconomics on market connectedness will also help achieve different policy purposes.

To address these shortcomings, we do the following innovative work: First, we collect freely-available realized volatility data for 13 major commodity futures markets involving the agriculture, energy, and metals sector from the Risk Lab database of the University of Chicago Booth School of Business. These realized volatility data are calculated based on intraday prices. Hu et al. (2020) pointed out that realized volatility calculated based on intraday prices avoids model setting risks. Therefore, realized volatility is a good measure of commodity futures volatility (Zhang et al., 2024b). Second, we propose dynamic multilayer frequency networks that include short-, medium-, and long-term layers, and the proposed approach allows us to capture the frequency spillover mechanism of volatility connectedness. We apply the proposed method to examine the average and dynamic frequency connectedness among 13 commodity futures markets, and compare and analyze how the network topology among commodity markets changes with frequency. In addition, given the severe impact of the COVID-19 pandemic and the Russia-Ukraine conflict on commodity markets, we investigate the network topology between commodity markets before and after these two crises. Finally, we use the Shapley decomposition technique to examine the contribution of determinants, including climate policy uncertainty (CPU), geopolitical risk (GPR), global economic policy uncertainty (EPU), US personal consumption expenditures inflation index (PCE), financial stress index (FSI), US treasury spread (TS), monetary policy uncertainty (MPU), and news sentiment index (SEN), to the frequency connectedness among commodity markets.

Overall, our work has the following contributions. First, compared with the literature that used the single-layer network to examine spillover effects between commodity markets (Xiao et al., 2020; Zhang et al., 2023b; Rehman et al., 2023; Long et al., 2024), we propose the multilayer frequency network containing short-, medium-, and long-term layers. The proposed approach allows for a more flexible exploration of multiple spillover mechanisms between commodity markets and captures volatility contagion heterogeneity in the same market at different frequencies. Moreover, we focus on analyzing the frequency connectedness among commodity markets during the COVID-19 pandemic and the Russia-Ukraine conflict, which helps to clarify the frequency spillover mechanism of commodity markets in crises. This work expands the published papers on risk contagion in commodity futures under extreme situations (Izzeldin et al., 2023; Hu et al., 2023; Chishti et al., 2023; Mohammed et al., 2023). Finally, we use the Shapley decomposition method to examine the determinants of frequency connectedness among commodity futures. This helps us find the drivers of short-, medium-, and long-term connectedness of commodity markets and enriches the research on the determinants of commodity linkages (Bouri et al., 2021b; Hoque et al., 2023; Gong and Xu, 2022; Billah et al., 2023; Mensi et al., 2024c).

The remainder of this paper is organized as follows. In Section 2, we introduce the method used. Section 3 reports the data and empirical setup. Section 4 applies our method to commodity futures markets. Finally, we conclude the paper in Section 5.

2. Methodology

2.1. Measuring frequency connectedness

Referring to Ouyang and Zhou (2023) and Baruník and Ellington (2024), we consider a time series $\boldsymbol{X}_{t,T} = (\boldsymbol{X}^1_{t,T}, ..., \boldsymbol{X}^N_{t,T})^T$, where t refers to the time index and T is an additional index indicating the sharpness of the local approximation of the time series $\boldsymbol{X}_{t,T}$. We assume that the $\boldsymbol{X}_{t,T}$ follows a TVP-VAR of lag order p as

$$\boldsymbol{X}_{t,T} = \boldsymbol{\Phi}_1(t/T)\boldsymbol{X}_{t-1,T} + \cdots + \boldsymbol{\Phi}_p(t/T)\boldsymbol{X}_{t-p,T} + \boldsymbol{\epsilon}_{t,T} \tag{1}$$

where $\boldsymbol{\epsilon}_{t,T} = \sigma^{-1/2}(t/T)\boldsymbol{\eta}_{t,T}$ with $\boldsymbol{\eta} \sim NID(0, \boldsymbol{I}_M)$ and $\boldsymbol{\phi}_i(t/T)$ $(i = 1, 2, \cdots, p)$ are the time-varying autoregressive coefficient. In a neighborhood of a fixed time point $u = t/T$, the process $\boldsymbol{X}_{t,T}$ by a stationary process $\tilde{\boldsymbol{X}}_t(u)$ as

$$\tilde{\boldsymbol{X}}_t(u) = \boldsymbol{\Phi}_1(u)\tilde{\boldsymbol{X}}_{t-1}(u) + \cdots + \boldsymbol{\Phi}_p(u)\tilde{\boldsymbol{X}}_{t-p}(u) + \boldsymbol{\epsilon}_t \tag{2}$$

Then, it can be transformed into a $VMA(\infty)$ representation

$$\tilde{\boldsymbol{X}}_t(u) = \sum_{h=-\infty}^{\infty} \boldsymbol{\Psi}(u, h)\boldsymbol{\epsilon}_{t-h} \tag{3}$$

According to Baruník and Krehlík (2018) and Baruník and Ellington (2024), we know that $\boldsymbol{\Psi}(u)e^{-i\omega} = \sum_h e^{-i\omega h}\boldsymbol{\Psi}(u, h)$, where h is the forecast horizon and $i = \sqrt{-1}$. The spectral density of $\tilde{\boldsymbol{X}}_t(u)$ at frequency ω can be defined as a Fourier transform of $VMA(\infty)$ filtered series as

$$\boldsymbol{S}_x(u, \omega) = \sum_{h=-\infty}^{\infty} E\left[\tilde{\boldsymbol{X}}_{t+h}(u)\tilde{\boldsymbol{X}}_t^T(u)\right] e^{-i\omega h} = \{\boldsymbol{\Psi}(u)e^{-i\omega}\}\Sigma(u)\{\boldsymbol{\Psi}(u)e^{+i\omega}\}^T \tag{4}$$

Next, we calculate the shock of the jth variable to the ith variable on frequency band d, where $d = (a, b) : a, b \in (-\pi, \pi)$, $a < b$.

$$\boldsymbol{\theta}(u,d)_{jk} = \frac{\sigma_{kk}^{-1} \int_a^b \left([\boldsymbol{\Psi}(u) e^{-i\omega} \boldsymbol{\Sigma}(u)]_{jk} \right)^2 d\omega}{\int_{-\pi}^{\pi} \left[\{\boldsymbol{\Psi}(u) e^{-i\omega}\} \boldsymbol{\Sigma}(u) \{\boldsymbol{\Psi}(u) e^{+i\omega}\}^{\mathrm{T}} \right]_{jj} d\omega} \tag{5}$$

It is important to note that $\boldsymbol{\theta}(u,d)_{jk}$ is a natural disaggregation of traditional variance decompositions to time-varying frequency bands. Assuming that $d_\alpha \, (\alpha \in \{1, 2, \cdots, s\})$ is a specific frequency band, sum up the shock in different frequency bands to get the shock in the time domain

$$\boldsymbol{\theta}(u)_{jk} = \sum_{\alpha=1}^{s} \boldsymbol{\theta}(u, d_\alpha)_{jk} \tag{6}$$

For the convenience of explanation, we normalize the shock

$$\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk} = \frac{\boldsymbol{\theta}(u, d_\alpha)_{jk}}{\sum_{k=1}^{N} \boldsymbol{\theta}(u)_{jk}} \times 100 \tag{7}$$

Furthermore, we obtain the dynamic connectedness matrix $\boldsymbol{C}(u, d_\alpha)$ of N variables at time $u = t/T$ and frequency band d_α.

$$\boldsymbol{C}(u, d_\alpha) = \begin{bmatrix} \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{11} & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{12} & \cdots & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{1N} \\ \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{21} & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{22} & \cdots & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{N1} & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{N2} & \cdots & \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{NN} \end{bmatrix} \tag{8}$$

2.2. Multilayer frequency networks

Through the dynamic connectedness matrix $\boldsymbol{C}(u, d_\alpha)$, where $\alpha \in \{1, 2, ..., s\}$, we can construct a dynamic multilayer frequency networks. In detail, the $\Omega = (G(u, d_1), \cdots, G(u, d_s))$ is the multilayer frequency networks, where $G(u, d_\alpha) = G(V, \boldsymbol{C}(u, d_\alpha))$, $V = \{1, 2, \cdots, N\}$ is the set of nodes (commodity futures markets), and $\boldsymbol{C}(u, d_i)$ is the set of edges at the frequency band d_α. The element $\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk}$ in $\boldsymbol{C}(u, d_\alpha)$ is a directed and weighted edge in the network with frequency band d_α, representing the corresponding shock from the kth variable to the

jth variable. Notably, the matrix $\boldsymbol{C}(u, d_\alpha)$ is a fully connected network, it will obscure some important risk information. Hence, we need filter connected networks to obtain a valuable network. Following Ouyang and Zhou (2023) and Ren et al. (2022), we take the mean value of the matrix $\boldsymbol{C}(u, d_\alpha)$ as the threshold, and remove the edges below the threshold to obtain the filtered multilayer frequency networks. Finally, the multilayer frequency networks of this paper are defined as the set of nodes in each layer that is the same, but the nodes in each layer are connected at different frequencies.

2.3. Network measures

2.3.1. Average connectedness strength

We follow the work of Ouyang et al. (2024) and apply the average connectedness strength (ACS) to capture the connectedness strength of multilayer frequency networks.The ACS of layer d_α is defined as

$$\mathrm{ACS}^{d_\alpha} = \frac{1}{N} \sum_{j,k=1, j \neq k}^{N} \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk} \tag{9}$$

where $\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk}$ represents the volatility spillover of the variable k to j on the frequency band d_α and N is the number of commodity futures markets.

2.3.2. Network density

In order to capture the closeness of the network edges, we introduce the network density (ND). The ND of layer d_α is defined as

$$\mathrm{ND}^{d_\alpha} = \frac{2L^{d_\alpha}}{N(N-1)} \tag{10}$$

where L^{d_α} is the actual number of connected edges of layer d_α. Higher ND implies a more complex network.

2.3.3. Global efficiency

According to Wang et al. (2021), we calculate the global efficiency (GE) of multilayer frequency networks, which reflects the propagation efficiency of financial risks in the connectedness network. The GE of the layer d_α is defined as

$$\mathrm{GE}^{d_\alpha} = \frac{1}{N(N-1)} \sum_{j,k=1,j\neq k}^{N} \frac{1}{l_{jk}^{d_\alpha}} \tag{11}$$

where $l_{jk}^{d_\alpha}$ is the shortest path length from the variable k to j on band d_α. Greater GE means more effective risk propagation.

2.3.4. Uniqueness edge ratio

Next, we construct the uniqueness edge ratio (UER), which reflects the uniqueness of network structure. The UER of the layer d_α is defined as

$$\mathrm{UER}^{d_\alpha} = \frac{1}{K^{d_\alpha}} \sum_{j=1}^{N} \sum_{k=1,k\neq j}^{N} a_{jk}^{d_\alpha} \prod\nolimits_{\beta=1,\beta\neq\alpha}^{s} (1 - a_{jk}^{d_\beta}) \tag{12}$$

where $a_{jk}^{d_\alpha} = sign(\tilde{\theta}(u, d_\alpha)_{jk})$. If $\tilde{\theta}(u, d_\alpha)_{jk} \neq 0$, $a_{jk}^{d_\alpha} = 1$. $K^{d_\alpha} = \sum_{j=1}^{N} \sum_{k=1,k\neq j}^{N} a_{jk}^{d_\alpha}$ is the number of all connected edges on the layer d_α. If UER^{d_α} is close to 1, which means that most of the edges on the layer d_α do not appear on the other s-1 layers, i.e., the network structure of layer d_α is peculiar.

2.3.5. Average overlap degree

Following Wang et al. (2021) and Ouyang et al. (2023), we calculate the average overlap degree (AOD) to measure the edge structural similarity of multilayer frequency networks. The AOD is defined as

$$\mathrm{AOD} = \frac{1}{K} \sum_{j,k=1,j\neq k}^{N} \sum_{\alpha=1}^{s} a_{jk}^{d_\alpha} \tag{13}$$

where $a_{jk}^{d_\alpha} = sign(\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk})$, $K = \sum_{j,k=1,j\neq k}^{N} \left[1 - \prod_{\alpha=1}^{s} (1 - a_{jk}^{d_\alpha})\right]$. If $\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk} \neq 0$, $a_{jk}^{d_\alpha} = 1$. AOD takes value s when the edge structures of s layers are identical, while it takes value 1 if every edge only exists in one layer

2.3.6. Network correlation coefficient

We employ Spearman's rank correlation to investigate the network correlation coefficient (NCC) of multilayer frequency networks from the market level. The NCC is defined as

$$\mathrm{NCC}^{\alpha\beta} = 1 - \frac{6\sum_{j=1}^{N}(R_j^{d_\alpha} - R_j^{d_\beta})^2}{N(N^2-1)} \tag{14}$$

where N is the number of commodity futures markets, R_i^α and R_i^β represent the rank of market j about its out-strength (in-strength) on layer d_α and d_β, respectively. The out-strength represents the risk emitted by market j, i.e., $\mathrm{OS}_j^{d_\alpha} = \sum_{k=1,k\neq j}^{N} \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{kj}$, and the in-strength refers to the risk received by market j, i.e., $\mathrm{IS}_j^{d_\alpha} = \sum_{k=1,k\neq j}^{N} \tilde{\boldsymbol{\theta}}(u, d_\alpha)_{jk}$. The $\mathrm{NCC}^{\alpha\beta}$ falls into [-1,1], where $\mathrm{NCC}^{\alpha\beta} = 1(-1)$ suggests that the out-strength (in-strength) of markets in layers d_α and d_β are strong positive (negative) correlated.

