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# Realized higher-order moments spillovers between commodity and stock markets: Evidence from China

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ABSTRACT

We construct daily realized volatility, skewness, and kurtosis using 5-min data of eight Chinese commodity futures and the Chinese stock market index from March 26, 2018 to October 22, 2020, then analyse the dynamic spillovers of realized moments among these markets. The results show that the spillover effects between commodity and stock markets intensify during shock periods such as 'trade disputes between China and the United States' and 'COVID-19'. Volatility spillovers are relatively stronger than spillovers in skewness or spillovers in kurtosis; however, spillovers in higher-order moments seem to contain additional information. Shocks from the silver market influence realized moments of other markets. Soybean, corn, aluminium, and oil markets are affected by other markets. The contribution of wheat as a net transmitter to the system of spillovers between stock and commodity markets is only observed at higher-order realized moments. The results from OLS and quantile regressions show that the total spillovers are generally affected by the US stock market, economic uncertainties, and the COVID-19 outbreak.

## 1. Introduction

Spillovers across financial markets are a significant part of international financial research. They matter to many economic and market agents who are keen to understand market integration and systemic risk propagation for the sake of financial stability. They also have implications for asset pricing, portfolio allocation, and risk management. Spillovers of returns and volatility across financial markets have been extensively studied in the empirical financial literature (Awartani and Maghyereh, 2013; Chang et al., 2019; Kocaarslan et al., 2017; Saeed et al., 2021; Song et al., 2021). Most of the related research is based on the restrictive and unrealistic assumption that the conditional distribution of asset returns is normal, and therefore spillovers in higher-order moments such as skewness and kurtosis are little addressed in the academic literature. However, the distribution of asset returns is generally non-normal, skewed, and fat-tailed, indicating that studying conditional higher moments would be very informative and help market participants to infer asymmetric or fat tail risk related to extreme or downside (upside) risks under adverse and bright markets conditions (e.g., Finta and Aboura, 2020; He and Hamori, 2021; Zhang et al., 2022). In fact, information transmission through the

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asymmetry of return distributions (skewness) and fat tail (kurtosis) matters to portfolio strategies (Boudt et al., 2020), option-valuation, value-at-risk, and derivative pricing (He and Hamori, 2021). Surprisingly, their application is so far limited to stock markets where the transmission of downside (upside) risk is found to be different from the transmission of volatility risk (He and Hamori, 2021). Therefore, in this study, we examine the time-varying spillover effects of realized moments between the stock and commodity markets in China, the largest emerging economy.

Our current study makes significant contributions by extending the related literature on spillovers between commodity and stock markets in several dimensions. Firstly, recent literature mainly discusses returns and volatility spillovers which correspond to first and second moments (e.g., Ahmed and Huo, 2021; Bouri et al., 2021a,b; Song et al., 2021), even though higher-order moments are important to characterize the whole return distribution that departs from normality. In fact, higher-order moments allow for measuring various risks related to markets, such as downside risk and tail risk (He and Hamori, 2021).[1] We therefore extend these studies by focusing on spillovers of realized high-order moment risk estimators (i.e., realized skewness and kurtosis) constructed from high-frequency (5-min) data to provide more useful and refined information on market spillovers.[2]

Secondly, we investigate the dynamic spillover connectedness between Chinese stock and commodity markets relying on the time-varying parameter vector autoregressive (TVP-VAR) methodology, which avoids missing samples due to rolling window analysis and the arbitrary choice of window size. Importantly, this allows us to examine the dynamics of the spillover index over time covering the two recent crises, 'trade disputes between China and the United States' and 'COVID-19', which may directly affect the information spillover structure of the Chinese stock and commodity markets (Shen et al., 2021; Zhu et al., 2021). The dynamics of the spillover index enable us to distinguish the spillover effects of the stable versus volatile periods. Moreover, we study the net directional spillovers to distinguish the net contributors and net recipients in these markets.

Thirdly, we uncover the drivers of higher-order moment spillovers, which matters to participants in the derivative markets and those who seek to optimize their equity-commodity portfolios beyond the first and second moments of return distribution. This adds to previous studies that consider the drivers of return spillovers across energy and non-energy commodities (Saeed et al., 2021b) or volatility spillovers across commodities (Bouri et al., 2021a,b).

The rest of the paper proceeds as follows. In section 2, we review the related studies. In section 3, we describe our methodological approaches, explain how to construct the three realized estimators, and present a preliminary analysis of the dataset. In section 4, we report and discuss our main results on higher-order moments spillover between stock and commodity markets and analyse the determinants of the total spillover connectedness. In section 5, we conclude the paper.

## 2. Related studies

Most of the existing literature on the information spillover across financial markets considers returns and volatility spillovers (Johansson and Ljungwall, 2009; Kim, 2009; Liow, 2015; Mukherjee and Mishra, 2010; Theodossiou and Lee, 1993; Tsai, 2015), where the spillover of returns reflects the linkage of prices between different markets, whereas the spillover of volatility reflects risk contagion (Wang and Wang, 2019; Zhang et al., 2020). For example, the cointegration between commodities and stock indices due to their irreplaceable role in the economy is examined (Awartani and Maghyereh, 2013; Cong et al., 2008; Filis et al., 2011; Jain and Biswal, 2016; Kocaarslan et al., 2017; Mensi et al., 2013; Sun et al., 2020), and the prices of commodities and their related estimators seem to have impacts on stock prices (Bouri et al., 2017; Gokmenoglu and Fazlollahi, 2015; Jain and Biswal, 2016; Lin et al., 2019; Mensi et al., 2013; Raza et al., 2016; Tursoy and Faisal, 2018). In general, significant information transmission is witnessed among commodity and stock markets in terms of returns and realized volatility.[3]

However, more spillover information can be uncovered by studying spillovers in higher-order moments such as skewness that measures asymmetric risk, and kurtosis that measures fat tail risk (Bonato et al., 2020; Del Brio et al., 2017; Gkillas et al., 2020; Li and Giles, 2015), and this field of research remains understudied. This issue can be relevant to the relationship between commodity and stock markets, which has intensified in light of several factors such as the financialization phenomenon in the commodity markets and their detachment from simple supply-demand dynamics, the reallocation of a portion of investment position into commodity markets and use of commodities as a hedging tool against stock market risk, the trade disputes between China and the United States, and the emergence of crisis periods such as the 2008 global financial crisis and unprecedented COVID-19 outbreak. Furthermore, the dynamics of commodity and stock prices might respond to common macroeconomic shocks involving interest rates, inflation rates, and economic activities. The most related studies on measuring spillovers by higher-order moments are Bonato et al. (2020), Gkillas et al. (2020) and Bouri et al. (2021a,b). Bonato et al. (2020) use estimators of higher-order moments to detect the spillover connectedness between gold and oil markets by conducting linear, nonparametric and time-varying test of causality approaches. Gkillas et al. (2020) analyse spillovers in jumps and realized second, third, and fourth moments among crude oil, gold, and Bitcoin markets via Granger causality and generalized impulse response analyses. Bouri et al. (2021a,b) examine the dynamics of spillover effects on realized estimators of return distributions across US stock, crude oil and gold markets.

Our current paper is different, given that it uncovers the realized higher moments spillovers between the Chinese commodity and

[1] Barbaglia et al. (2020) study the volatility spillovers in commodity markets using a t-Lasso method to estimate a high-dimensional VAR, and, notably, point to the importance of accounting for fat tails.

[2] As argued by Yang et al. (2012), Cao et al. (2014) and Luo and Ji (2018), 5-min high-frequency data are widely used in research of the Chinese markets, for reaching the balance between white noise and computation accuracy.

[3] Bahel et al. (2013) consider the economics of crude oil, biofuel and food commodities.

Chinese stock markets. There are various reasons for our choice to consider China. Firstly, the Chinese stock market is the second largest, after the US, and its market participants have gained importance in terms of investment choices and affecting the global trading. It is now open to foreign investors, and attracts foreign capital due to its high economic growth and contribution to global economic growth. Secondly, China is a leading consumer of crude oil, gold and copper, and at the same time the second largest producer of copper. Furthermore, it is the world's largest importer of soybeans and other crops. However, there are significant structural and institutional differences between Chinese commodity markets and other developed commodity markets. Thus, Chinese commodity markets may exhibit unique characteristics from an empirical perspective, which are interesting cases for research, and of great research value. It is well known that the characters of the agricultural markets, metal commodities, energy markets and stock markets are periodic sharp fluctuations and noisy signals. Given these volatile dynamic properties, it is crucial to understand the dynamic connectedness among widely traded commodities and the stock markets. Therefore, it is necessary to carry out a deeper analysis of the spillover effects among these markets from the perspective of China. This adds to existing studies such as Ahmed and Huo (2021) who limit their spillover analysis of Chinese stock and commodities to return and spillovers and Mensi et al. (2021) who examine asymmetric connectedness between crude oil, gold, and Chinese sector stock markets.

Methodologically, the existing literature generally examines the relationship among commodity and stock markets using common economic methodologies, such as the traditional vector autoregressive model (VAR), vector error correction model (VECM), autoregressive distributed lag model (ARDL), or multivariate GARCH models (Ahmed and Huo, 2021; Barbaglia et al., 2020; Cong et al., 2008; Miller and Ratti, 2009; Tursoy and Faisal, 2018). The framework proposed by Diebold and Yilmaz (2012) (hereafter, DY) is based on generalized forecast error variance decompositions (GFEVD) from VAR models. It provides quantitative measures of the magnitude and direction of spillovers across markets in returns or volatilities, which not only quantify the total spillovers, net directional spillover, and net pairwise spillovers across markets, but also describe the risk spillover effects from a dynamic (time--varying) perspective through a rolling window approach. A fairly sizable number of studies use the DY approach to investigate dynamic spillovers across markets (Abosedra et al., 2020; Chang et al., 2019; Cong et al., 2008; Guesmi and Fattoum, 2014). However, the DY method uses a rolling window to calculate spillovers dynamically, which means the results are sensitive to the width of the window when a time-varying analysis is conducted, and the rolling window method can cause a loss in the size of the sample period. In addition, the current spillover index of the DY method cannot deliver the causal inference unambiguously because it is based on generalized VAR (Yang et al., 2021). The TVP-VAR model and Kalman filter estimation with forgetting factors can effectively overcome most of the above limitations (Antonakakis et al., 2020). Recent studies investigate connectedness across markets based on this combined approach (e.g. Adekoya and Oliyide, 2021; Bouri et al., 2021a,b). Therefore, our current study employs the spillover index approach with time-varying factors mentioned above to examine the spillover connectedness influenced by various periods of shocks such as the 'trade disputes between China and the United States' and 'COVID-19', between Chinese stock and commodity markets in the time domain, dynamically. It also examines the drivers of spillover effects using standard ordinary least squares (OLS) and quantile regressions.