2.3.7. Systemic importance

We want to know which markets are the drivers of risk diffusion. Thus, following to Hué et al. (2019), we calculate the systemic importance of commodity futures markets to identify the key nodes in multilayer frequency networks. The systemic importance of market k on layer d_α is defined as

$$\mathrm{TN}^{d_\alpha} = \sum_{i=1}^{N} \sum_{j=1,j\neq i}^{N} I_{ij}^{d_\alpha} \tag{15}$$

$$\mathrm{TN}_{-k}^{d_\alpha} = \sum_{i=1,i\neq k}^{N} \sum_{j=1,j\neq i,j\neq k}^{N} I_{ij}^{d_\alpha} \tag{16}$$

$$\mathrm{LOO}_k^{d_\alpha} = \frac{\mathrm{TN}^{d_\alpha} - \mathrm{TN}_{-k}^{d_\alpha}}{\mathrm{TN}^{d_\alpha}} \tag{17}$$

where $I_{ij}^{d_\alpha} = sign(\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{ij})$, if $sign(\tilde{\boldsymbol{\theta}}(u, d_\alpha)_{ij}) \neq 0$, $I_{ij}^{\alpha} = 1$, it means that there is a directed edge from markets j to i. Hence, TN^{d_α} is the total number of edges of the layer d_α, $\mathrm{TN}_{-k}^{d_\alpha}$ is the total number of edges between the remaining N-1 markets after removing market k. The larger $\mathrm{LOO}_k^{d_\alpha}$ means that market k is of systemic importance, indicating that it is a key node that promotes interconnectedness and risk spillovers among markets.

2.4. Shapley decomposition

Following Israeli (2007) and Zhang et al. (2023b), we use the Shapley decomposition approach to examine the contribution of macroeconomics to frequency connectedness among commodity futures markets. The Shapley decomposition approach is defined as

$$M_{k,t} = \frac{1}{L!}\left\{R^2\left[y_t = a + \sum_{j\in S} b_j x_{j,t-p} + b_k x_{k,t-p} + u_t\right] - R^2\left[y_t = a^* + \sum_{j\in S} b_j^* x_{j,t-p} + u_t^*\right]\right\} \tag{18}$$

where the dependent variable y represents the average connectedness strength (ACS) of multilayer frequency networks, and $M_{k,t}$ is the marginal utility of the macroeconomic variable k to goodness of fit R^2, i.e., the contribution of the macroeconomic variable k to dependent variable y. In addition, L is the number of global macroeconomic variables, S is the set of all macroeconomic variables except the macroeconomic variables k, and p is the lag of macroeconomic economic variables. Referring Chen et al. (2020) and Baruník et al. (2024), we set the lag equal to 1 to solve the potential endogeneity problem.

3. Data and empirical results

3.1. Data description

In this paper, we apply the multilayer frequency networks to examine the volatility connectedness among 13 commodity futures markets. Specifically, we select important commodity futures markets from agriculture, energy, and metals sectors, including cocoa, corn, soybean, sugar, wheat, light crude oil, heating oil, natural gas, gold, copper, palladium, platinum, and silver. The reason for choosing these markets is that they exhibit a substantial level of financialization, that is, they are highly traded commodity classes (Kang et al., 2017). In addition, these commodities are considered most active assets in futures investments (Abricha et al., 2023). Some previous works also use similar samples (Bouri et al., 2021b; Zhang et al., 2023b). We

Table 1. Commodity futures markets list.

Sector	Market	Symbol
Agricultural	Cocoa Futures	CC
	Corn Futures	CO
	Soybean Futures	SO
	Sugar Futures	SU
	Wheat Futures	WH
Energy	Light Crude Oil Futures	CL
	Heating Oil Futures	HO
	Natural Gas Futures	NG
Metals	Gold Futures COMEX	GC
	Copper High Grade Futures	HG
	Palladium Futures	PA
	Platinum Futures	PL
	Silver Futures	SI

collect daily high-frequency realized volatility of 13 futures markets from September 22, 2008, to May 26, 2023, obtained from the Risk Lab database of the Booth School of Business at the University of Chicago, where it is maintained by Professor Dacheng Xiu, and is available for download from: https://dachxiu.chicagobooth.edu. Risk Lab collects trades at their highest frequencies available, and then cleans them based on the prevalent national best bid and offer that are available, up to every second. The estimation procedure for realized volatility follows Xiu (2010), and uses the quasi-maximum likelihood estimates of volatility, building on moving-average models, where non-zero returns of transaction prices are sampled up to their highest frequency available, for days with at least 12 observations. The study period covers several turbulent and crises, including the global financial crisis in 2008, the European debt crisis in 2009-2012, the COVID-19 pandemic in 2020, and Russia-Ukraine war in 2022, allowing us to explore financial connectedness under global crisis. Table 1 describes the necessary information on 13 commodity futures markets.

Table 2 reports the descriptive statistics of data, including minimum, mean, maximum, standard deviation, skewness, kurtosis, and ADF test. According to Table 2, we find that the standard deviation of the energy sector is significantly higher than that of the agricultural

Table 2. Data descriptive statistics and Pearson correlation coefficent.

Panel A: Data descriptive statistics													
	CC	CO	SO	SU	WH	CL	HO	NG	GC	HG	PA	PL	SI
Min	0.0013	0.0514	0.0643	0.0470	0.0904	0.0814	0.0800	0.1200	0.0406	0.0026	0.0005	0.0002	0.0871
Mean	0.2413	0.2363	0.1984	0.2710	0.2915	0.3486	0.2921	0.4410	0.1591	0.2379	0.3350	0.2420	0.2867
Max	1.1937	1.7592	0.8543	1.0295	1.9965	3.0000	1.6945	1.6977	0.7550	1.3105	3.0000	2.1899	1.7645
Std.dev	0.0809	0.1143	0.0806	0.0975	0.1182	0.2144	0.1538	0.1884	0.0750	0.1188	0.1898	0.1188	0.1432
Skewness	1.8414	2.4897	2.0668	1.0831	3.1453	4.4238	2.3939	1.2667	2.6331	3.0360	3.4894	4.0786	3.0194
Kurtosis	15.4707	18.5275	10.2912	6.1095	27.7251	38.2629	13.6049	5.2888	13.8743	16.9429	28.6781 4	0.0817	18.8699
ADF	-32.0633***	-29.0736***	-23.7827***	-23.6918***	-25.5414***	-11.4940***	-13.8668***	-18.4713***	-18.9838***	-13.8243***	-24.8777***	-18.5173***	-19.5579***

Panel B: Pearson correlation coefficent													
	CC	CO	SO	SU	WH	CL	HO	NG	GC	HG	PA	PL	SI
CC	1.0000												
CO	0.1759	1.0000											
SO	0.2055	0.7966	1.0000										
SU	0.2591	0.2737	0.2300	1.0000									
WH	0.1933	0.7334	0.6855	0.2667	1.0000								
CL	0.1876	0.2578	0.2846	0.2375	0.2914	1.0000							
HO	0.1978	0.2947	0.3485	0.2189	0.3997	0.8929	1.0000						
NG	0.0696	0.1221	0.1807	0.0286	0.1924	0.3860	0.4941	1.0000					
GC	0.1648	0.4196	0.4780	0.2101	0.3313	0.4952	0.4892	0.2062	1.0000				
HG	0.3166	0.4910	0.6029	0.3109	0.4449	0.5224	0.5745	0.3019	0.7072	1.0000			
PA	0.1738	0.2411	0.2729	0.1791	0.3521	0.5341	0.5948	0.3906	0.5070	0.4835	1.0000		
PL	0.1954	0.3017	0.3727	0.1593	0.3015	0.5695	0.5975	0.3733	0.6809	0.5996	0.6963	1.0000	
SI	0.1856	0.4068	0.4386	0.2484	0.3487	0.4087	0.4051	0.2251	0.8235	0.6519	0.4513	0.6284	1.0000

Notes: *** denotes rejection of the null hypothesis at the 1% level. ADF refers to the statistics from the Augmented Dickey-Fuller unit-root test.

and financial sectors, which means that there is more volatility risk in the energy market. In addition, the results of the ADF test show that we can reject the null hypothesis that all variables have a unit root at the 1% significance level. This suggests that all variables are stationary. Furthermore, the Pearson correlation coefficient in Table 2 lists that there is a positive correlation between all series, which provides positive evidence for us to explore the volatility connectedness among futures markets.

3.2. Empirical setup

Furthermore, following Dai et al. (2022) and Rehman et al. (2023), we use the Schwarz Information Criterion (SIC) to select the optimal lag order of the TVP-VAR model and set the lag p=3. According to Baruník and Ellington (2024), we know that the forecast horizon h has no practical economic significance in the frequency domain. It is recommended to choose a larger h to obtain better estimation results. Hence, we set forecast horizon h=100.[1] Finally, referring

[1]We compared the 4.1 average connectedness analysis for h = 50, 100, and 200, and the results display that our conclusions are robust. To save space, the test results are not reported, which can be available from the authors upon request.

to Baruník and Krehlík (2018), Ouyang and Zhou (2023), and Baruník and Ellington (2024), we developed three frequency bands $d_1 = (0, \pi/20)$, $d_2 = (\pi/20, \pi/5)$, and $d_3 = (\pi/5, \pi)$, representing the low-frequency band over 20 days (long-term), the medium frequency band between 5 and 20 days (medium-term), and the high-frequency band between 1 and 5 days (short-term), respectively.

4. Empirical results

4.1. Average connectedness analysis

In this section, we explore average connectedness among commodity futures markets. In detail, we average the dynamic connectedness matrices to obtain average connectedness matrices of short-, medium-, and long-term. Then, we filter the matrix using the mean value to obtain multilayer frequency networks.

4.1.1. System-level analysis

Figure 1 shows the static multilayer frequency networks. First, we find similar risk spillover behavior in short-, medium-, and long-term networks. For example, we observe that the agriculture sector (red nodes) is at the periphery of the three networks and they have significant internal risk contagion. However, we note that the agriculture sector does not have strong risk linkages with the other two sectors. Our findings support the work of Zhang et al. (2023b) and Abricha et al. (2023), who found weaker cross-market risk spillovers in the agriculture sector. In the long-term network, we observe that there is a risk spillover from soybean to copper. Therefore, for long-term investors in soybean futures and copper futures, they need to be wary of risk resonance between the two. In addition, we find that the energy (blue nodes) and metals (green nodes) sectors are active in multilayer frequency networks, with strong risk connectedness between the two sectors in the short-, medium-, and long-term. Second, from node size, we find that gold (GC), silver (SI), and platinum (PL) dominate the multilayer frequency network, which means that they are sources of systemic risk in the commodity futures market. Finally,

Table 3. Single-layer network measures.

	ACS	ND	GE	UER	AOD
Short-term	19.84	0.2692	0.2885	0.0000	
Medium-term	5.95	0.2820	0.2949	0.0000	2.9111
Long-term	2.41	0.2884	0.3526	0.0222	

we find that cocoa (CO), sugar (SU), and natural gas (NG) are isolated nodes, suggesting that they do not have strong risk connections with other futures markets. Therefore, we recommend that futures investors include cocoa, sugar, and natural gas in their portfolios to avoid market connectedness risk.

Furthermore, we report the average connectedness strength (ACS), network density (ND), global efficiency (GE), uniqueness edge ratio (UER), and average overlap degree (AOD) in Table 3. According to Table 3, we find that the ACS of short-, medium-, and long-term networks are 19.84, 5.95, and 2.41, respectively. This indicates that risk contagion among commodity futures market changes with frequency, and they have more drastic risk spillovers in the short-term. The possible reason is that futures participants prefer short-term investments (Hoque et al., 2023), resulting in strong short-term volatility spillovers among futures markets. This result also enriches existing research (Billah et al., 2023; Hu et al., 2023; Elsayed et al., 2024) and reveals that short-term factors are the drivers of risk spillovers in commodity futures. Moreover, we observe that network density (ND) and global efficiency (GE) increase with decreasing frequency, which suggests the existence of a more complex linking structure in the long-term network. In UER, we observe weak uniqueness (0.0222) in the edge structure of the long-term network. The results of the AOD also confirm the above finding, that is, there is homogeneity in the edge structure of the multilayer frequency networks.

Table 4 shows the network correlation coefficient (NCC) of multilayer frequency networks in terms of the out-strength and in-strength. In Table 4, we find that there is a strong positive

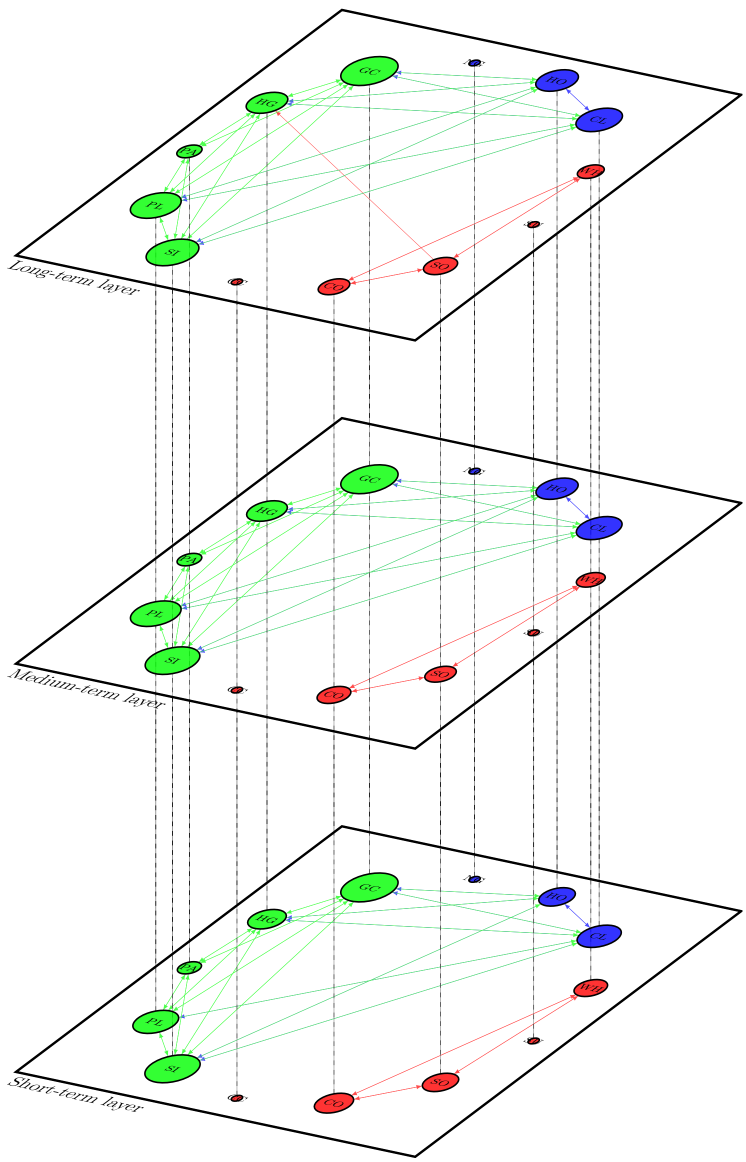


Figure 1: Static multilayer frequency networks. Notes: The red nodes denote the agriculture sector, blue nodes denote the energy sector, green nodes denote the metals sector, and arrows indicate the direction of risk transmission. In addition, node size depends on the out-strength, i.e., the volatility risk emitted by that node, with interlayer edges connecting the same node in each layer.

Table 4. Network correlation coefficient.

	Out-strength	In-strength
Short-term and medium-term	0.9778***	0.9944***
Short-term and long-term	0.9611***	0.9722***
Medium-term and long-term	0.9944***	0.9778***

Notes: *** indicates rejection of the null hypothesis of no correlation at the 1% level.

correlation between the short-, medium-, and long-term networks, and the null hypothesis of no correlation is rejected at the 1% level. This means that the risk spillovers of 13 commodity futures markets are homogeneous in frequency. In other words, when a market is a risk emitter (risk receiver) in the short-term network, it is also a risk emitter (risk receiver) in the medium- and long-term networks. However, it should be noted that although the risk role of each market does not change with frequency, its risk spillover intensity may change with frequency.

4.1.2. Market-level analysis

Then, we present the top 5 commodity futures markets ranked by out-strength and in-strength in Table 5. In out-strength, we observe that gold (GC), silver (SI), platinum (PL), and light crude oil (CL) are always in the top four in the short-, medium-, and long-term networks, which means that they are the main contributors to volatility connectedness among commodity futures markets. But it is worth noting that we find that short-term volatility spillovers are more active in these four markets, at 35.93, 34.68, 28.72, and 27.73 respectively. This finding complements existing research (Gong and Xu, 2022; Chishti et al., 2023; Abricha et al., 2023), revealing transitory shocks to futures markets from metals and energy commodities. Therefore, policy designers should strengthen the monitoring of short-term risks in futures markets to avoid systemic crises triggered by short-term volatility. Meanwhile, we find that gold (GC), silver (SI), platinum (PL), and light crude oil (CL) also rank high in in-strength, which means that they not only release a large amount of volatility risk but also bear volatility shocks from other markets. Moreover, we need to be wary of short-term spillovers (24.65) from corn (CO)

Table 5. Top 5 out-strength and in-strength commodity futures markets.

Rank	Market	Out-strength	Market	In-strength
Panel A: Short-term				
1	GC	35.93	GC	33.80
2	SI	34.68	SI	32.84
3	PL	28.72	PL	28.34
4	CL	27.73	CL	27.10
5	CO	24.65	HG	25.16
Panel B: Medium-term				
1	GC	10.79	GC	9.95
2	SI	10.30	SI	9.86
3	PL	9.55	PL	9.09
4	CL	8.62	CL	8.69
5	HO	7.95	HG	8.33
Panel C: Long-term				
1	GC	4.39	SI	4.02
2	SI	4.04	GC	4.01
3	PL	3.89	HG	3.86
4	CL	3.56	PL	3.63
5	HO	3.27	CL	3.60

as well as medium- and long-term spillovers (7.95 and 3.27) from heating oil (HO). Finally, we note that copper (HG) is also a risk receiver, which is mainly exposed to short-term risk shocks.

We list the top five systemic markets in Table 6. Systemic importance is used to measure the contribution of the market's edge structure to risk contagion. The higher the systemic importance of a market, it means that it controls the flow of information in the network. In Table 6, we observe similar results to Table 5, i.e., gold (GC), silver (SI), platinum (PL), light crude oil (CL), and copper (HG) have strong control over the multilayer frequency network. For example, when the gold market is removed, the edge number in the short-term network will decrease by 28.57%. Unexpectedly, we find that copper (HG) has the strongest control over the long-term network (28.89%), which means that copper (HG) is the hub of the long-term network. Our conclusions are lined with Xiao et al. (2020), Gong and Xu (2022), and Mensi et al. (2023), who argue that metals and energy sectors are net emitters of risk. However,

Table 6. Top 5 systemic markets.

Rank	Short-term		Medium-term		Long-term	
	Market	LOO	Market	LOO	Market	LOO
1	GC	28.57%	GC	27.27%	HG	28.89%
2	HG	28.57%	HG	27.27%	GC	26.67%
3	SI	28.57%	PL	27.27%	PL	26.67%
4	CL	23.81%	SI	27.27%	SI	26.67%
5	PL	23.81%	CL	22.73%	CL	22.22%

unlike these published papers, our work suggests that copper is the strongest hub for long-term risk spillovers between commodity futures markets. This result provides new insights into the findings of Qiao and Han (2023).

4.2. Dynamic connectedness analysis

4.2.1. System-level analysis

Figure 2 visualizes the dynamic average connectedness strength (ACS) of multilayer frequency networks. In Figure 2, we find clear differences in ACS for short-, medium-, and long-term networks. First, we observe that short-term connectedness (red line) is significantly higher than medium- (green line) and long-term (blue line) connectedness, suggesting that volatility spillovers between commodity futures markets are dominated by short-term spillovers. Our results are consistent with previous research showing that short-term spillovers in commodity futures market are more active (Hoque et al., 2023; Mensi et al., 2023). Second, we note that medium- and long-term connectedness between commodity futures markets rises sharply during periods of financial stress. For example, during the European debt crisis in 2011, the COVID-19 pandemic in 2020, and the Russian-Ukrainian conflict in 2022, we find that the ACS of medium- and long-term networks increase rapidly. This means that systemic crises promote the transformation of short-term (transitory) risks in commodity futures markets into long-term (persistent) risks. These findings provide new evidence to existing work (Ma et al., 2021; Rehman et al., 2023; Zhang et al., 2023b; Long et al., 2024), suggesting that shocks from

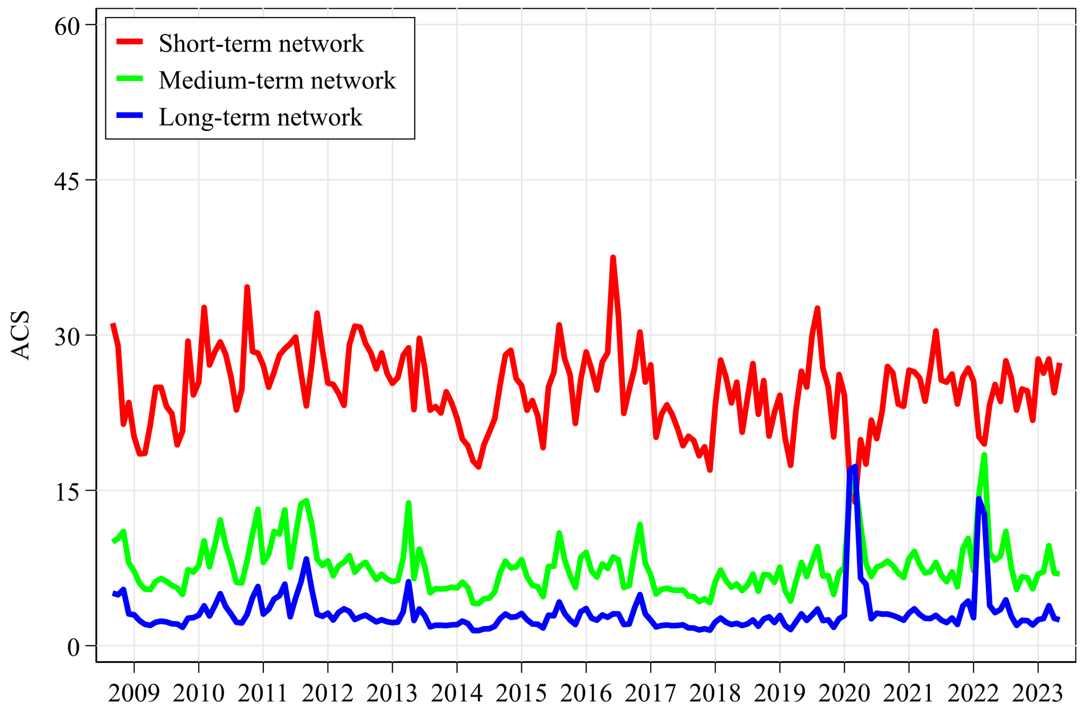


Figure 2: Dynamic average connectedness strength of multilayer frequency networks

systemic events on futures markets are persistent. We believe the main reason is that investors will continue to sell commodity futures during periods of systemic stress, leading to a long-term downward spiral in commodity futures prices (Izzeldin et al., 2023; Mohammed et al., 2023). In this case, persistent risk spillovers will occur among commodity futures markets.

Moreover, we present the dynamic network density (ND) and dynamic global efficiency (GE) of multilayer frequency networks in Figures 3 and 4. As can be seen in Figures 3 and 4, we find the same pattern for dynamic network density and dynamic global efficiency. This is not difficult to explain because the global efficiency depends on the network density (Wang et al., 2021; Ouyang and Zhou, 2023), and the greater the network density the more convenient the information transfer between nodes. Next, we focus on explaining the dynamic network density of multilayer frequency networks. In Figure 3, we find that the network densities of the short-, medium-, and long-term networks overlap with each other, which suggests that the

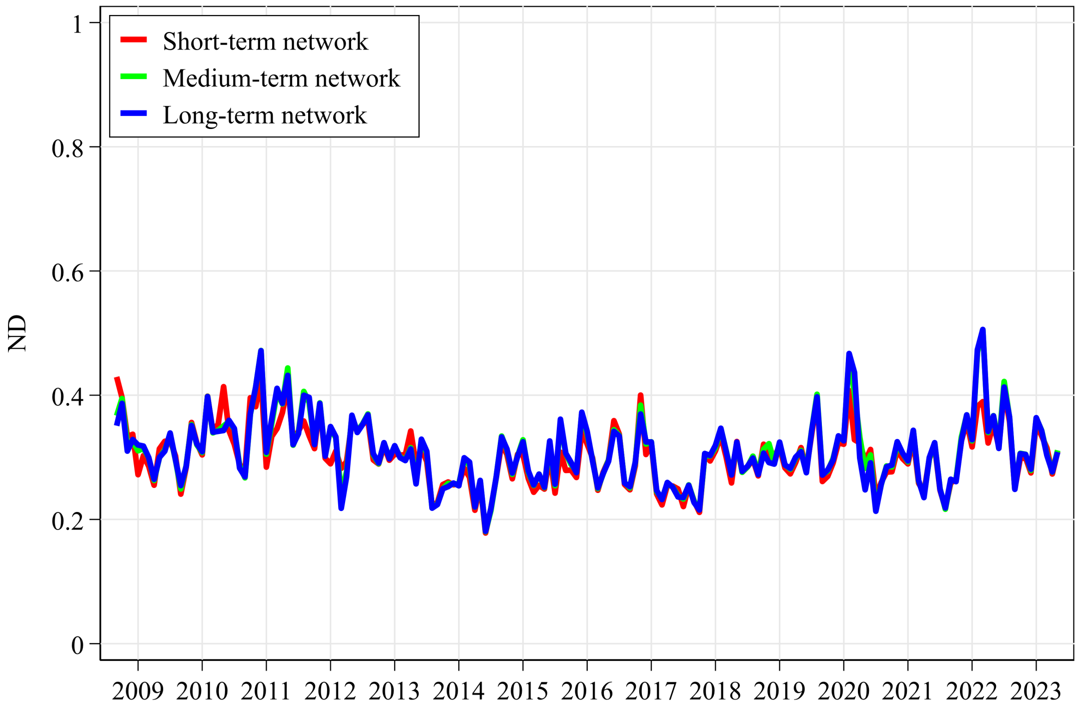


Figure 3: Dynamic network density of multilayer frequency networks

linkage degree between commodity futures markets does not vary with frequency. Furthermore, we find that the network density of the multilayer frequency network is at a local peak during crises, e.g., during the COVID-19 pandemic and the Russian-Ukrainian conflict. This suggests that global crises can increase the strength of connections between commodity futures markets. In other words, crisis events will increase risk transmission channels among commodity futures markets, thereby accelerating the spread of systemic risks.