## 3. Data and methodology

### 3.1. Data and realized estimators

To study the spillover effects of returns and realized estimators (volatility, skewness, and kurtosis) across Chinese stock and commodity markets, we first construct the daily estimators using intraday data at 5-min frequency following the model-free methodology used by Barndorff-Nielsen et al. (2008).

We focus on commodities that are not only widely traded in the Chinese futures markets, but also those most affected by US-China trade disputes and COVID-19 outbreak. These commodities play important roles in China's commodity markets. China relies heavily on imports of grain, energy, and minerals, so the supply and price of such commodities has a noteworthy impact on the background to trade disputes and COVID-19. Referring to previous related literature (Adekoya and Oliyide, 2021; Kang et al., 2017; Kang and Yoon, 2019), we choose three grain commodities (soybean, wheat, and corn), four metals (gold, silver, copper, and aluminium), and crude oil as representatives of the commodity markets, which are traded on the Dalian Commodity Exchange (DCE), Zhengzhou Commodity Exchange (CZCE) and Shanghai Futures Exchange (SHFE). All commodity data are actually commodity futures indices, which are based on all futures contracts and the weight of each contract considered is based on open interest. The Chinese stock market is represented by a capitalization-weighted index, the CSI300 index (Ahmed and Huo, 2021).[4]

Considering that China's crude oil future (SC) was first listed on March 26, 2018, we generate daily data based on high-frequency (5-min interval[5]) returns over the period March 26, 2018 to October 22, 2020, which covers major global events (trade disputes between China and the United States and the COVID-19 outbreak). The sample consists of 608 daily realized estimators over the period.

For each time series of prices under consideration, we construct intraday returns on day $t$ for the $i$th intraday observation (i.e., $r_{t,i}$) as the log difference between consecutive 5-min prices:

[4] The CSI300 index covers the 300 largest and most liquid stocks traded on the Shanghai Stock Exchange and Shenzhen Stock Exchange, representing around 60% of the total market capitalization.

[5] Most studies use 5-min high-frequency data to estimate intraday realized volatility, realized skewness and realized kurtosis to eliminate the trade-off between accuracy and market microstructure noise (Bonato et al., 2020; Gkillas et al., 2020).

$$r_{t,i} = log(p_{t,i}) - log(p_{t,i-1}), \tag{1}$$

where $p_{t,i}$ denotes the corresponding intraday price on day $t$ for the $i$th intraday observation and $r_{t,i}$ represents the corresponding intraday returns, with $i = 1, \cdots T$.

For each day $t$, we construct $RV_t$ as:

$$RV_t = \sum_{i=1}^{T} r_{t,i}^2, \tag{2}$$

where $RV_t$ is referred to as the realized estimator of the second moment and measures the dispersion risk of a univariate price process.

The realized skewness on day $t$ is constructed as:

$$RS_t = \frac{\sqrt{T}\sum_{i=1}^{T} r_{t,i}^3}{RV_t^{3/2}}, \tag{3}$$

where $RS_t$ denotes the realized skewness, that is, the third moment, which measures the asymmetry of the conditional asset return distribution (Barndorff-Nielsen et al., 2008). The realized skewness (positive or negative) estimates the conditional skewness of a univariate price process, which measures the asymmetry of the daily return distribution.

The daily realized kurtosis is constructed as:

$$RK_t = \frac{T\sum_{i=1}^{T} r_{t,i}^4}{RV_t^2}, \tag{4}$$

where $RK_t$ denotes the realized kurtosis, that is, the fourth moment, which is related to the 'fatness' of the tails of the return distribution (Barndorff-Nielsen et al., 2008).

Table 1 presents the descriptive statistics for the returns and realized estimators including realized volatility, skewness, and kurtosis. We find that the realized volatility and skewness are both right skewed compared to the normal distribution, and most of the returns and realized skewness are left skewed. We find that there is positive excess kurtosis, which suggests the presence of high peaks. In summary, we can infer that the distribution pattern of all the time series under study are very different from the normal distribution. The Jarque-Bera statistics indicate that all estimators are not normally distributed. The Phillips-Perron (PP) tests support the conclusion that all series are stationary at the 1% significance level. Therefore, these series can be used in the VAR-based analysis of spillovers.

### 3.2. Methodology

To explore the spillover connectedness from a time-varying perspective, we use the time-varying parameter vector autoregression (TVP-VAR) spillover framework of Antonakakis et al. (2020) which extends the original spillover approach proposed by Diebold and Yilmaz (2012). Specifically, the TVP-VAR method uses a stochastic volatility Kalman filter estimation with forgetting factors to deal with the variance-covariance in a time-varying setting.

The TVP-VAR(p) model is given as:

$$X_t = \sum_{i=1}^{p} \alpha_i x_{t-1} + \varphi w_t + \mu_t \mu_t \Big| \Omega_{t-1} \% N(0, S_t), \tag{5}$$

where $X_t$ is an $N \times 1$ vector of conditional volatilities, $w_t$ represents an $N_p \times 1$ conditional vector, $\alpha_t$ denotes an $N\times$ $N_p$ dimensional time-varying coefficient matrix, and $\mu_t$ is an $N \times 1$ vector of dimensional error distribution with an $N \times N$ time-varying variance-covariance matrix denoted by $S_t$.

After Koop et al. (1996) and Pesaran and Shin (1998) who propose the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD), respectively, Diebold and Yılmaz (2014) suggest a VAR-based connectedness approach and compute various spillover indices. The approach transforms the VAR model into a vector of moving average (VMA) to estimate the GIFR and GFEVD. The Wold representation theorem is presented as:

$$X_t = \alpha_t Y_{t-1} + \beta_t, \tag{6}$$

$$X_t = A_t \mu_t, \tag{7}$$

$$A_{0,t} = I, \tag{8}$$

$$A_{i,t} = \tau_{1,t} A_{i-1,t} + \cdots + \alpha_{p,t} A_{i-p,t}, \tag{9}$$

where $\alpha_{i,t}$ and $A_{i,t}$ represent an $N \times N$ dimensional matrix and $\alpha_t = [\alpha_{1,t}, \cdots \alpha_{p,t}]'$ and $A_t = [A_{1,t}, \cdots, A_{p,t}]'$.

Thus, all variables follow a shock in variable $i$ from the GIRF model. If the model is not structural, the responses of a $j$-step-ahead

**Table 1**
Descriptive statistics.

| | Mean | Variance | Skewness | Kurtosis | J-B stat | PP |
|---|---|---|---|---|---|---|
| ***Returns*** | | | | | | |
| Soybean | 0.006 | 0.541 | 0.768 | 4.138 | 493.447*** | −25.095*** |
| Wheat | 0.008 | 0.191 | −0.091 | 2.190 | 122.290*** | −25.241*** |
| Corn | −0.046 | 0.391 | −1.078 | 14.654 | 5557.674*** | −24.205*** |
| Gold | 0.001 | 0.127 | −0.669 | 5.893 | 925.065*** | −26.948*** |
| Silver | −0.022 | 0.666 | −0.413 | 10.102 | 2602.771*** | −27.574*** |
| Copper | 0.006 | 0.286 | −0.320 | 9.246 | 2176.156*** | −28.327*** |
| Aluminium | 0.001 | 0.249 | −0.280 | 4.127 | 439.361*** | −23.672*** |
| Oil | −0.017 | 1.103 | 1.086 | 14.798 | 5667.205*** | −24.482*** |
| CSI300 | 0.060 | 1.168 | 0.106 | 1.523 | 59.895*** | −26.033*** |
| ***Realized volatility*** | | | | | | |
| Soybean | 0.562 | 0.390 | 3.514 | 17.375 | 8899.712*** | −17.681*** |
| Wheat | 0.215 | 0.034 | 3.289 | 15.592 | 7254.925*** | −15.979*** |
| Corn | 0.664 | 3.240 | 11.895 | 179.409 | 829759.725*** | −16.163*** |
| Gold | 0.129 | 0.069 | 6.438 | 55.781 | 83024.190*** | −16.755*** |
| Silver | 0.561 | 1.474 | 5.073 | 32.201 | 28876.032*** | −27.574*** |
| Copper | 0.245 | 0.213 | 8.061 | 89.255 | 208399.321*** | −12.660*** |
| Aluminium | 0.229 | 0.079 | 4.382 | 26.338 | 19519.991*** | −16.094*** |
| Oil | 0.972 | 5.216 | 7.757 | 78.721 | 163087.350*** | −17.100*** |
| CSI300 | 0.929 | 0.873 | 3.866 | 21.922 | 13689.523*** | −15.529*** |
| ***Realized skewness*** | | | | | | |
| Soybean | −0.041 | 1.147 | −0.100 | 0.726 | 14.371*** | −25.419*** |
| Wheat | −0.031 | 1.063 | −0.157 | 1.236 | 41.168*** | −24.181*** |
| Corn | −0.116 | 5.112 | −0.007 | 1.268 | 40.735*** | −24.852*** |
| Gold | −0.030 | 1.383 | −0.132 | 0.645 | 12.300*** | −24.951*** |
| Silver | −0.018 | 1.479 | −0.258 | 2.414 | 154.352*** | −27.574*** |
| Copper | −0.051 | 1.399 | −0.049 | 1.534 | 59.815*** | −28.427*** |
| Aluminium | −0.020 | 1.069 | 0.049 | 1.051 | 28.203*** | −22.327*** |
| Oil | −0.038 | 1.455 | −0.246 | 1.601 | 71.094*** | −23.100*** |
| CSI300 | 0.193 | 0.617 | 0.998 | 6.901 | 1307.400*** | −26.622*** |
| ***Realized kurtosis*** | | | | | | |
| Soybean | 5.079 | 8.743 | 2.617 | 9.500 | 2980.497*** | −24.205*** |
| Wheat | 4.779 | 7.191 | 3.015 | 12.245 | 4719.349*** | −16.335*** |
| Corn | 11.911 | 85.321 | 1.742 | 2.949 | 527.882*** | −23.630*** |
| Gold | 5.178 | 9.588 | 2.599 | 8.923 | 2701.594*** | −23.984*** |
| Silver | 5.248 | 14.401 | 4.154 | 26.857 | 20021.525*** | −22.946*** |
| Copper | 5.123 | 10.858 | 3.659 | 18.322 | 9861.477*** | −22.256*** |
| Aluminium | 4.789 | 7.551 | 3.415 | 16.649 | 8204.237*** | −24.238*** |
| Oil | 5.420 | 11.849 | 3.207 | 17.410 | 8720.916*** | −21.573*** |
| CSI300 | 3.840 | 5.733 | 9.419 | 145.251 | 543473.106*** | −23.223*** |