To investigate the edge uniqueness of multilayer frequency networks, we show the dynamic unique edge ratio (UER) and dynamic average overlap degree (AOD) in Figures 5 and 6, respectively. First, we find that the UERs of the short-term (red line) and long-term (blue line) networks are significantly dynamic, while the UER of the medium-term network converges to 0 over the entire sample. This suggests that there is no uniqueness in the edge structure of the medium-term network, i.e., risk contagion information in the medium-term network can be

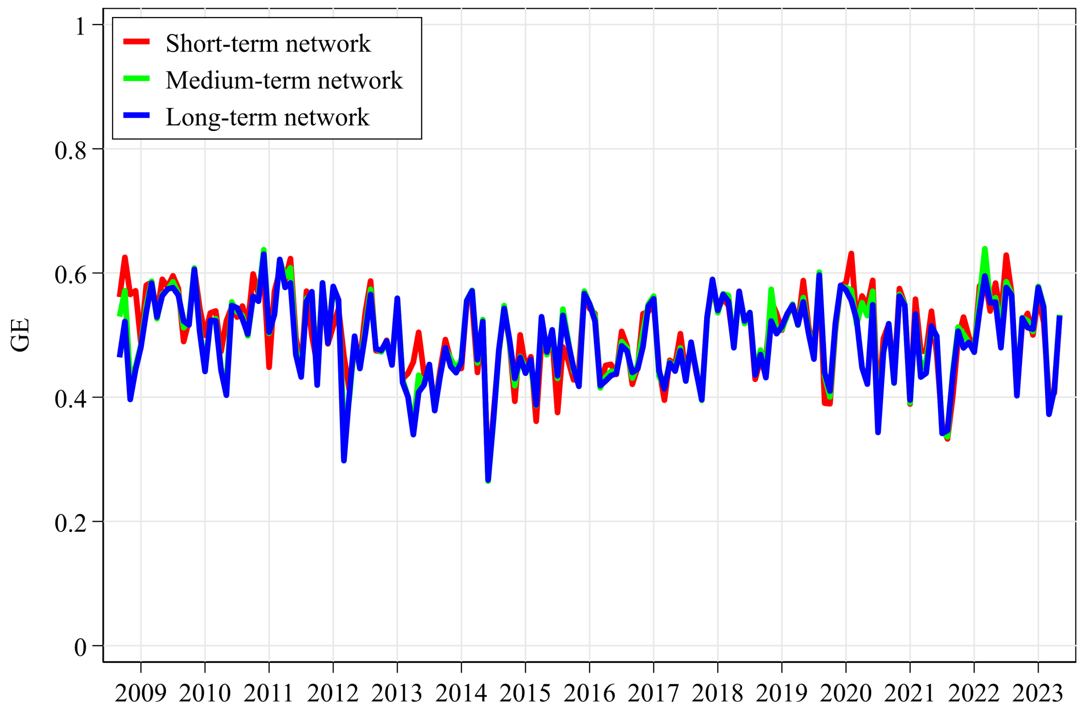


Figure 4: Dynamic global efficiency of multilayer frequency networks

captured by the short- and long-term networks. Second, we find that the UER of the short-term network is the largest, especially during the 2008 global financial crisis, the 2011 European debt crisis, the 2020 COVID-19 pandemic, and the 2022 Russia-Ukraine war, the UER of the short-term network rose sharply. This means that there are more unique contagion channels in short-term networks during crises. Finally, we observe that the UER of the long-term network is at its peak during the COVID-19 pandemic and the Russian-Ukrainian conflict. This implies that there are hidden volatility contagion mechanisms in the long-term network that cannot be captured by the short- and medium-term networks. These findings are confirmed by the results of the dynamic average overlap degree (AOD) in Figure 6. For example, we observe that AOD is at the bottom during the four crises, implying that the edge structure among commodity futures markets is heterogeneous in the short-, medium-, and long-term. The above conclusions enrich the finding of Kang et al. (2019), Wen et al. (2022), and Mensi et al. (2023), indicating

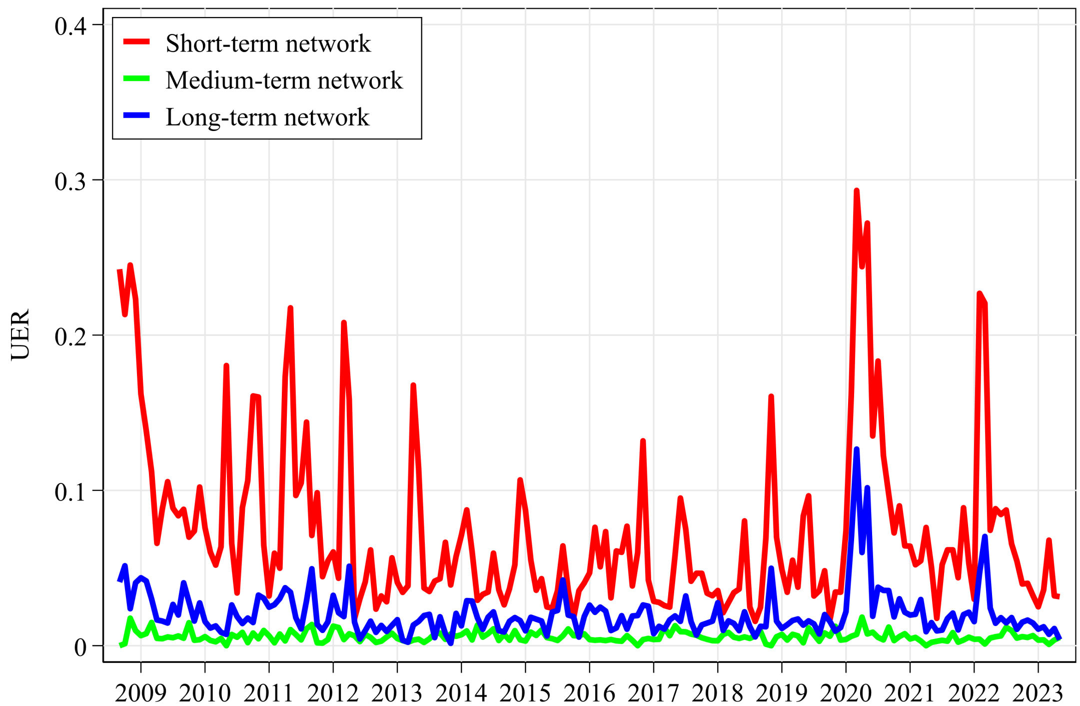


Figure 5: Dynamic uniqueness edge ratio of multilayer frequency networks

that the contagion structure among commodity futures depends on frequency, especially short- and long-term.

Figure 7 illustrates the correlation of multilayer frequency networks from the perspective of out-strength and in-strength. In Figure 7(a), we find that the three curves are all positive, which means that the out-strength of the commodity futures market is similar in the short-, medium-, and long-term. It should be noted that during periods of systemic stress such as the European debt crisis in 2011 and the COVID-19 pandemic in 2020, volatility spillovers from commodity futures markets diverge in frequency. In detail, during the COVID-19 pandemic period, we observe that the red and green lines reached the lowest points at 0.53 and 0.33, respectively, which means that the commodity futures market plays different roles in the short-, medium-, and long-term. In addition, we find that the blue line is always greater than 0.80, which illustrates that there is a strong correlation between the out-strength of the medium- and

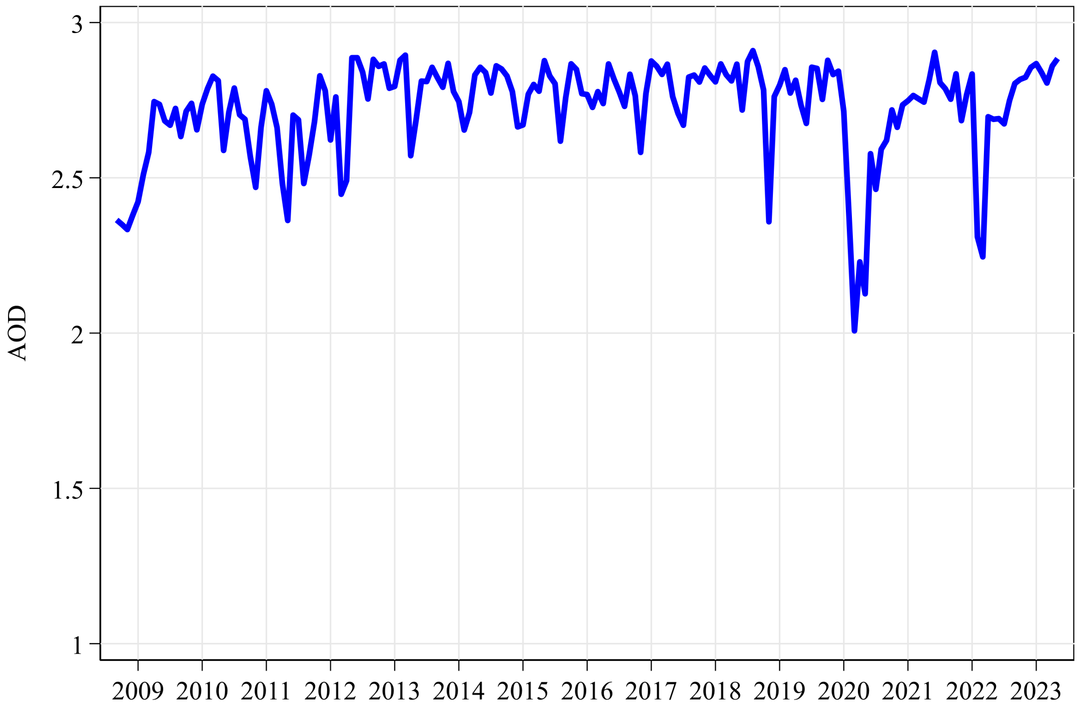
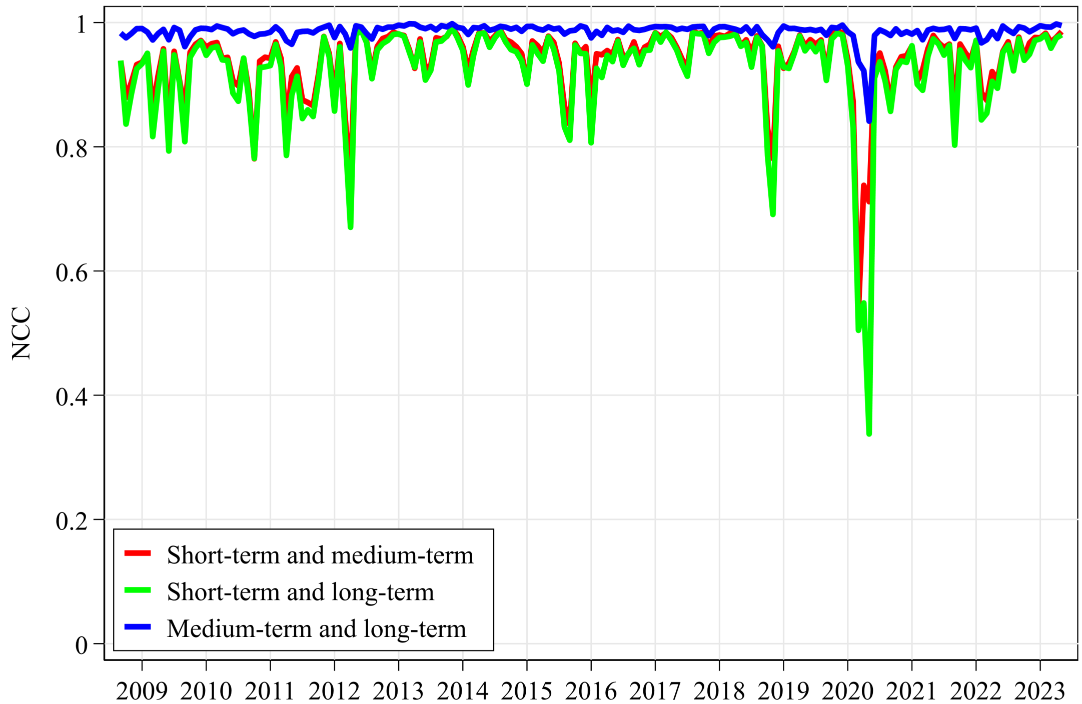


Figure 6: Dynamic average overlap degree of multilayer frequency networks

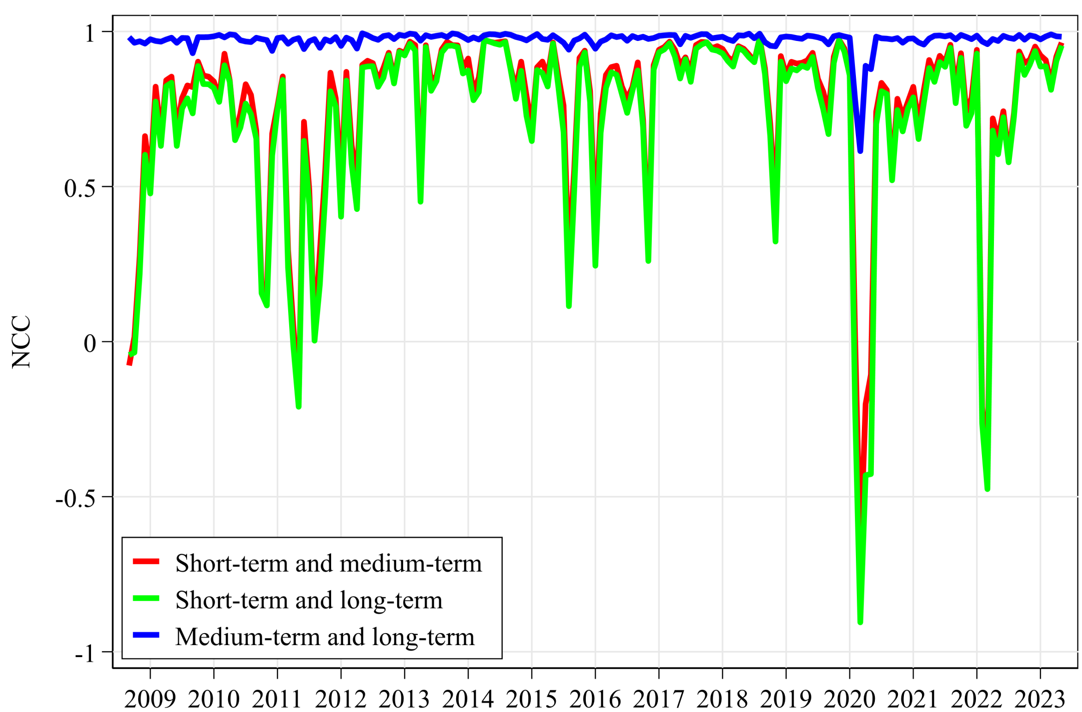
long-term networks. In Figure 7(b), we find different results from Figure 7(a). We observe that the red and green lines are negative during crisis times, even close to -1 (COVID-19 pandemic period). This implies that the volatility risk received by the commodity futures market reverses in the short- and long-term. Namely, a market may receive a large number of volatility shocks in the short-term network, but it may not be affected by other markets in the long-term network.

4.2.2. Market-level analysis

Figure 8 presents the dynamic out-strength of commodity futures markets, with darker node colors implying greater risk spillovers. First, we find that the node color is darker in the short-term, which implies that short-term risk shocks among commodity futures markets are more powerful. Second, Figure 8(a) shows that commodity futures such as corn (CO), gold (GC), and silver (SI) have higher out-strength, which means that they are the drivers of the interconnectedness between commodity futures markets. This result provides additional insight



(a) Out-strength



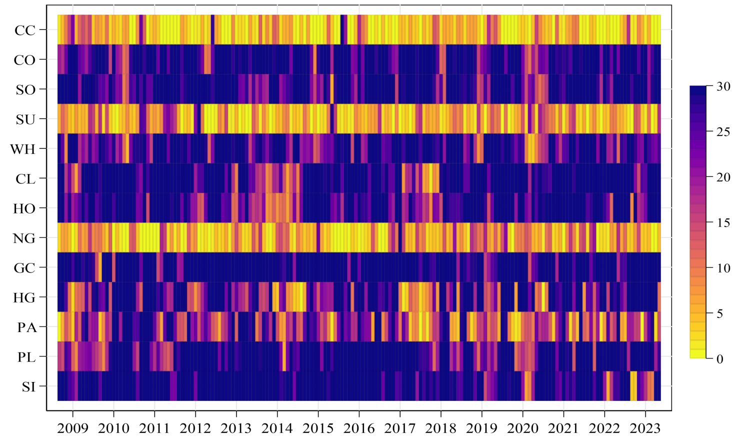
(b) In-strength

Figure 7: Dynamic network correlation coefficient of multilayer frequency networks

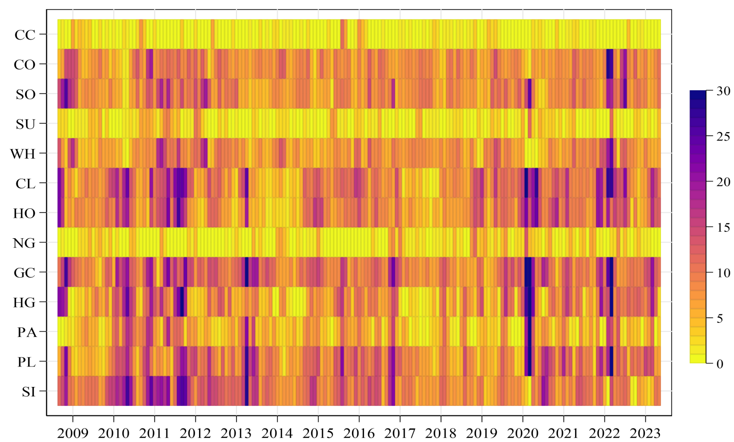
into existing papers (Izzeldin et al., 2023; Qiao and Han, 2023), suggesting that the spillover effects of corn futures are also strong. Moreover, it is important to note that gold (GC) and light crude oil (CL) continue to act as transmitters of risk during the COVID-19 pandemic in 2020 and the Russia-Ukraine war in 2022. In Figure 8(b) and (c), we see that the colors of gold (GC) and light crude oil (CL) changed from light to dark during the two crises, which shows that gold and oil are still the main sources of risk in the commodity futures market. On the contrary, the dynamic out-strength of cocoa (CC), sugar (SU), and natural gas (NG) is weaker, and they can serve as tools for investors to hedge risks.

Similarly, we show the dynamic in-strength of 13 commodity futures markets in Figure 9. We find that markets with the high out-strength, such as corn (CO), gold (GC), and silver (SI), also suffer from sharp short-term fluctuations. Also, we find that commodity futures markets receive weaker risk shocks in the medium- and long-term networks. However, during the Russia-Ukraine war in 2022, we observe a significant increase in the risks received by light crude oil (CL), heating oil (HO), platinum (PL), and silver (SI) in the medium- and long-term networks. This implies that these markets are vulnerable in the medium to long term and are susceptible to risk shocks from crisis events. Therefore, regulators need to strengthen risk prevention for light crude oil, heating oil, platinum, and silver futures during the crisis.

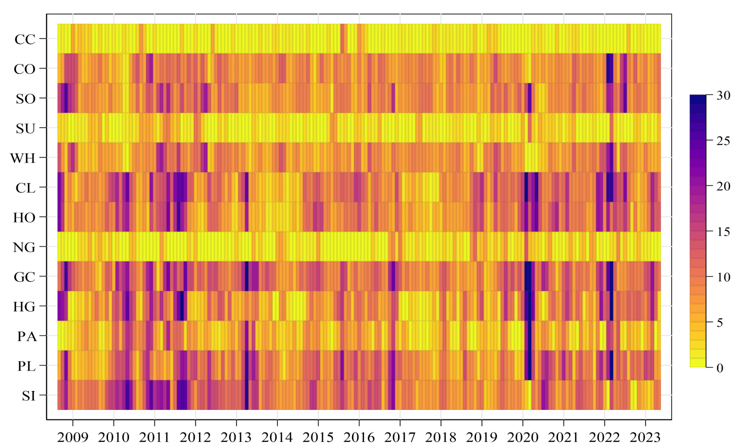
Next, we present the dynamic systemic importance of 13 commodity futures markets in Figure 10 to identify the driving nodes of multilayer frequency networks. First, we note that the systemic importance of commodity futures exhibits time-varying characteristics, e.g., wheat futures show dark nodes during the 2022 Russia-Ukraine war period, but their nodes appear lighter during other periods. The main possible reason is that Ukraine is a significant supplier of wheat, and the outbreak of the Russia-Ukraine war disrupted the global wheat supply chain, exacerbating the volatility risk of wheat futures (Izzeldin et al., 2023). In addition, we find that the metals sector, especially GC, HG, and PL, exhibits large areas of dark shading in the



(a) Short-term

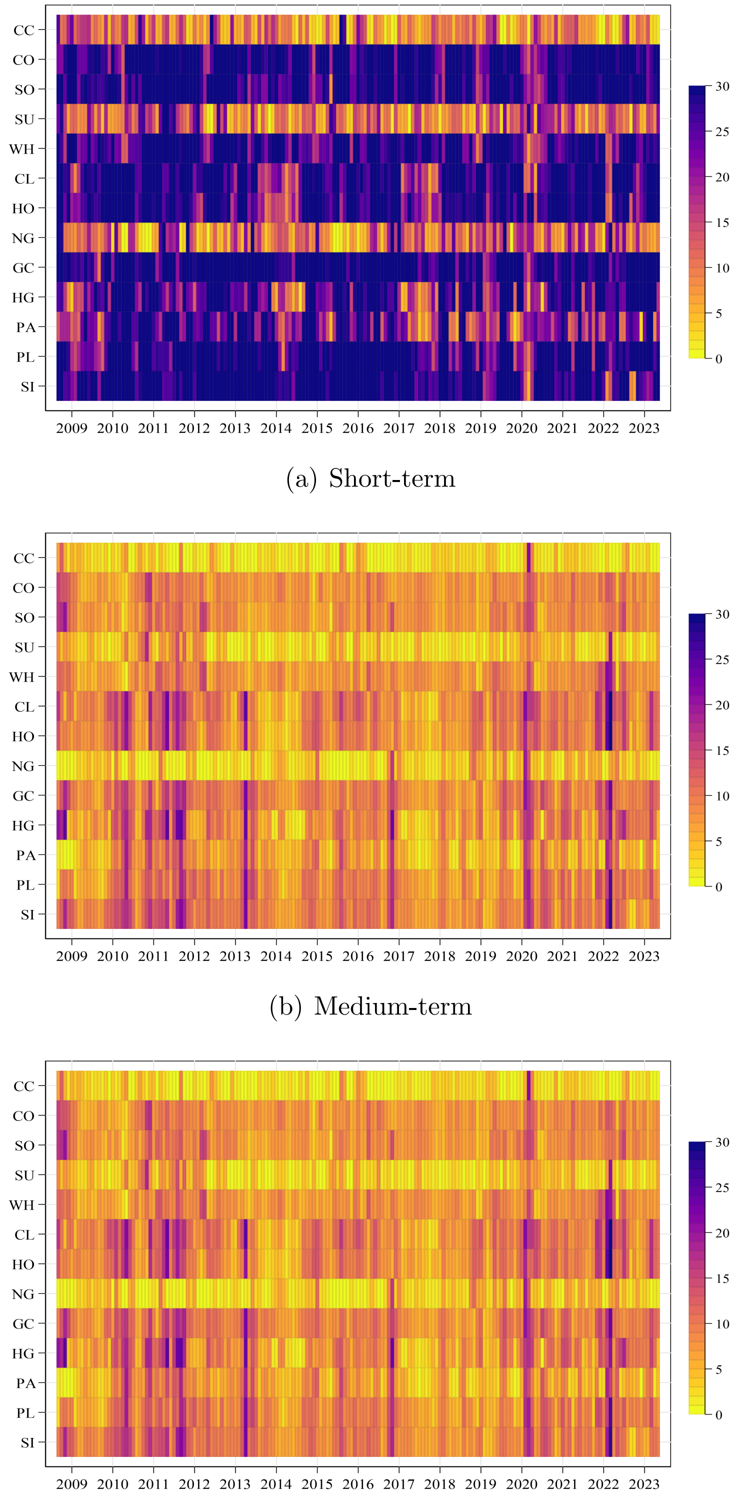


(b) Medium-term



(c) Long-term

Figure 8: Dynamic out-strength of commodity futures markets



(a) Short-term

(b) Medium-term

(c) Long-term

Figure 9: Dynamic in-strength of commodity futures markets

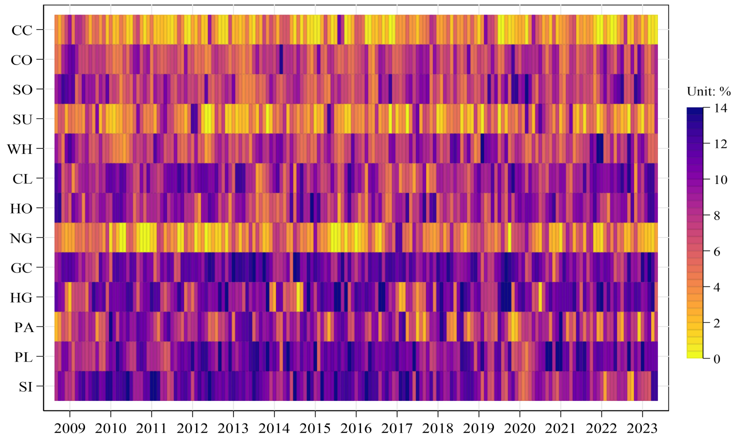
short-, medium-, and long-term networks, indicating that metal futures are the main driving force for the interconnection of commodity futures. As a result, regulators should strengthen risk prevention measures for metal futures.