**Note:** This table shows the summary statistics of returns, realized volatilities, realized skewness and realized kurtosis. In the table, Oil, Gold and Stock represent the oil, gold and stock markets. The Jarque-Bera test is for the null hypothesis of normality for the distribution of the series. PP is the Phillips-Perron test for stationarity.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

forecast function differ depending upon whether variable *i* is shocked or not. When there is a shock in variable *i*, the difference can be determined by:

$$GIR_t(J, \eta_{j,t}, \Lambda_{t-1}) = E(X_{t+J} | \eta_{j,t}, \Lambda_{t-1}) - E(X_{t+J} | \Lambda_{t-1}), \tag{10}$$

$$\Psi^g_{j,t}(J) = \frac{A_{J,t} S_t \mu_{j,t}}{\sqrt{S_{jj,t}}} \cdot \frac{\eta_{j,t}}{\sqrt{S_{jj,t}}},\ \eta_{j,t} = \sqrt{S_{jj,t}}, \tag{11}$$

$$\Psi^g_{j,t}(J) = S_{jj,t}^{-\frac{1}{2}} A_{J,t} S_t \mu_{j,t}, \tag{12}$$

where $J$ represents the horizon of the forecast and $\eta_{j,t}$ denotes the selection vector with a value of 1 in the $j$-th position, and 0 otherwise, which is related to the set of information available up to $t-1$ as captured by $\Lambda_{t-1}$.

Next, the GFEVD is computed and normalized, which can be interpreted as the share of variance one variable has with respect to the others. After normalizing these variance shares, each row sums up to 1. This means all variables together explain 100% of the forecast error variance of variable *i*. This step is represented as:

$$\widetilde{\sigma}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{j=1}^{J-1} \Psi^{2,g}_{ij,t}}, \tag{13}$$

where $\sum_{j=1}^{N} \widetilde{\sigma}^{N}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\sigma}^{N}_{ij,t}(J) = N$. To measure time-varying spillover connectedness, we calculate the total spillover index, total directional spillover index and net total directional connectedness.

First, we use the GFEVD to calculate the total spillover index, constructed as:

$$TSI^{g}_{t}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\sigma}^{g}_{ij,t}(J)}{\sum_{i,j=1}^{N} \widetilde{\tau}^{g}_{ij,t}(J)} \times 100. \tag{14}$$

Since $\sum_{i,j=1}^{N} \widetilde{\tau}^{g}_{ij,t}(J) = N$, we have:

$$TSI^{g}_{t}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\sigma}^{g}_{ij,t}(J)}{N} \times 100. \tag{15}$$

Next, we build the total directional spillover index which measures the degree of a shock to one variable that is transmitted to other variables. When variable *i* transmits its shock to another variable *j*, the total directional spillover index is constructed as:

$$TDSI^{g}_{i\rightarrow j,t}(J) = \frac{\sum_{i=1, i\neq j}^{N} \widetilde{\sigma}^{g}_{ij,t}(J)}{\sum_{i=1}^{N} \widetilde{\sigma}^{g}_{ij,t}(J)} \times 100. \ (TO) \tag{16}$$

We can calculate the degree of shock one variable receives from other variables. When variable *i* receives a shock from another variable *j*, the total directional spillover index can be constructed as:

$$TDSI^{g}_{j\rightarrow i,t}(J) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\sigma}^{g}_{ji,t}(J)}{\sum_{j=1}^{N} \widetilde{\sigma}^{g}_{ji,t}(J)} \times 100. \ (FROM) \tag{17}$$

Finally, we can measure the net total directional spillover index by subtracting the value of the total directional spillover index *TO* others from the value of the total directional spillover index *FROM* others. The net spillover directional spillover index shows the influence of variable *i* on others within the context of connectedness, which can be defined as:

$$NTDSI^{g}_{i,t} = TDSI^{g}_{i\rightarrow j,t}(J) - TDSI^{g}_{i\leftarrow j,t}(J). \tag{18}$$

Given the nature of the *NTDSI*, we can find the role of a given variable in terms of connectedness as either a net-contributor or net-recipient. A positive *NTDSI* indicates that the influence of variable *j* in the system is less than the influence of the system on variable *i*. Similarly, a negative *NTDSI* implies that the influence from the system on variable *j* is more significant than the influence from variable *i* in the system.

## 4. Empirical results

In this section, we firstly provide an overview of the average total connectedness of returns and realized estimators (i.e., volatility, skewness, and kurtosis) across Chinese stock and commodity markets. Secondly, we investigate the dynamic total connectedness of these estimators in order to reveal the time-varying nature of overall spillovers. Thirdly, we focus on the net total directional connectedness to reveal the dynamic spillover effects of each market based on various estimators. Fourthly, we examine the determinants of TSI using OLS and quantile regressions.

### *4.1. Average total connectedness*

Table 2 reports the average total connectedness of returns, realized volatility, realized skewness and realized kurtosis across the selected Chinese commodity markets and stock market. All results are based on VAR of order 1 and generalized variance decompositions of 10-day-ahead forecast errors. We estimate the total average spillover index across eight commodity futures markets and CSI300 and decompose the index using directional spillover transmitters (TO) and receivers (FROM) for all four estimator spillovers. The row labelled NET indicates the total sum of the net-pairwise directional spillovers expressed as either a positive value (net-contributor) or a negative value (net-recipient).

As shown in Panel A, the average total return spillover index is 25.4% and there is a bi-directional return spillover effect across the eight commodity futures and the CSI300 index. In terms of the directional spillovers transmitted TO, silver is the largest contributor (44.1%) to the other markets, followed by copper (42.8%), gold (36.1%) and CSI300 (33.5%). Regarding the directional spillover received FROM, silver is the largest receiver of return spillover from the other markets (38.2%), closely followed by copper (38.0%), and gold (37.6%). In the net term, silver is the strongest net-contributor to return spillovers, while corn is the largest net-recipient of return spillovers.

Panel B shows the spillover matrices of realized volatility across the commodity markets and the stock market index. The average total spillover index of realized volatility is 42.5%, which is significantly stronger than that of returns (25.4%) indicating that volatility contains more information on spillovers than returns. Silver is the largest net-contributor to realized volatility spillovers in the other markets (48.2%), which is significantly higher than the contribution from other markets. In net terms, Panel B identifies the CSI300