4.3. Crisis events analysis

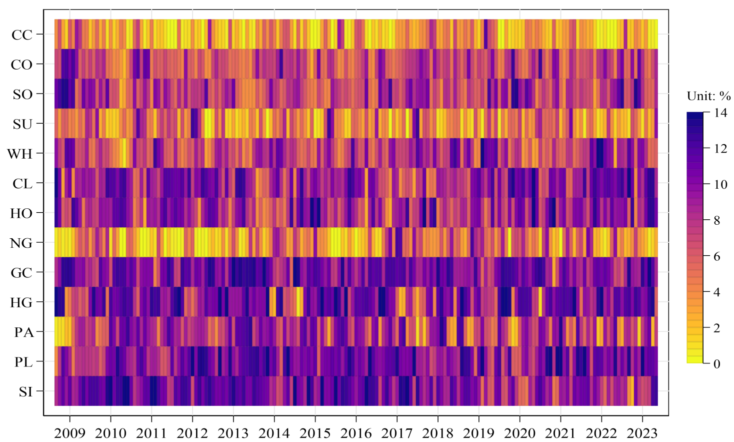
In sections 3.3 and 3.4, we examine the average connectedness and dynamic connectedness among commodity futures markets and do not present how the multilayer frequency networks change during the global crisis. The COVID-19 pandemic in 2020 and the Russia-Ukraine war in 2022 are two recent events that have seriously affected global commodity markets (Mohammed et al., 2023; Ouyang et al., 2023; Izzeldin et al., 2023; Billah et al., 2024). Compared to the global financial crisis and the European debt crisis, these two crises had a more widespread impact on commodity futures markets (please see Figure 2), bringing uncertainty and disruption to the stability of global commodity markets. Thus, in section, we investigate multilayer frequency networks during the COVID-19 pandemic and the Russia-Ukraine war to discuss whether and how network edges change during these two global crises.

4.3.1. COVID-19 pandemic

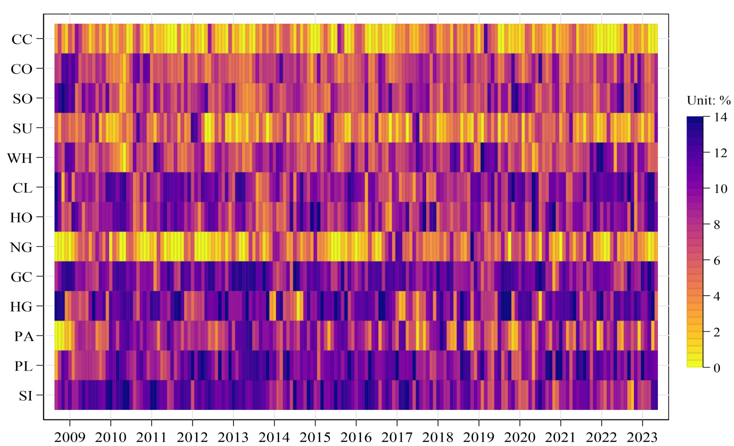
Following Liu et al. (2022) and Ouyang et al. (2023), we select January 13, 2020, as the start date of the COVID-19 pandemic. Then, we show multilayer frequency networks on December 13, 2019 (before the COVID-19 pandemic) and February 13, 2020 (after the COVID-19 pandemic) in Figures 11 and 12. Unlike before the COVID-19 pandemic outbreak, the connectedness among commodity futures markets increases dramatically after the outbreak, e.g., CC-HG, SI-HG, and CL-HG in the short-term network, CL-PL, GC-WH, and NG-CO in the medium-term network, and PA-SI, HO-CO, and CL-WH in the long-term network. These findings are consistent with the work of Liow and Song (2020), Bouri et al. (2021a), Iqbal et al. (2023), and Billah et al. (2024), who observed that the COVID-19 pandemic significantly increased risk contagion among commodity. Moreover, we notice that cross-sector connectedness



(a) Short-term



(b) Medium-term



(c) Long-term

Figure 10: Dynamic systemic importance of commodity futures markets

such as CC-PL, CC-NG, and CC-CL are greatly enhanced after the outbreak of the COVID-19 pandemic. This finding is different from the results of Qiao and Han (2023), who believe that commodity risk contagion after the COVID-19 outbreak was characterized by sectoral agglomeration.

From the perspective of risk spillover effects, we find that key nodes of the multilayer frequency network change after the outbreak of the COVID-19 pandemic. For example, before the COVID-19 pandemic, we find that the agricultural sector, e.g., soybean (SO) and corn (CO), has strong risk spillovers in multilayer frequency networks. But after the COVID-19 outbreak, the risk emission sources of multilayer frequency networks are concentrated in the metal and energy sectors. For example, we observe that the risk spillover effects of copper (HG), gold (GC), and light crude oil (CL) are more significant in the post-collapse network. The above findings imply that the COVID-19 pandemic has not only changed the edge structure among commodity futures markets, but also generated new risk emitters. Furthermore, we note that commodity futures markets play different roles in short-, medium-, and long-term networks after the system collapse. For example, in the short-term network, SU establishes connecting edges with HO, NG, HG, and CO, and in the medium-term network SU establishes connecting edges with HO and HG, but in the long-term network SU is an isolated node. This suggests that SU is more vulnerable to short-term risk shocks, and the same phenomenon occurs in the CC market. As a result, for long-term investors, they can increase the asset weights of sugar (SU) and cocoa (CC) to cope with the connectedness risk arising from market crashes.

4.3.2. Russia-Ukraine war

Referring to Boubaker et al. (2022) and Karkowska and Urjasz (2023), we set 24 February 2022 as the outbreak date of the Russian-Ukrainian conflict. In line with the COVID-19 pandemic, we visualize the multilayer frequency network of 24 January 2022 (before the Russia-Ukraine war) and 24 March 2022 (after the Russia-Ukraine war) in Figures 13 and 14. Roughly

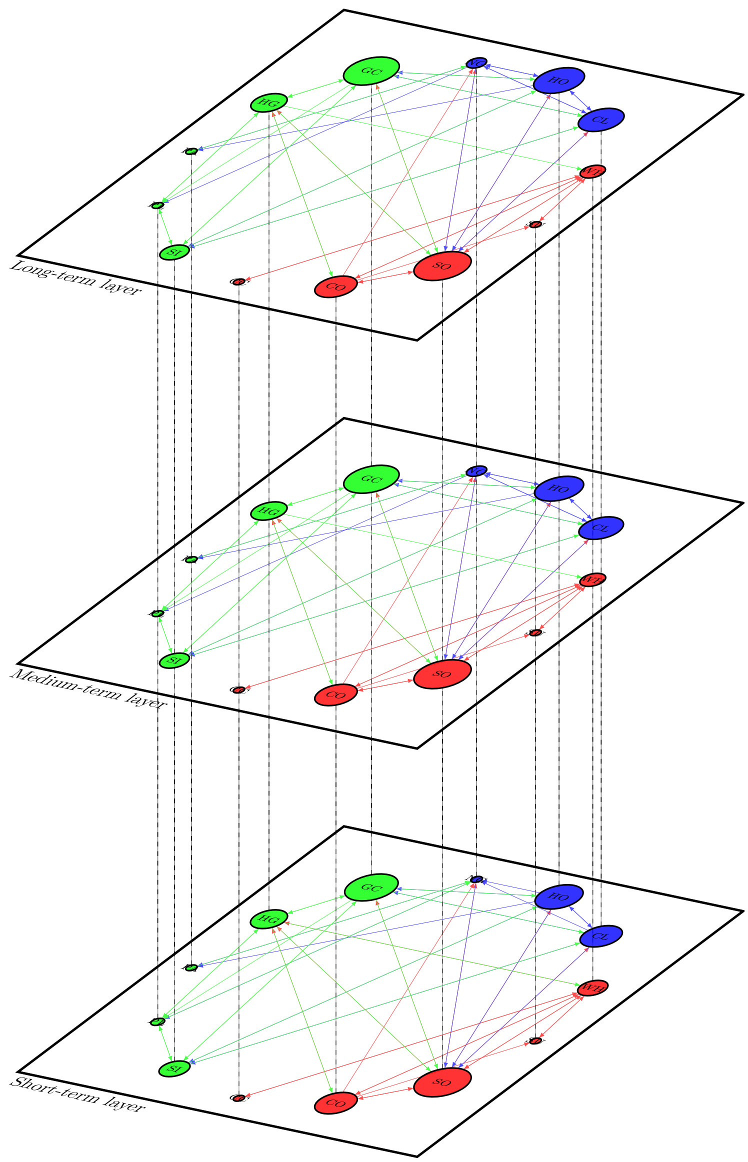


Figure 11: Multilayer frequency networks before the COVID-19 pandemic. Notes: The red nodes denote the agriculture sector, blue nodes denote the energy sector, green nodes denote the metals sector, and arrows indicate the direction of risk transmission. In addition, node size depends on the out-strength, i.e., the volatility risk emitted by that node, with interlayer edges connecting the same node in each layer.

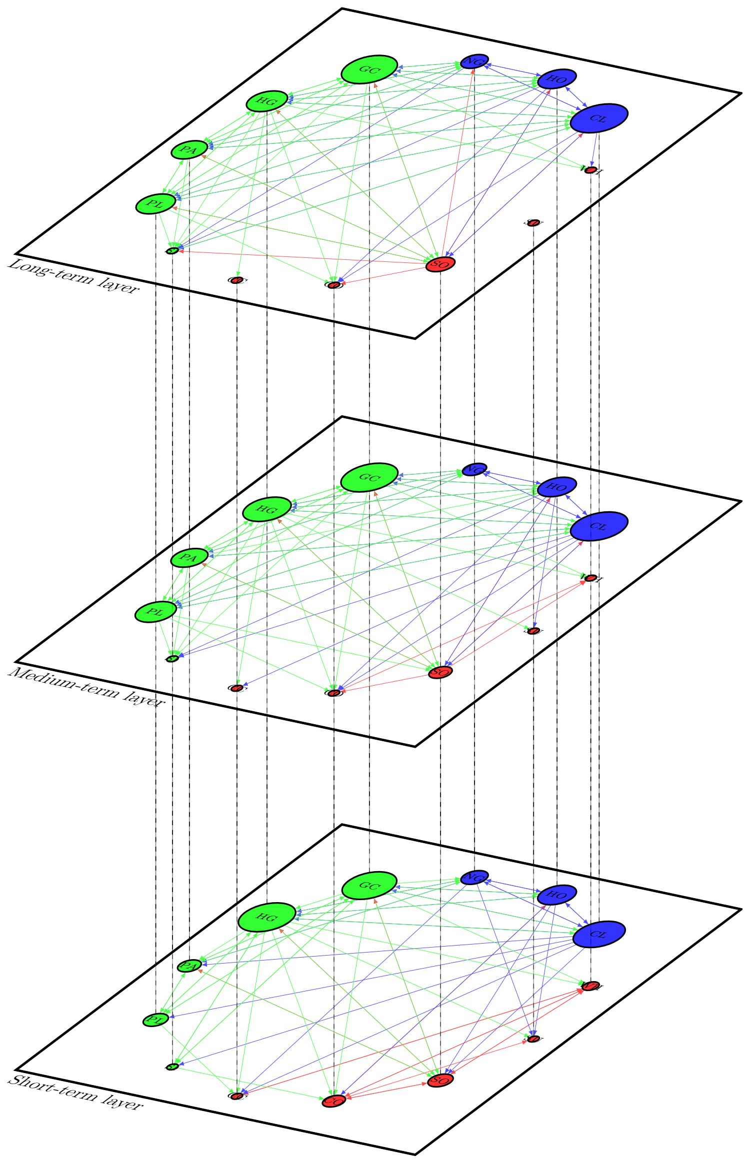


Figure 12: Multilayer frequency networks after the COVID-19 pandemic. Notes: The red nodes denote the agriculture sector, blue nodes denote the energy sector, green nodes denote the metals sector, and arrows indicate the direction of risk transmission. In addition, node size depends on the out-strength, i.e., the volatility risk emitted by that node, with interlayer edges connecting the same node in each layer.

speaking, there are more connections between commodity futures markets after the crisis than before the crisis, especially a significant increase in cross-sector connectedness, e.g., CO-SI, CL-SO, and CL-PA. Similar to the COVID-19 pandemic, the metal and energy sectors play an important role in the post-crisis interconnections between commodity futures markets, and in particular, the risk spillover from platinum (PL) has been significantly enhanced in the post-crisis period. However, in terms of node scale, we find that wheat (WH) has a strong risk spillover effect in the medium-and long-term networks before and after the crisis. Our results enrich the conclusions of Izzeldin et al. (2023) and Abricha et al. (2023) and illustrate the medium- and long-term risk spillovers of wheat futures during the Russia-Ukraine war. One possible explanation is that Ukraine is an important global food supplier, and the conflict between Russia and Ukraine has hindered Ukraine's food exports, leading to a systemic crisis in the agricultural sector (Ghorbali et al., 2023; Saadaoui et al., 2022; Chishti et al., 2023). Furthermore, during the post-crisis, we observe that the natural gas (NG) suffers from risk spillovers from other markets in the short-term, but it is an isolated node in the medium- and long-term. Finally, we find that the CC is an isolated node in the short-, medium-, and long-term, which means that cocoa (CC) has weak connections with other commodity futures markets.

4.4. Determinants analysis

4.4.1. Contribution analysis

In this section, we apply the Shapley decomposition approach to capture the drivers of frequency connectedness (i.e., average connectedness strength in the short-, medium-, and long-term) among commodity futures markets. Following Hu et al. (2020), Bouri et al. (2021b), Saadaoui et al. (2022), Hoque et al. (2023), and Mensi et al. (2024c), we investigate the contribution of climate policy uncertainty (CPU), geopolitical risk (GPR), global economic policy uncertainty (EPU), US personal consumption expenditures inflation index (PCE), financial

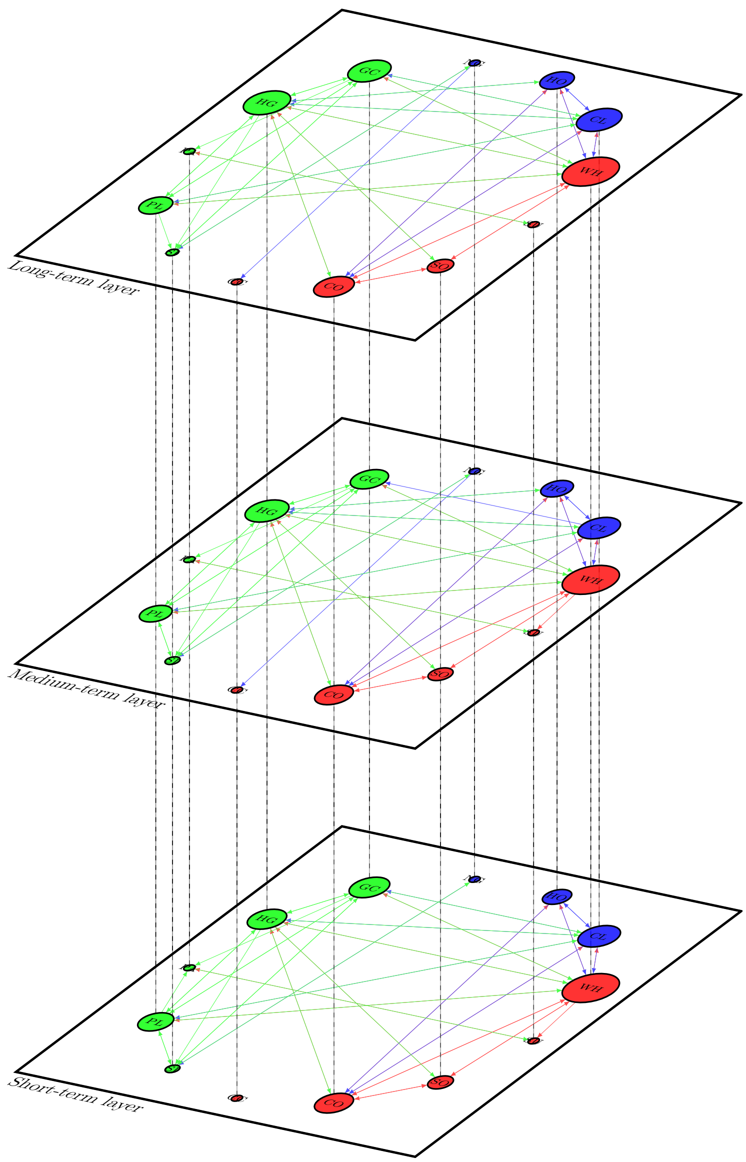


Figure 13: Multilayer frequency networks before the Russia-Ukraine war. Notes: The red nodes denote the agriculture sector, blue nodes denote the energy sector, green nodes denote the metals sector, and arrows indicate the direction of risk transmission. In addition, node size depends on the out-strength, i.e., the volatility risk emitted by that node, with interlayer edges connecting the same node in each layer.

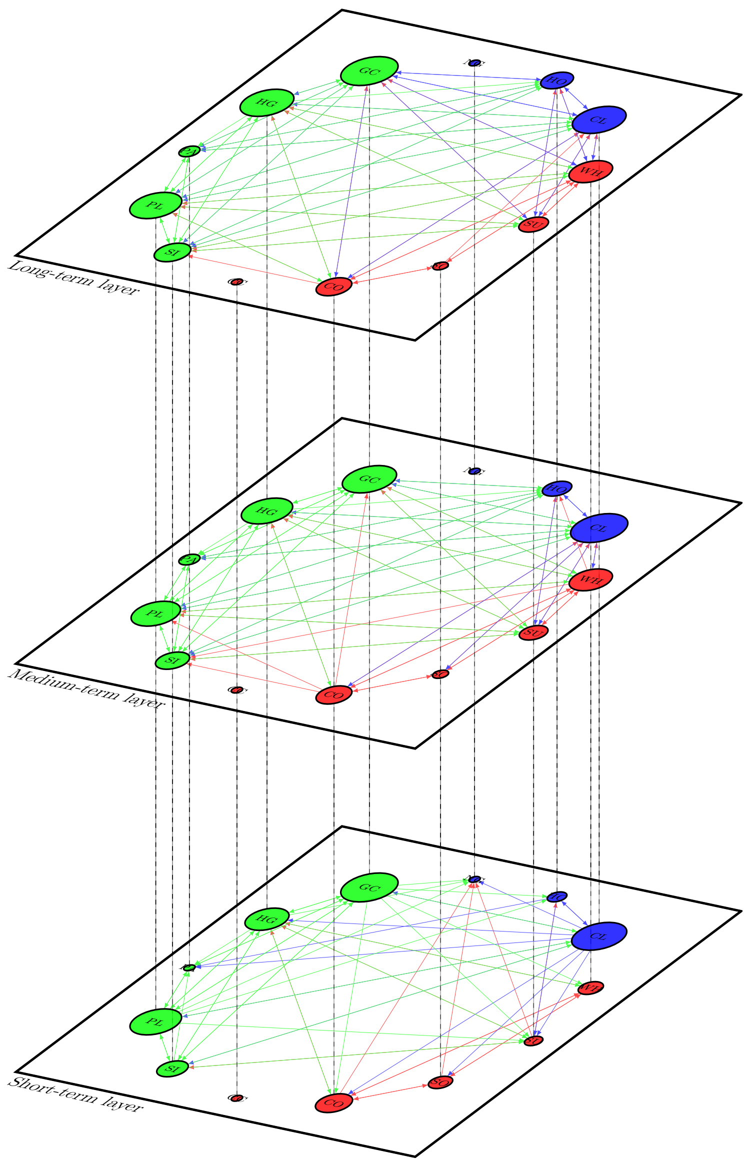


Figure 14: Multilayer frequency networks after the Russia-Ukraine war. Notes: The red nodes denote the agriculture sector, blue nodes denote the energy sector, green nodes denote the metals sector, and arrows indicate the direction of risk transmission. In addition, node size depends on the out-strength, i.e., the volatility risk emitted by that node, with interlayer edges connecting the same node in each layer.

Table 7. Data descriptive statistics of determinants.

	Min	Mean	Max	Std. Dev	Skewness	Kurtosis
CPU	38.0921	141.8146	411.2888	68.3154	1.0936	3.9871
GPR	58.4208	95.6954	318.9549	28.2597	3.6451	25.5579
EPU	86.3516	180.5720	431.5649	72.7231	0.8898	3.0660
PCE	-1.4660	1.9903	7.1169	1.7410	1.2515	4.4227
FSI	-0.8510	0.0774	8.2710	1.2342	3.8837	20.7538
TS	-1.6135	1.6880	3.6845	1.0859	-0.4031	2.9742
MPU	18.6833	87.1034	304.2905	54.8863	1.3707	5.2053
SEN	-0.6354	-0.0558	0.3124	0.1785	-0.6178	3.4933

stress index (FSI), US treasury spread (10-Year Treasury Minus 3-Month Treasury, TS), US monetary policy uncertainty (MPU), and news sentiment index (SEN). In particular, the CPU, GPR, EPU, and MPU are obtained from https://www.policyuncertainty.com, the PCE and SEN are obtained from the Federal Reserve Bank of San Francisco database, and the FSI and TS are obtained from the Federal Reserve Bank of St. Louis database. The data span is from September 2008 to May 2023. Besides, the data on macro variables are mainly monthly data, and the frequency connectedness among commodity futures markets is daily data. To address the data frequency issue, we refer to the work of Baruník et al. (2024) and average the frequency connectedness indices (including short-, medium-, and long-term connectedness) at the monthly level. Table 7 shows the descriptive statistics of macro variables, including minimum, mean, maximum, standard deviation, skewness, and kurtosis.

Figure 15 shows the contribution of the determinants, with red representing short-term connectedness, green representing medium-term connectedness, and blue representing long-term connectedness. First, we notice that PCE has the strongest explanatory power for the frequency connectedness between commodity futures, which are 25.81%, 35.15%, and 26.31% in the short-, medium-, and long-term, respectively. This means that more than a quarter of the frequency connectedness between commodity futures is driven by the PCE. Our conclusions differ from those of Bouri et al. (2021b), who argue that inflation risk has a negative impact on commodity connectedness. One possible explanation is that Bouri et al. (2021b) examined the mechanism of macro variables on commodity correlation based on the time domain framework, ignoring the frequency heterogeneity of commodity connectedness.

Second, we find that the CPU, GPR, and FSI contribute more than 15% to the short-term connectedness between commodity futures markets. In recent years, extreme weather outbreaks have severely shocked the extraction and cultivation of commodities, leading to increased turmoil in commodity markets (Rao et al., 2023; Jia et al., 2023; Guo et al., 2023; Hoque et al., 2023). Moreover, geopolitical risks and global financial stress have always been regarded as important factors affecting oil price fluctuations and will also accelerate risk contagion among commodities (Hu et al., 2020; Saadaoui et al., 2022; Mensi et al., 2024c). The TS, MPU, and SEN mainly drive medium- and long-term risk spillovers among commodity futures markets. Among them, the long-term contribution of the MPU reaches a maximum of 25.40%. On the one hand, these findings complement the research on news sentiment and commodity risk contagion (Agyei et al., 2023; Naeem et al., 2023), emphasizing the long-term impact of news sentiment on commodity markets. On the other hand, our results also provide additional explanations for the transmission mechanism research of monetary policy uncertainty to commodity connectedness (Cao et al., 2023). Finally, compared with other determinants, the EPU contributes less to frequency connectedness among commodity futures markets. This is in line with Hu et al. (2020). The possible reason is that economic policy mainly focuses on macroeconomic conditions, such as GDP growth, employment rate, and household consumption expenditure, making its impact on the commodity futures market less obvious (Bouri et al., 2021b; Wu et al., 2023a).