**Table 2**
Average total connectedness.

| | Soybean | Corn | Wheat | Gold | Silver | Copper | Aluminium | Oil | CSI300 | FROM |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Panel A: Returns*** | | | | | | | | | | |
| Soybean | 88.3 | 4.4 | 1.6 | 1.2 | 0.8 | 0.8 | 0.8 | 1.4 | 0.7 | 11.7 |
| Corn | 4.4 | 83.7 | 1.9 | 1.2 | 2.9 | 1.8 | 1.7 | 1.4 | 1.1 | 16.3 |
| Wheat | 1.3 | 1.6 | 90.3 | 0.6 | 0.8 | 1.1 | 0.8 | 1.5 | 2.1 | 9.7 |
| Gold | 0.9 | 0.4 | 0.5 | 62.4 | 30.2 | 1.0 | 0.5 | 1.4 | 2.6 | 37.6 |
| Silver | 0.6 | 0.5 | 0.5 | 29.1 | 61.8 | 3.2 | 1.6 | 1.2 | 1.6 | 38.2 |
| Copper | 1.3 | 1.2 | 0.7 | 0.8 | 3.2 | 62.0 | 11.3 | 5.3 | 14.1 | 38.0 |
| Aluminium | 0.9 | 1.2 | 1.0 | 0.7 | 2.3 | 13.3 | 71.9 | 1.5 | 7.3 | 28.1 |
| Oil | 0.9 | 0.7 | 1.0 | 0.7 | 1.4 | 6.8 | 1.7 | 82.8 | 4.0 | 17.2 |
| CSI300 | 0.7 | 0.7 | 0.9 | 2 | 2.5 | 14.8 | 6.3 | 3.4 | 68.8 | 31.2 |
| TO | 11.0 | 10.7 | 8.1 | 36.1 | 44.1 | 42.8 | 24.8 | 17.1 | 33.5 | 228.1 |
| NET | −0.7 | −5.6 | −1.6 | −1.5 | 5.9 | 4.8 | −3.3 | −0.1 | 2.3 | **TSI=25.4** |
| **Panel B: Realized volatility** | | | | | | | | | | |
| Soybean | 54.5 | 2.5 | 0.4 | 5.5 | 8.7 | 11.3 | 8.6 | 5.4 | 3.0 | 45.5 |
| Corn | 5.1 | 71.5 | 1.0 | 2.5 | 7.8 | 2.5 | 4.5 | 3.2 | 2.0 | 28.5 |
| Wheat | 0.8 | 0.7 | 85.4 | 3.4 | 5.8 | 0.8 | 0.7 | 2.1 | 0.4 | 14.6 |
| Gold | 3.1 | 1.1 | 0.8 | 43 | 31.8 | 6.2 | 3.2 | 8.1 | 2.7 | 57.0 |
| Silver | 4.0 | 2.6 | 0.5 | 19.8 | 49.2 | 9.6 | 6.5 | 7.0 | 0.7 | 50.8 |
| Copper | 7.8 | 1.0 | 0.5 | 7.5 | 12.2 | 47.1 | 13.1 | 5.7 | 5.1 | 52.9 |
| Aluminium | 5.9 | 2.6 | 0.8 | 5.8 | 15.7 | 14.9 | 46.5 | 4.6 | 3.1 | 53.5 |
| Oil | 5.7 | 1.0 | 0.6 | 9.6 | 12.0 | 9.7 | 6.8 | 52.5 | 2.3 | 47.5 |
| CSI300 | 2.9 | 1.9 | 1.1 | 6.3 | 5.0 | 7.2 | 3.9 | 3.7 | 68.0 | 32.0 |
| TO | 35.2 | 13.4 | 5.8 | 60.5 | 99.0 | 62.1 | 47.1 | 39.8 | 19.3 | 382.3 |
| NET | −10.3 | −15.0 | −8.8 | 3.5 | 48.2 | 9.2 | −6.4 | −7.6 | −12.8 | **TSI=42.5** |
| **Panel C: Realized skewness** | | | | | | | | | | |
| Soybean | 89.1 | 1.2 | 1.1 | 1.4 | 1.3 | 1.0 | 1.1 | 2.5 | 1.4 | 10.9 |
| Corn | 1.9 | 90.3 | 0.8 | 1.4 | 1.8 | 1.1 | 1.2 | 1.0 | 0.4 | 9.7 |
| Wheat | 1.3 | 0.9 | 91.7 | 0.5 | 0.8 | 0.8 | 0.9 | 0.8 | 2.2 | 8.3 |
| Gold | 0.8 | 0.6 | 1.0 | 70.5 | 23.2 | 0.7 | 0.8 | 1.3 | 0.9 | 29.5 |
| Silver | 0.7 | 0.8 | 2.1 | 22.8 | 68.6 | 2.2 | 0.8 | 1.1 | 0.9 | 31.4 |
| Copper | 1.8 | 2.0 | 0.8 | 0.7 | 2.6 | 76.2 | 6.3 | 2.8 | 6.9 | 23.8 |
| Aluminium | 1.0 | 1.0 | 2.2 | 0.9 | 1.0 | 6.9 | 83.7 | 1.7 | 1.6 | 16.3 |
| Oil | 2.1 | 1.0 | 3.9 | 2.0 | 1.7 | 2.8 | 1.5 | 82.9 | 2.2 | 17.1 |
| CSI300 | 1.1 | 0.5 | 1.9 | 0.8 | 1.4 | 7.3 | 1.7 | 2.2 | 83.2 | 16.8 |
| TO | 10.8 | 8.0 | 13.9 | 30.5 | 33.8 | 22.8 | 14.3 | 13.3 | 16.5 | 163.8 |
| NET | −0.1 | −1.7 | 5.6 | 0.9 | 2.3 | −1.0 | −2.0 | −3.8 | −0.4 | **TSI=18.2** |
| **Panel D: Realized kurtosis** | | | | | | | | | | |
| Soybean | 89.4 | 1.3 | 1.5 | 1.2 | 1.5 | 1.8 | 1.0 | 1.4 | 0.9 | 10.6 |
| Corn | 1.6 | 91.3 | 0.9 | 0.6 | 1.3 | 0.6 | 2.7 | 0.6 | 0.4 | 8.7 |
| Wheat | 0.7 | 0.4 | 92.6 | 1.7 | 2.3 | 0.8 | 0.5 | 0.6 | 0.4 | 7.4 |
| Gold | 1.2 | 0.4 | 2.6 | 86.2 | 5.6 | 1.1 | 0.9 | 1.0 | 0.8 | 13.8 |
| Silver | 0.4 | 0.8 | 3.0 | 5.8 | 86.1 | 1.7 | 0.8 | 0.8 | 0.6 | 13.9 |
| Copper | 1.3 | 1.0 | 3.1 | 1.2 | 2.5 | 85.1 | 3.2 | 2.0 | 0.5 | 14.9 |
| Aluminium | 0.6 | 2.8 | 1.2 | 0.7 | 0.9 | 4.6 | 87.3 | 0.9 | 1.0 | 12.7 |
| Oil | 0.5 | 0.8 | 2.7 | 1.7 | 0.9 | 1.3 | 0.7 | 90.5 | 0.8 | 9.5 |
| CSI300 | 1.3 | 0.6 | 1.4 | 0.7 | 0.5 | 1.0 | 0.9 | 0.7 | 92.9 | 7.1 |
| TO | 7.6 | 8.1 | 16.4 | 13.6 | 15.5 | 12.9 | 10.7 | 8.1 | 5.7 | 98.5 |
| NET | −3.1 | −0.7 | 9.0 | −0.2 | 1.6 | −2.0 | −2.0 | −1.4 | −1.4 | **TSI=10.9** |

**Note**: Spillovers are calculated based on the method proposed by Antonakakis et al. (2020). The index in the lower right corner of each panel is the average total connectedness index. The TO row, FROM column and NET row describe the directional spillover index. The *ji* th value reflects the share of shocks in market *i* spilled over to market *j*. The results are expressed as percentages. Under the TVP-VAR dynamic connectedness framework, we use a 10-step ahead forecast to calculate the spillover index under the TVP-VAR dynamic connectedness framework.

index is a net-recipient (−12.8%) in contrast to its status as a net-contributor (2.3%) in Panel A, and gold switches from a net-recipient (−1.5%) to a net-contributor (3.5%) in the financial markets. The main contributors in terms of net volatility spillovers are silver, gold, and copper, and the overall directional spillovers transmitted by these three metals is 70.3%, which points to the important position of the metal markets in the system of spillovers among financial markets.

Panel C shows the spillover index for Chinese commodity and stock markets based on realized skewness. The average total spillover index is 18.2%, and silver is also the largest contributor in these markets (33.8%). Regarding the directional spillover index, gold market transmits 22.8% of the spillover to the silver market and receives 23.2% spillover from the silver market, which is higher than the spillovers between any two other markets, showing that gold and silver are closely related. The main net contributors are wheat (5.6%), silver (2.3%), and gold (0.9%), which differs from the above-mentioned results shown in panels A and B.

Turning to Panel D, we observe that the average total spillover index of realized kurtosis is 10.9%, which is the lowest spillover across the four moments. Similar to the total skewness spillover, the total kurtosis spillover is also lower than the total volatility spillover generally. However, the main net contributors of the market spillover exhibit some changes. Gold changes from a net-contributor (0.9%) to a net- recipient (−0.2%), while wheat (9.0%) and silver (1.6%) remain the main net contributors to the overall market spillover. Additionally, the increasing net spillover contribution of wheat shows the significance of this major agricultural commodity in these financial markets.

The total average spillovers of returns, realized volatility, realized skewness and realized kurtosis are 25.4%, 42.5%, 18.2%, and 10.9% respectively, suggesting that the connectedness of markets is mixed across the four estimators. The total average spillover index of realized volatility is the largest, the total spillover index of the returns is slightly smaller, and the total spillover index of the higher-order moments (realized skewness and realized kurtosis) are relatively small. Compared with the extremely strong linkage of the first and second moments (returns and volatility), when a low-probability event occurs, although the linkages among financial markets still exist (the total spillover indices of realized skewness and kurtosis are larger than 10%), different financial markets may have different reactions.

Based on Table 2, the three indexes with the strongest spillover capacity are silver, copper and gold, which is basically in line with China's current economic situation. As a big manufacturing country, China's industrial product industry and raw material industry have extremely important positions as upstream industries, which may lead to the large spillovers of metal markets among Chinese stock and commodity markets.

According to Panels A–D of Table 2, there are similarities and differences in the spillover effects of different financial markets at different moments. The similarities are that the strongest contributors to spillover effects are consistently the silver, copper, and gold markets and that the agricultural product markets always display a relatively weak spillover effect. The differences lie in the following: compared with the spillover effects of the first and second moments, in the framework of high-order moment volatility spillovers, each financial market has greatly improved its spillover to itself，which means each market is mainly influenced by its internal shocks. In kurtosis-based spillover connectedness, the total spillover of the soybean market to other markets is only 7.6%, whereas the soybean market's spillover to itself is as high as 89.4%. Other markets exhibit similar characteristics. The above characteristics of high-order moment volatility spillover show that when a major shock occurs in one market, the market itself suffers the strongest impact and there is a relatively weak impact spillover to other markets.

Specifically, we observe that, no matter which indicators are used to study the spillover relationships between financial markets, the silver market is always the largest net contributor to overall market spillover, and the soybean, corn, aluminium, and oil markets are always net recipients. With respect to spillovers for higher-order moments, the spillover relationship between markets changes; for example, the wheat market gradually transforms into a net contributor, and the extent of its spillover to the market increases with the order of the moment estimation.

### 4.2. Dynamic total connectedness

Although the full-sample average total spillover results (Table 2) provide a useful summary of average behaviour, they do not reveal the changes taking place during our sample period. In this section, we present and discuss the results of dynamic spillovers between the higher-order moments of eight Chinese commodity futures and the Chinese stock market index. Our approach enables us to examine the time-varying spillovers of higher-order moments which are returns, realized volatility, realized skewness, and realized kurtosis. Fig. 1 plots the time-varying total volatility spillover index between Chinese commodity markets and the Chinese stock market. The graphical evidence illustrates that spillovers vary greatly over time and respond to crisis events.

Fig. 1(a) presents the dynamic total spillover of returns among these financial markets. We can observe that the spillover effects of returns among markets change over time, ranging from 18.1% to 36.2%. They attain their highest levels in the second and third quarters of 2018 and the first quarter of 2020, but these peaks are not very prominent compared to other periods. We consider these subperiods corresponding to the trade disputes between China and the United States and the COVID-19 pandemic. Although the changes in dynamic spillover of returns is not obvious from Fig. 1(a), the dynamic spillover of returns can reflect the market's response to external financial and political events.

Fig. 1(b) shows that the dynamic volatility spillover index fluctuates between 32.8% and 68.2%. One distinct peak can be observed during the first quarter of 2020, corresponding to the COVID-19 pandemic. The COVID-19 pandemic started in China in January 2020, and the World Health Organization (WHO) classified the outbreak as a pandemic on March 11, 2020. The spillover index for China's commodity and stock markets gradually increases before that date and then rises sharply, reaching a maximum (68.2%) on March 13, 2020. These figures indicate that these commodity and stock markets were widely affected by the global epidemic. Moreover, we find that the spillovers among these markets remain at a relatively stable level during the period of the trade disputes between China and the United States. The multiple changes in China/US tariff policies have little impact on the relationships among China's commodity futures and stock markets.

In Fig. 1(c), the skewness spillover index starts at a low value of around 11.6%, and then rises sharply until it reaches 28.5% in April 2018, which corresponds to the time of trade disputes between China and the United States. The skewness spillover index declines gradually after May 2018, reaching a stable level of approximately 17.0% by December 2018. Furthermore, during the COVID-19, the index of spillovers of realized skewness is relatively stable, which indicates that such spillovers do not describe the influence of the COVID-19 pandemic.

Fig. 1(d) shows the evolution of the time-varying kurtosis spillover index between the Chinese commodity and stock markets. The graph indicates considerable variability across the sample period, implying that the connectedness between Chinese commodity futures and stock markets responds to economic events such as the trade disputes between China and the United States and health events such as the COVID-19 outbreak. The kurtosis spillover index values range from 4.6% to 22.6% and describe the reactions of financial markets to external shocks more clearly than the skewness spillover index. Kurtosis spillover effects grow rapidly during the trade disputes between China and the United States. Considering that the US government imposed tariffs on Chinese products on March 22, 2018, these results indicate that changes in tariff policies have a substantial impact on Chinese commodity and stock markets. In early April 2018, the US government announced additional tariffs on Chinese products, and the kurtosis spillover index rises significantly. After a second round of negotiations between China and the United States in May 2018, the two countries agreed not to fight a trade war and to stop imposing tariffs on each other. As a result, the kurtosis spillover index drops significantly to a moderate level. This implies that kurtosis spillovers between the Chinese commodity futures and stock market are affected by important international events, such as changes in tariff policies.

The COVID-19 epidemic began to spread widely in China in January 2020. Correspondingly, the kurtosis spillover indices gradually increase, indicating that the epidemic had a direct impact on China's financial markets. The market spillover index rises rapidly from early March 2020, reaching its maximum value (19.2%) on March 13th, which is related to the WHO's declaration of the COVID-19

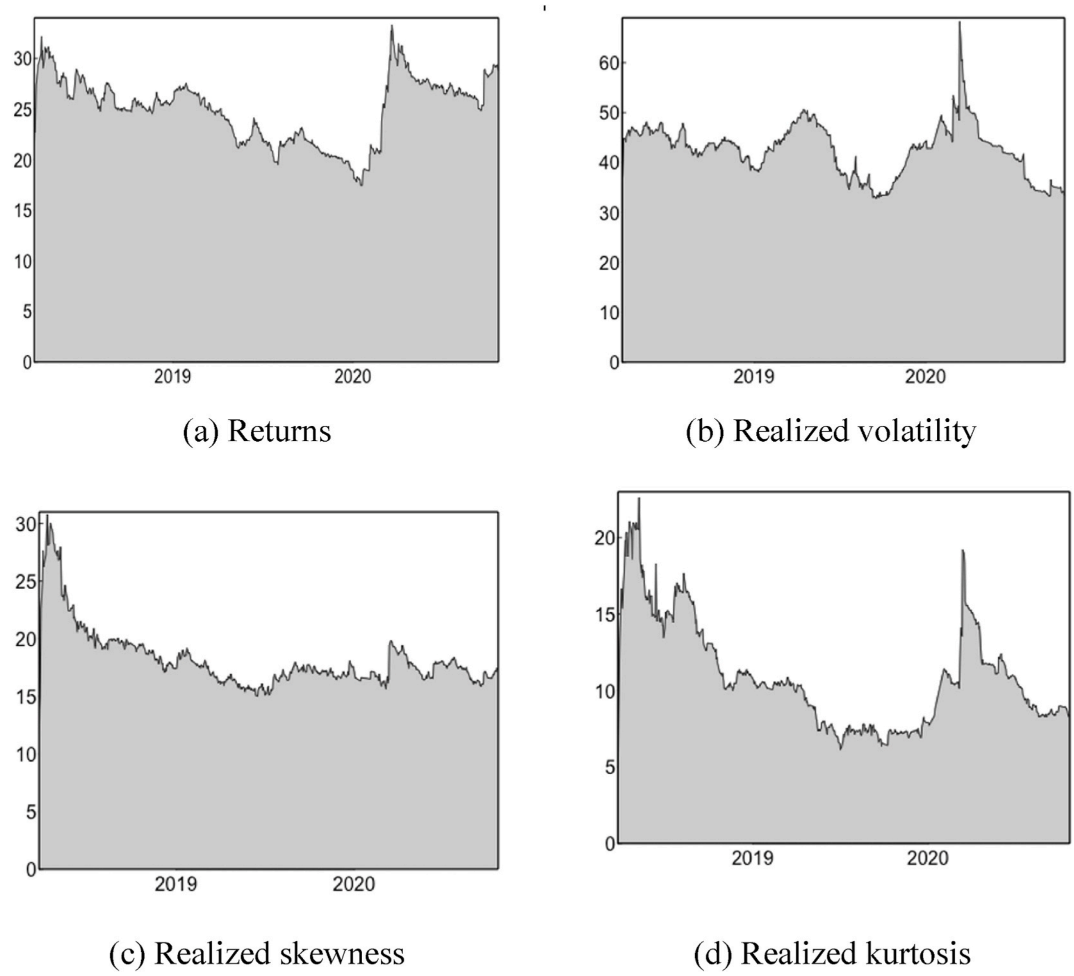
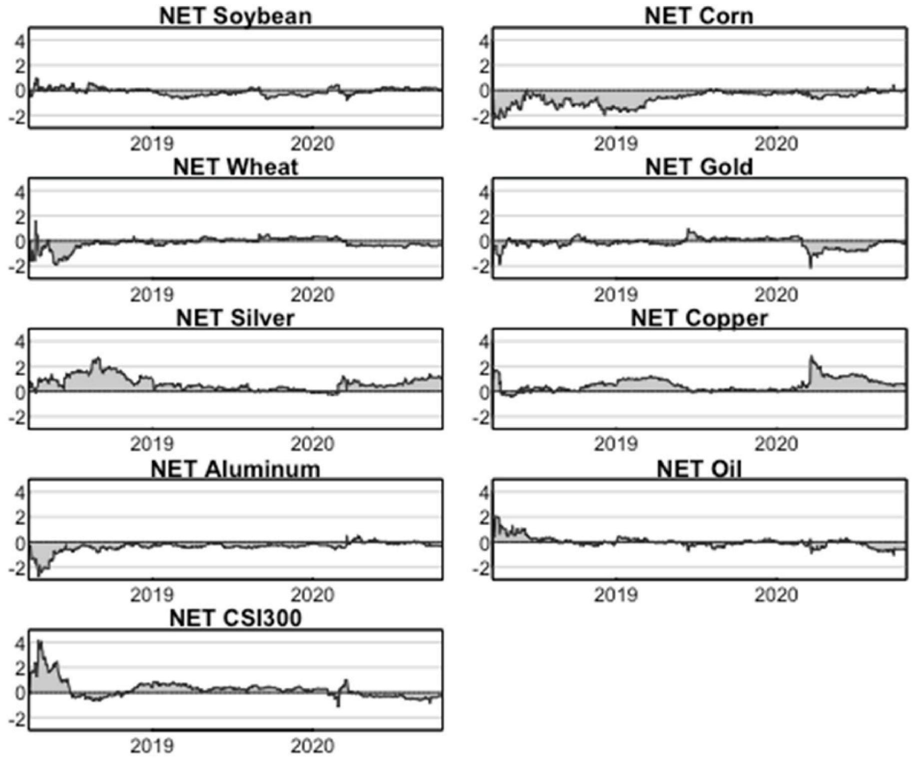
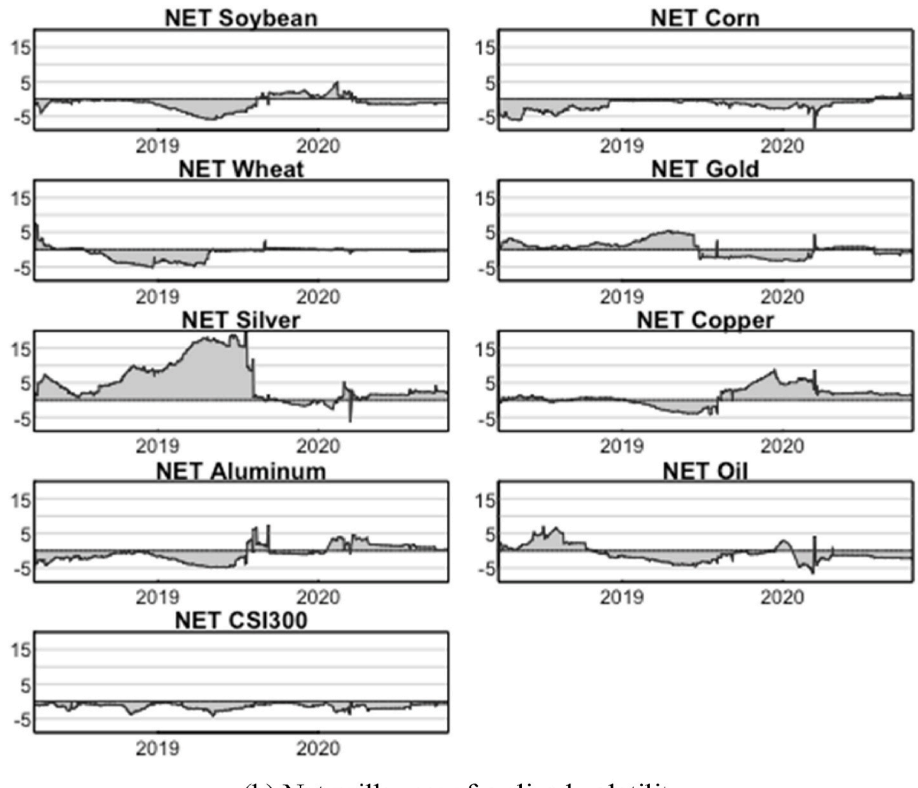



**Fig. 1.** Dynamic total connectedness. Note: These figures show the dynamic total connectedness of returns, realized volatility, realized skewness, and realized kurtosis based on the time-varying parameter vector autoregression framework.