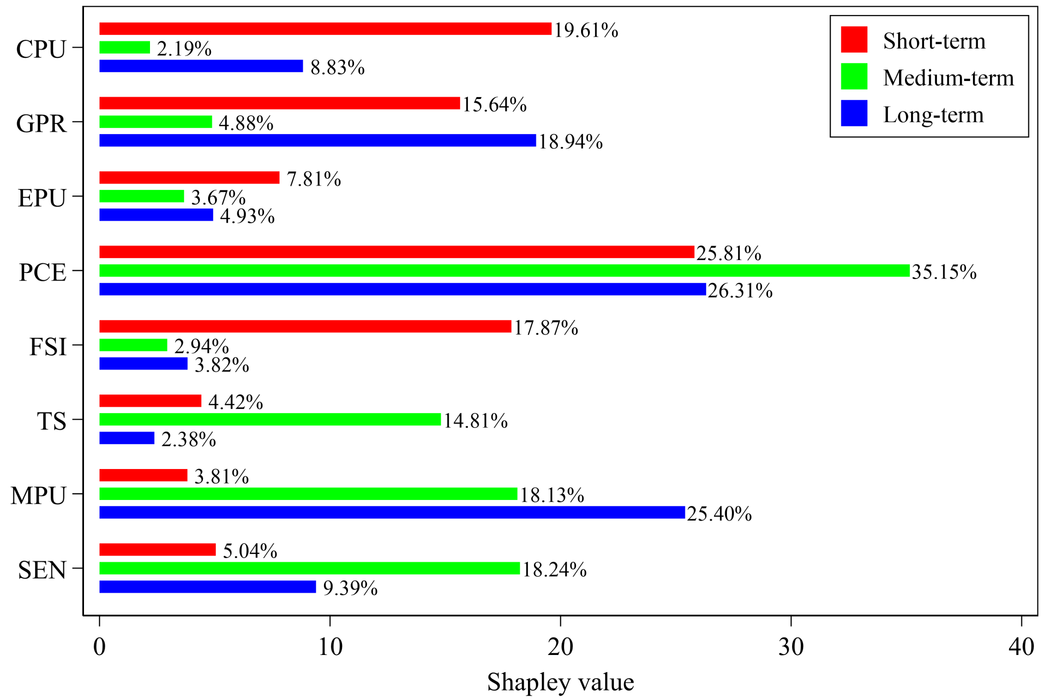


Figure 15: Contribution of determinants

4.4.2. Robustness test

To ensure that the conclusions are robust, we perform three robustness tests: (1) We replace the dependent variable (frequency connectedness) with the last day of each month instead of the monthly average. (2) We replace the dependent variable with the estimated result of the forecast horizon h equals to 50. (3) We replace the dependent variable with the estimation result of the forecast horizon h equals to 200. Figures 16-18 show the robustness results and we find they have the same pattern as Figure 15. This implies that our results are reliable.

5. Conclusions

In recent years, rising global financial stress has triggered turbulence in commodity markets. In particular, the COVID-19 pandemic and the outbreak of the Russian-Ukrainian conflict have led to a significant increase in systemic linkages in global energy markets. This paper examines the frequency connectedness among 13 commodity futures markets by constructing multilayer

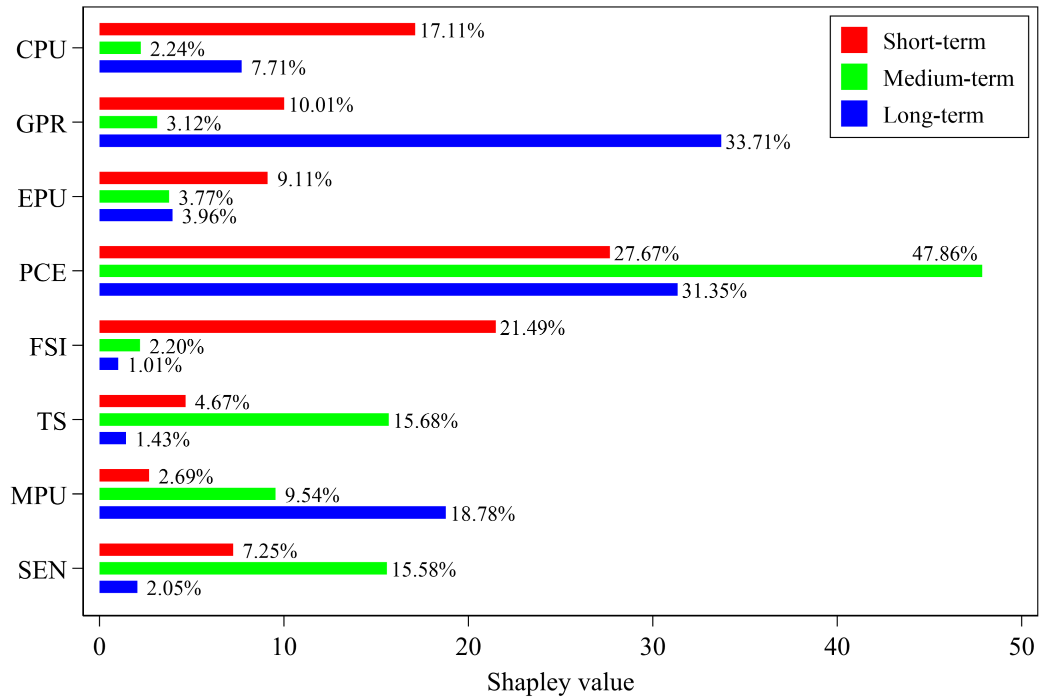


Figure 16: Contribution of determinants with the dependent variable is equal to the last day of each month

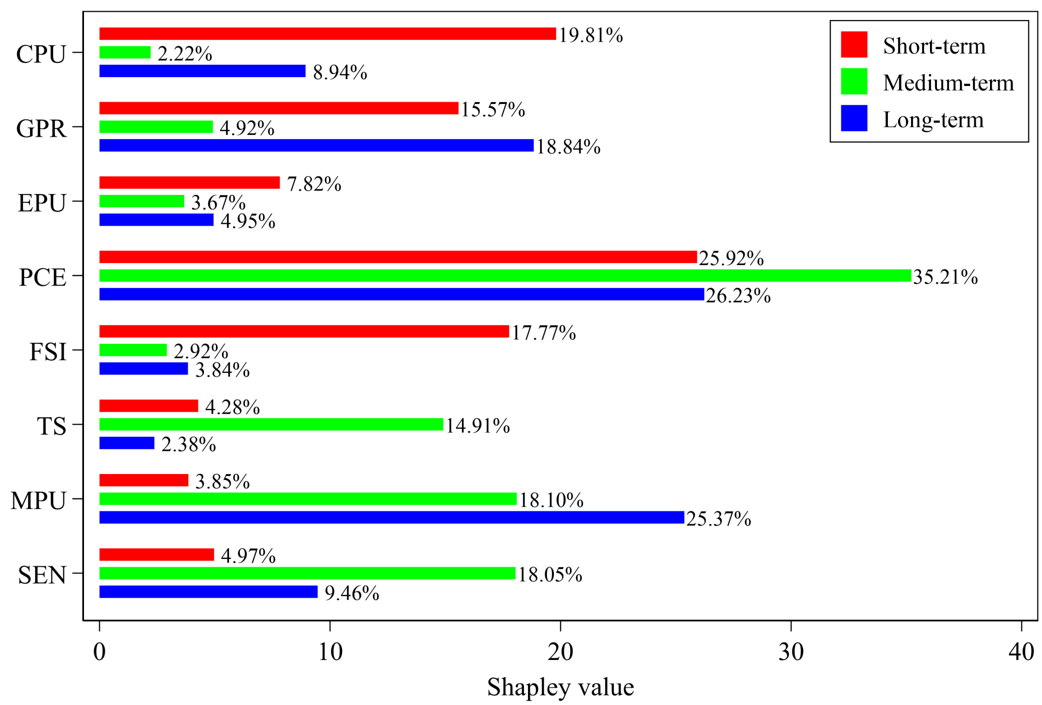


Figure 17: Contribution of determinants with the forecast horizon h is set to 50

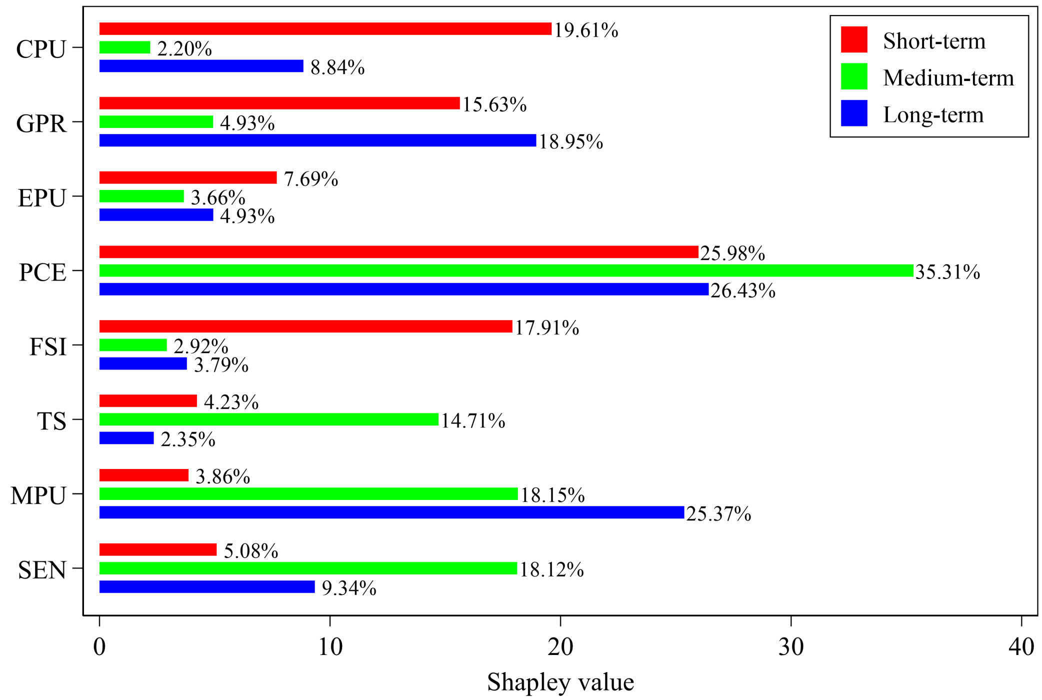


Figure 18: Contribution of determinants with the forecast horizon h is set to 200

networks, including short-, medium-, and long-term layers. Specifically, we explore the frequency connectedness among commodity futures markets at the average and dynamic levels. To investigate the impact of global crisis events on commodity futures connectedness networks, we visualize multilayer frequency networks during the COVID-19 pandemic and the Russian-Ukrainian conflict. In addition, we apply the Shapley decomposition approach to identify the key determinants that drive the frequency connectedness between commodity futures. Of course, to ensure the robustness of our findings, we also execute a robustness test. Overall, our findings are summarized as follows:

Our results indicate frequency heterogeneity in connectedness among commodity futures markets. First, during calm periods, we observe that connectedness among commodity futures markets is dominated by short-term factors. In contrast, in times of crisis, we find that long-term connectedness among commodity futures markets rises rapidly. This means that systemic crises strengthen persistent linkages between commodity markets. Also, during the COVID-19 pandemic and the Russia-Ukraine conflict, we observed a significant rise in uniqueness edge ratio for short- and long-term networks. This shows that the edge structure of short- and long-term networks are heterogeneous, i.e., short- and long-term networks contain more unique risk information. The market level analysis shows that gold, silver, and platinum are the main risk emitters in the commodity futures market. At the same time, we note that gold, copper, platinum, silver, and oil are systemically important, implying that they are the main drivers of interconnectedness among commodity futures markets.

Crisis event analysis shows that after the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict, cross-sector risk spillovers between commodity futures markets increased sharply. In detail, we find that risk emitters among commodity futures markets have changed during the COVID-19 pandemic, with gold, copper, and oil releasing significant amounts of risk after the crisis. Moreover, we note that sugar and cocoa received risk shocks primarily in the short term during the COVID-19 pandemic. During the Russia-Ukraine conflict, we observed a clear increase in volatility spillovers of the metals and energy sectors. Meanwhile, wheat futures are more active in the medium- and long-term networks. Also, we find that increasing the investment weight in cocoa futures helps to hedge against frequency-linkage risk in commodity markets. Finally, determinant analysis shows that inflation risk is the dominant player in promoting frequency connectedness among commodity futures markets, contributing more than 25%. Furthermore, we find that climate policy uncertainty, geopolitical risk, and global financial stress mainly promote short-term connectedness among commodity futures markets, while term spread, monetary policy uncertainty, and news sentiment play a role in the long-term.

Our findings provide valuable insights for policymakers and investors. For example, for policymakers, they can design different strategies to deal with frequency connectedness among commodity futures markets. Specifically, policy designers should focus on short-term connectedness in normal times and long-term connectedness in times of crisis. In addition, our results suggest that cocoa futures have lower exposure during crises, so we recommend that investors increase their investment weight in cocoa futures during times of financial stress. Of course, our work can be extended further. In future work, we can explore the frequency spillovers between commodity, stock, and foreign exchange markets. In addition, we can investigate hedging strategies for commodity futures at different frequencies.

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