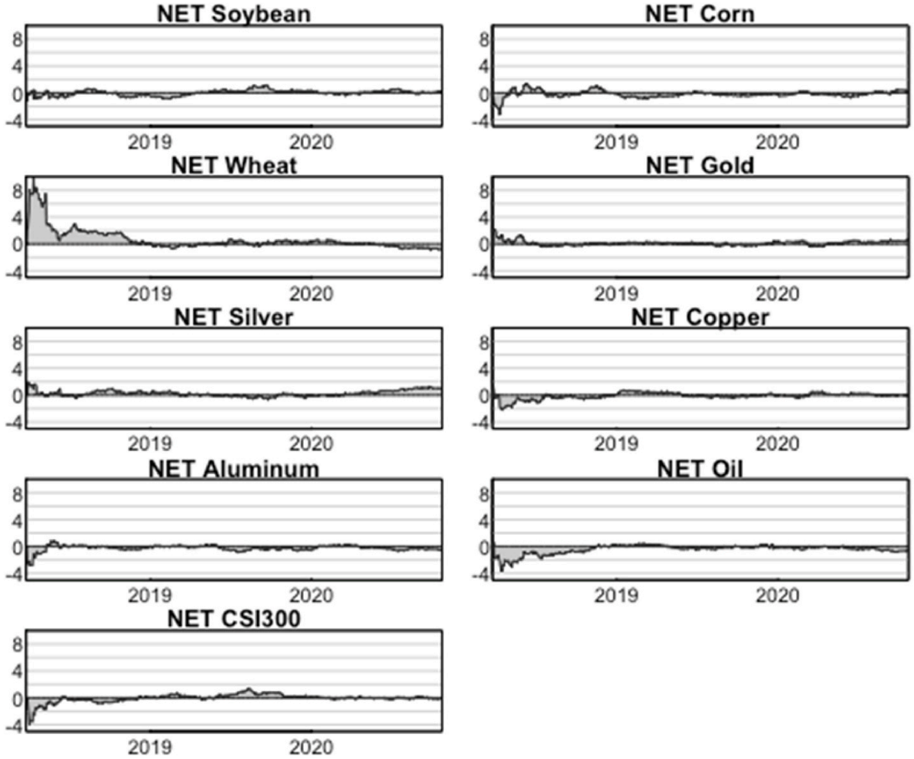



(a) Net spillovers of returns

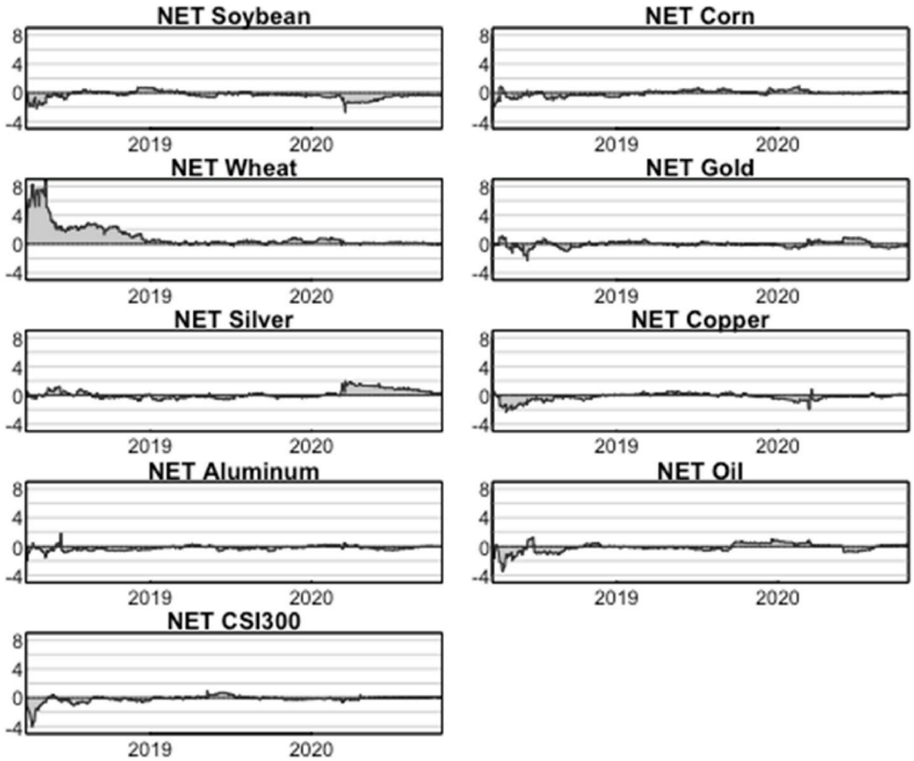



(b) Net spillovers of realized volatility

**Fig. 2.** Net spillovers of Chinese commodity and stock markets for different order moments. Note: Positive values indicate that the market is a net contributor to other markets; negative values indicate that the asset is a net recipient from other markets.




(c) Net spillovers of realized skewness




(d) Net spillovers of realized kurtosis

**Fig. 2.** (*continued*).

outbreak as a global pandemic. Therefore, we conclude that the high-order moment risk levels of China's domestic financial markets are related to worsening global and domestic crises. This result is quite comparable to studies indicating that spillovers in higher-order moments across stock markets increase during periods of stress (Finta and Aboura, 2020).

Analysing the dynamic total spillover index shows that the spillover effects of moment risks in the Chinese commodity and stock markets are relatively strong. Compared to the gradual changes observed in return spillover, the responses of the realized higher-order moment volatility spillover indices to important market events are stronger. Furthermore, the fluctuating characteristics of the realized higher-order moment spillover indices are more obvious, and the curve tends to be steeper. When crises occur, the volatility spillover index rises sharply, indicating that such events can quickly trigger a large risk spillover effect. Major events such as trade disputes between China and the United States and the COVID-19 pandemic make the external environment faced by China's economic system increasingly complex. These uncertainties related to domestic and international economic environments exacerbate the volatilities of stock and commodity markets; thus, the spillover effects increase significantly.

Overall, major crises or events significantly enhance the connectedness of returns and realized higher-moments across China's commodity and stock markets, indicating that market shocks strengthen the relationships among markets (Finta and Aboura, 2020; Zhu et al., 2021). We find that major financial risks are often reflected by higher-order moments spillovers because these realized higher-order moments contain information about extreme market risk. Furthermore, the overall spillover of volatility is, on average, higher than that of the other three realized estimators, which indicates that volatility can provide more information than higher-order moments in capturing changes in markets. However, analysing higher-moment spillover effects is still worthwhile because they can detect some crisis events more precisely than volatility spillovers do (He and Hamori, 2021).

### *4.3. Dynamic net connectedness*

To observe the dynamic behaviours of returns, realized volatility, realized skewness, realized kurtosis, and spillover effects for Chinese commodity futures and stock markets directly, Fig. 2 shows the net directional spillovers obtained by subtracting TO spillovers from FROM spillovers. These net directional spillovers show time-varying patterns in these financial markets. During periods of unusual total spillovers, these markets also show unusual net directional spillovers. Fig. 2 shows that when significant economic or political events occur, these financial markets consistently play the role of either net recipient or net contributor.

Fig. 2(a) presents the net spillover of returns for each market over time. The spillover boom and bust are visible for all markets barring soybeans. Except the soybean market, the spillover connectedness of the markets changes drastically in response to external shocks. The corn, aluminium, and gold markets appear to be net spillover recipients throughout the sample period, and the silver, copper, and stock markets are net contributors.

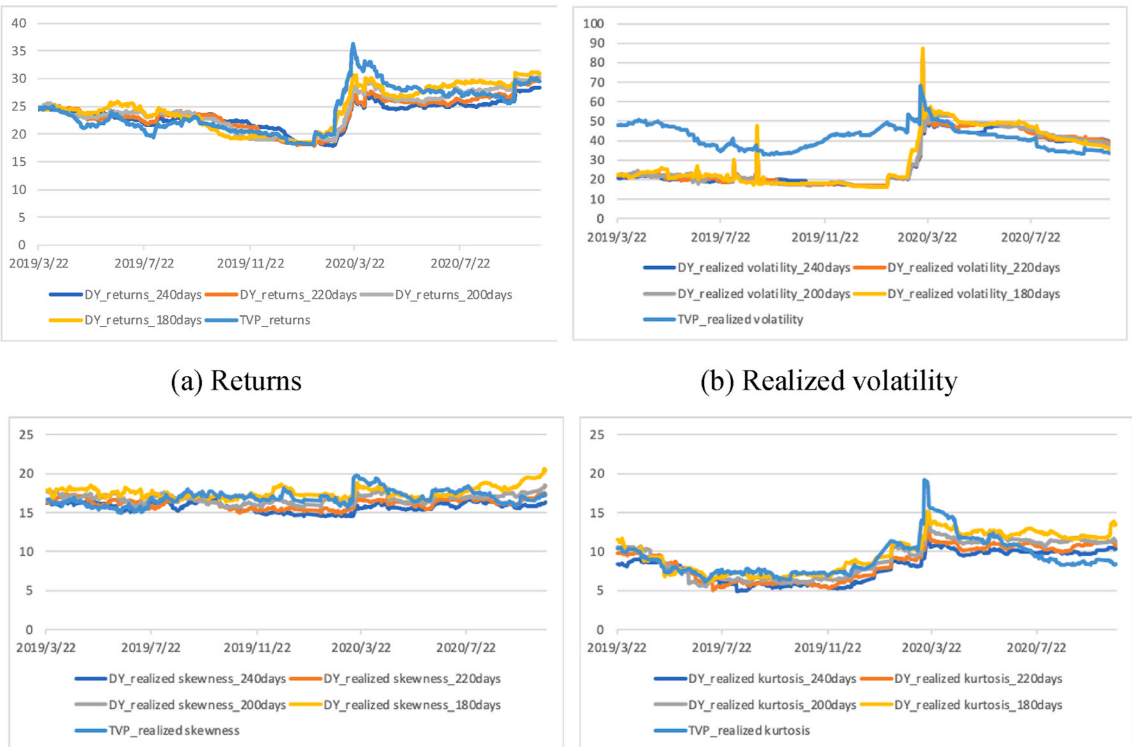



**Fig. 3.** Robustness check of dynamic spillover connectedness. Note: The blue line represents the results of the TVP-VAR method, and other lines represent the results of the DY spillover framework with different rolling window widths.

During the trade disputes between China and the United States, net spillovers in the corn and wheat markets are significantly negative, indicating that the agricultural futures markets are strongly affected by spillover effects. The aluminium market is also a net recipient, which is related to the increase in tariffs on China's aluminium products in the United States. The silver, oil, and stock markets are the main net contributors; therefore, the spillover from these three markets plays an important role across the commodity and stock markets. During the COVID-19 period, changes in net spillover connectedness in the metals market are more obvious. Silver and copper are the main net contributors, and gold plays the role of net recipient. During this period, silver and copper dominates market spillovers; gold is primarily affected in the early stage of the epidemic, but gradually stabilizes in the later stage, which is related to its safe-haven nature.

Fig. 2(b) shows the net spillover connectedness from realized volatility. Similar to return spillovers, the corn, silver, and aluminium markets are the main net recipients, and the silver and copper markets are the main net contributors. The difference is that the stock market is a net recipient with respect to volatility spillovers, which shows that the influence of the commodity market is larger than that of the stock market in terms of volatility spillover connectedness. Moreover, we find that silver is the most important net contributor and that its spillover effects are substantial from March 2018 to June 2019, which may be related to the sluggish performance and high volatility of silver prices.

Fig. 2(c) and (d) present net skewness and kurtosis spillovers, respectively. These net spillover relationships gradually stabilize. The wheat market is a net contributor during 2018 and 2019, and the crude oil, copper, and stock markets are net recipients over the same period, which can be explained by the stability of the wheat market during the China/US trade disputes. However, except for the wheat market, the net spillovers of realized kurtosis and skewness are less affected by external shocks. It appears that the net spillover relationships between these high-order estimates do not help describe the impact of significant market events.

When such events occur, spillover connectedness among these markets changes. During the trade disputes between China and the United States, the spillover changes in agricultural commodities, aluminium, silver, and stock markets are obvious. The silver market is a net contributor across these markets, which implies that changes in the silver market have a large impact across financial markets. The agricultural commodities and aluminium markets are the main recipients of market shocks during these economic and political events. Trade disputes between China and the United States have a substantial impact on agricultural commodities (including soybean and corn markets) and aluminium products, which is likely related to the tariff policies affecting these commodities. Based on the estimates of returns and realized volatility, the wheat market appears to be a contributor of shocks under the estimation of higher-order moments, and the degree of spillover is obvious. We theorize that the wheat market is a potential contributor to these shocks and find that estimating higher-order moments can provide hidden information related to other financial markets. During the COVID-19 period, spillovers among markets show some modest changes. The silver and copper markets are the main contributors, whereas gold and crude oil are the main recipients of spillovers. This indicates that the shocks from silver and copper markets have a noticeable effect on these financial markets although gold has attributes of a safe-haven asset, and the oil market can always be influenced by external shocks. These results are comparable to previous studies (Ahmed and Huo, 2021; Mensi et al., 2021), yet they are more informative as they find evidence of spillovers in higher-order moments that matters to asymmetric risk and tail risk spillovers.

Thus, the volatility spillover indices for different markets reflect the impacts of major events in a timely manner, whereas the higher-order moment spillover indices better reflect the characteristics of different markets and the magnitude of such impacts. This suggests that regulatory agencies could formulate early warning and preventive measures for various markets, to improve the stability of China's financial system.

### 4.4. Robustness assessment

To check the robustness of our main results, we use the DY method with a rolling window to calculate the dynamic spillover index. In this part, we choose 240, 220, 200 and 180 days as the window width and 10 steps as the forecast horizon to compute the total dynamic spillover index. The results of the DY method and TVP-VAR spillover framework are represented by line charts. The distances between polylines reflect the differences of the spillovers. If the trends of polylines are similar or the distances between lines are narrow, the results are robust.

In Fig. 3(a), (c), and (d), the polylines have similar trends and there are similar distances between polylines, so we can consider the risk spillover results based on returns, realized skewness, and realized kurtosis to be robust to the choice of spillover approach. In addition, the realized volatility spillover index of the TVP-VAR connectedness framework is higher than that of the DY method until March 2020, but the trend of the overall change in both results is consistent. All spillover effects between Chinese commodity and stock markets increase significantly in March 2020, which confirms that the spillovers between markets are influenced by COVID-19.

**Table 3**
Descriptive statistics of total spillover index.

| | Mean | Variance | Skewness | Kurtosis | J-B stat |
|---|---|---|---|---|---|
| TSI_Returns | 25.351 | 11.299 | −0.022 | 2.473 | 6.807*** |
| TSI_Realized volatility | 42.494 | 26.779 | 0.22 | 3.838 | 21.800*** |
| TSI_Realized skewness | 18.209 | 7.315 | 2.294 | 9.268 | 1467.900*** |
| TSI_Realized kurtosis | 10.966 | 12.421 | 0.921 | 3.214 | 83.653*** |

**Note:** The Jarque-Bera test is for the null hypothesis of normality for the distribution of the series. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

**Table 4**
Determinants of TSI.

| Variable | OLS | Quantile 0.10 | Quantile 0.90 |
|---|---|---|---|
| ***Panel A: Determinants of daily returns connectedness*** | | | |
| VIX | 0.0986*** | 0.1144*** | 0.1060*** |
| OVX | 0.0124*** | 0.0138 | 0.0419*** |
| USDI | −0.4372*** | −0.5099*** | −0.5207*** |
| TERM | 3.4955*** | 3.7000*** | 3.2341*** |
| USEPU | 0.0098*** | 0.0084*** | 0.0036*** |
| EMV | 0.0056 | 0.0070 | −0.0221 |
| GPR | 0.0099* | 0.0255** | −0.0027 |
| DCOVID | −1.236*** | −1.4268** | −0.7402** |
| Constant | 61.2476*** | 64.5453*** | 72.2285*** |
| Adjusted $R^2$ | 0.7429 | | |
| Pseudo $R^2$ | | 0.4311 | 0.5535 |
| ***Panel B: Determinants of daily realized volatility connectedness*** | | | |
| VIX | 0.1045*** | 0.0725** | 0.2460*** |
| OVX | −0.0025 | 0.0000 | −0.0176 |
| USDI | 1.0348*** | 0.8916*** | 0.6077*** |
| TERM | 6.3141*** | 12.0109*** | −0.6103 |
| USEPU | −0.0093*** | 0.0110*** | −0.0087* |
| EMV | 0.1319*** | 0.0563** | 0.0715 |
| GPR | 0.0529*** | 0.0244*** | 0.0685*** |
| DCOVID | −2.5531*** | −6.6309*** | −2.9679** |
| Constant | −65.1851*** | −56.8545*** | −18.9882 |
| Adjusted $R^2$ | 0.3293 | | |
| Pseudo $R^2$ | | 0.3562 | 0.2127 |
| ***Panel C: Determinants of daily realized skewness connectedness*** | | | |
| VIX | 0.0186 | −0.0001 | 0.0079 |
| OVX | 0.0050 | 0.0017 | 0.0217** |
| USDI | −0.2513*** | 0.0414 | −0.6425*** |
| TERM | 3.2757*** | 3.6188*** | 2.4448*** |
| USEPU | 0.0033*** | 0.0021*** | 0.0007 |
| EMV | −0.0051 | 0.0114 | −0.0146 |
| GPR | 0.0553*** | 0.0127*** | 0.0873*** |
| DCOVID | −1.3194*** | −1.8313*** | 0.2048 |
| Constant | 35.2898*** | 10.3149*** | 71.9026*** |
| Adjusted $R^2$ | 0.6484 | | |
| Pseudo $R^2$ | | 0.3336 | 0.5806 |
| ***Panel D: Determinants of daily realized kurtosis connectedness*** | | | |
| VIX | 0.0387** | 0.0528** | 0.0823*** |
| OVX | 0.0010 | −0.0003 | −0.0004 |
| USDI | 0.1387*** | 0.1332* | −0.2155*** |
| TERM | 6.2379*** | 4.4152*** | 5.4290*** |
| USEPU | 0.0008 | 0.0054*** | −0.0028* |
| EMV | 0.0369** | 0.0093 | −0.0048 |
| GPR | 0.0858*** | 0.0458*** | 0.0907*** |
| DCOVID | −0.6657** | −1.2018*** | 2.2664*** |
| Constant | −13.7846*** | −11.7560* | 21.6083*** |
| Adjusted $R^2$ | 0.7313 | | |
| Pseudo $R^2$ | | 0.3094 | 0.5952 |

**Note:** This table shows the statistical significance of the determinants of the TSI using standard ordinary least squares and quantile regressions. Robust P-values are based on the Newey–West (1987) estimator. VIX and OVX are the CBOE 30-day volatilities of the S&P 500 Index and crude oil, respectively. USDI is the US Dollar Index. TERM is the spread between the 10-year Constant Maturity Treasury (BC_10YEAR) and 3-month Constant Maturity Treasury (BC_3MONTH) from the US Treasury Department. USEPU is the US Economic Policy Uncertainty Index. EMV reflects infectious disease. GPR is the geographical risk index. DCOVID is a dummy variable representing the outbreak of the COVID-19 pandemic, which takes the value of 1 from January 2, 2020 to the end of the sample period and 0 otherwise. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

However, the results of spillovers during the year 2018 are not included in the comparison presented in Fig. 3 because the DY method based on a rolling window leads to the loss of some results in the sample analysis. Based on the above, we can assume that the results of the spillover index framework relying on TVP-VAR methodology are robust.

### 4.5. Determinants of connectedness

Having examined the dynamic spillovers among China's stock and commodity markets, we uncover, in this section, the potential determinants of the TSI of returns and realized estimators, via a set of explanatory variables designed to capture other dimensions of the economic and financial environment. However, before presenting the determinants of the TSI, we apply Jarque-Bera tests to check the normal distribution of the data series. The results are shown in Table 3.

As shown, the Jarque-Bera statistic tests indicate that all TSI series are not normally distributed, which suggests that the use OLS regressions might be suboptimal. Therefore, given the distribution of the data series and considering the methods applied in previous studies (e.g. Bouri et al., 2021a,b; Saeed et al., 2021a), we not only use OLS regressions but also quantile regressions.

Following the existing literature, we select eight explanatory variables relevant to financial and economic conditions of domestic and foreign markets that are available at daily frequency: (1) the CBOE Volatility Index (VIX), which measures equity market expectation of near term volatility conveyed by stock index option prices, regarded as the panic index of financial markets, and often referred to as the "fear index" (Bouri et al., 2018); (2) the CBOE crude oil ETF Volatility Index (OVX), which reflects the market's expectation of 30-day volatility of the oil market and is widely used in studies of financial markets (Gokmenoglu and Fazlollahi, 2015; Ji and Fan, 2016; Saeed et al., 2021); (3) the US Dollar Index (USDI), which reflects the exchange rate of the US dollar in the international foreign exchange market against a basket of six major currencies, the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona and Swiss Franc (Bunnag, 2016; Sun et al., 2017); (4) the US Term Spread Index (TERM), measured as the difference between the 10-year and 3-month US treasury bond yields (D10Y-3M), which reflects the macroeconomic situation and is often used to study the determinants that influence inter-market relations (Bouri et al., 2021a,b); (5) US Economic Policy Uncertainty (USEPU), proposed by Baker et al. (2016), based on US newspaper coverage frequency and used by previous studies as the relationship between changes in EPU and financial markets (Antonakakis et al., 2014; Bai et al., 2019; Yang, 2019); (6) the Infectious Disease Equity Market Volatility (EMV) Tracker a newspaper-based index often used to study the unprecedented stock market impact of COVID-19 (Baker et al., 2020); (7) the Geographical Risk Index (GPR) of Caldara and Iacoviello (2022), which previous studies associate with returns of crude oil and stock markets (Alqahtani et al., 2020; Saeed et al., 2021); and (8) DCOVID, a dummy variable representing the outbreak of COVID-19, reflecting how COVID-19 drives connectedness between financial markets (Adekoya and Oliyide, 2021; Amar et al., 2021; Hung, 2021).

The estimated results are reported in Table 4. As shown in Panel A, the results of the OLS regression indicate that the total return spillover index is affected by the VIX, OVX, US Dollar Index, TERM spread, US EPU, and COVID-19 outbreak. The VIX, OVX, TERM spread, and US EPU are positively related to the total spillover index of returns, whereas the US Dollar Index and COVID-19 outbreak have a negative effect on the total spillover index. The results of the quantile regression are comparable to the results of the OLS regression, although they show some heterogeneity between upper and lower quantiles regarding the effect of OVX and GPR. The importance of OVX and VIX to the total spillover index reflects the correlation between stock and commodity markets, as argued by Creti et al. (2013). The impact of the COVID-19 outbreak on the overall spillover index is negative. In terms of the magnitude of influence, the term spread is highest, followed by COVID-19 and the US Dollar Index, indicating that the spillover effects between the Chinese stock and commodity markets are affected by the US and other important financial markets. These findings are generally consistent with previous studies highlighting the effect of the US financial markets on the commodity markets (Luo and Ji, 2018; Uddin et al., 2020; Wang and Chueh, 2013).

Panel B of Table 4 presents the determinants of the spillover of realized volatility. The results of the OLS regression show that the determinants of realized volatility connectedness mainly depend on the US Dollar Index, TERM spread, and COVID-19 outbreak. The impact of TERM on the total spillover index of realized volatility is positive and the magnitude of influence is the highest among the explanatory variables, which is quite similar to our analysis of the determinants of returns connectedness. The results show some differences in the coefficients between the lower and upper quantiles of the distribution of the TSI. The model estimated at the left tail ($\tau = 0.10$) has more explanatory power than the model estimated at the right tail ($\tau = 0.90$), based on the pseudo $R^2$. At the left and right tails, the VIX is positively related to the spillover index, which may be due to market panic being widespread among investors. Changes in the US financial markets have a positive relationship with the spillover effect of Chinese financial markets, which may be due to the impact of the trade disputes between China and the United States. This evidence is consistent with the conclusions made in the dynamic spillover analysis.

Panel C of Table 4 shows the determinants of the connectedness of realized skewness. We note a similarity in the significant explanatory variables from the OLS regression and the quantile regression estimated at the left tail ($\tau = 0.10$). The TERM spread, US EPU, GPR and COVID-19 outbreak have a significant relationship with the realized skewness spillover index across Chinese stock and commodity markets. These influencing variables involving geographical risk, changes in the US economy and related policies, indicate that risks in other regions and changes in the US market can affect the skewness spillover index in Chinese markets. Moreover, combined with the analysis of the dynamic spillover results of skewness, the significant increase in the TSI during the trade disputes between China and the United States can be explained by the expected volatility in US stock prices, crude oil prices, the US Dollar Index and other factors related to economic and policy changes.

Panel D of Table 4 shows the results for the determinants of realized kurtosis connectedness. Several variables are shown to be significant in the OLS regression model. The effect of GPR on TSI is positive, suggesting that an increase in geographic risk leads to an increase in the kurtosis spillover index in the system of Chinese commodity and stock markets. Furthermore, USDI, EMV, and DCOVID are important to the realized kurtosis connectedness index. The US term spread is related to the performance of crude oil and prices of energy stocks, which suggests that changes in crude oil and energy stock prices can influence the total spillover connectedness. Because this variable reflects the spread between 10-year and 3-month Constant Maturity Treasury yields, which describes expectations for future economic development and recession probabilities, we speculate that the spillover relationship between the stock and commodity markets in China can be affected by developments in the US economy and financial markets. Another significant explanatory variable, DCOVID, is positively correlated with TSI, which means that those markets are affected by the pandemic, and that the prices of stock and commodities changes drastically during that period, deepening the spillover across markets, leading to an increase in TSI. Applying quantile regressions, we note slight differences in the results compared to OLS regressions. Notably, the effect of EPU is significant at lower quantiles, whereas the impact of EMV is insignificant at lower and higher quantiles.

Overall, the above results indicate that the drivers of the TSI are not necessarily the same across various quantiles and estimators. The spillover effects between the Chinese stock and commodity markets are affected by various factors. Combining the common points of the results obtained using different models and estimators, we can infer that the COVID-19 outbreak, geographical risk, economic development, changes in US market volatility, and US economic uncertainty are the main drivers of the total spillover indices across stock and commodity markets in China, which adds to the existing literature (e.g. Kang and Yoon, 2019; Ahmed and Huo, 2021; Mensi et al., 2021).

## 5. Conclusion

We apply high frequency data to examine the dynamic spillover effects of return and realized higher-order moments between stock and commodity markets in China. To this end, we employ a time-varying connectedness approach, showing how the various spillover effects are shaped by various shock periods. Accordingly, we extend the nexus among these markets by considering spillovers in realized higher-order moments, which is based on empirical foundations that spillovers in realized second, third and fourth moments have an influence on cross-asset linkages and asset pricing. We extend empirical studies on the relationship between stock and commodity markets in China by providing new insights into the drivers of the higher-order spillover using mean-based and quantile-based regressions. The main findings are summarized as follows.

Firstly, we show that the Chinese stock and commodity markets are linked not only through returns and realized volatility channel but through the realized skewness (asymmetry risk) and realized kurtosis (fat tail risk). Notably, the spillover index of higher-order moments is not as high as the realized volatility, yet the higher-order moments reflect changes in external shocks instead of the size of spillovers between markets. This suggests the pertinence of considering spillover effects in third and fourth moments across stock and commodity markets in China for the sake of risk management, derivative pricing and portfolio management. Accordingly, a more comprehensive understanding of the transmission mechanism of risk across Chinese stock and commodity markets requires an analysis that goes beyond the conventional measure of volatility spillover to cover the spillover effects of downside (upside) risk and tail risk.

Secondly, results for the time-varying spillover connectedness show that total spillovers of all realized estimators increase quite significantly during shock periods (such as trade disputes between China and the United States and COVID-19), which reflects changes in market risks. Accordingly, investors, portfolio managers, and policymakers should be aware of the impact of such shocks on the dynamics of spillovers in the domestic Chinese markets of stocks and commodities for the sake of investment decisions and financial stability.

Thirdly, the results show that silver is the main net contributor whereas soybean, corn, aluminium, and crude oil are the main net recipients. However, wheat, gold, and copper behave differently under the estimates of various higher-order moment spillovers. Changes in the silver market have large impacts on all financial markets, while soybean, corn, aluminium, and oil are affected by changes in other markets. As the order of moments increases, wheat gradually transforms into a net contributor, and copper into a net recipient, indicating that changes in the wheat market may have a hidden impact on the other markets, and that the copper market is largely affected by other markets, which are not observable by looking at the spillover connectedness of returns and realized volatility only. This suggests the utility of moving beyond spillovers in return and volatility to get a more complete picture of the dynamics of transmission among various commodities and the stock market index in China.

Fourthly, the results from OLS and quantile regressions show that the total spillover index is mostly driven by COVID-19, economic development, changes in the US market volatility, and US economic uncertainty, which indicates that the pandemic and US market and economic shocks lead to changes in the spillover effects of the stock and commodity markets in China. Therefore, investors and portfolio managers as well as policymakers in China should take a close look at developments in US stock and economic uncertainties to better understand the dynamics of higher moment spillovers among stock and commodity markets in China.

Overall, our findings reveal cross-market linkages that represent a major concern for traders and risk managers in the stock and commodity markets in China. They imply the importance of considering spillovers among these financial markets via higher-order moments; otherwise, ignorance of the spillover information that can materialize through realized skewness and kurtosis might lead to sub-optimal decisions regarding asset pricing risk management. Considering that policymakers have to take widespread and thorough decisions and make action plans during periods of turbulence in financial markets, it is economically vital to deepen the econometric understanding of the behaviour of higher-order moments according to the real generating mechanism and deal with the transmission of not only return and volatility but also downside (upside) risk and tail risk.

The presence of cross-market and cross-moment risk spillovers opens the door for assessing whether cross-market and cross-moment risk contain useful information capable of refining the prediction of the Chinese stock market based on return, volatility, and higher-order moments from the Chinese commodity markets. This issue is left to future studies. Another line of future research consists of studying the information transmission in higher-order moments while differentiating between higher and lower frequency scales.

## Credit author statement

H.Z.: Data curation; Methodology; Roles/Writing - original draft. C.J.: Methodology; Writing - review & editing. E.B.: Supervision; Visualization; Writing - original draft; Revising. W.G.: Writing - review & editing. Y.X.: Conceptualization; Formal analysis; Roles/Writing - original draft.

## Declaration of competing interest

We hereby declare that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in the paper entitled “Realized Higher-Order Moments Spillovers between Commodity and Stock Markets: Evidence from China”.

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