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Analysis of Comovement Between China's Commodity Futures and World Crude Oil Prices*

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Abstract

We examine the comovement between China's commodity futures and world crude oil prices based on their daily return series. Using a dynamic time-varying approach, we combine the generalized autoregressive score (GAS) model with the copula approach, allowing for asymmetry and tail dependence. Our results demonstrate a significant nonlinear causal impact of world crude oil prices on each of China's commodities. The comovement between China's commodity futures and crude oil prices is positive, with varying degrees of significance across different commodity types. Notably, non-ferrous metal and chemical commodity futures are more vulnerable to rising crude oil prices. From a dynamic perspective, we observe continued volatility in the comovement between China's commodity futures and world crude oil prices in recent years. Moreover, the time-varying dependence between the three non-ferrous metals and crude oil prices is higher than that of other commodities. These findings hold significant implications for global investors, risk managers and policymakers.

Keywords: comovement, commodity futures, world crude oil prices, copula

JEL codes: C58, Q02, Q37

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1. Introduction

In recent decades, the global economy has experienced a surge in oil and non-oil commodity markets. Although the prices of these commodities do not always fluctuate in tandem, there has been a high correlation between oil prices and other commodities since the 1990s, as noted by Pindyck and Rotemberg (1990). From 2003, the price of a barrel of crude oil rose by over $40 and reached a peak of $145 in July 2008. The global financial crisis halted the surge in oil prices, causing them to bottom out at $32 by the end of 2008. Other non-oil commodities have also shown wide price fluctuations. Previous research has shown that fluctuations in the price of crude oil significantly affect the prices of various non-energy commodities (Rafiq and Bloch, 2016). Several studies have explored the degree of comovement in commodity prices (Alquist et al., 2020; Zhang and Broadstock, 2020). The similar price changes of oil and other commodities have led scholars to examine the nexus between them.

Commodity markets have been the subject of research into comovement patterns (Adhikari and Putnam, 2020). Two essential concepts on the global commodity market are worth noting: integration, which emphasizes price convergence, and comovement, which focuses on price interdependence (Uebele, 2013). In economics and finance, comovement is a term used to describe how much two or more variables or assets move in the same direction or show similar patterns of change over time. It measures the correlation or synchronicity between different economic or financial variables. Commodity market comovement is crucial for cross-market portfolio investment. China's commodity futures markets have seen a boom in transactions and trading value in recent years (Qian et al., 2023). According to the China Futures Association, China's commodity futures trading volume in 2021 was 7.514 billion contracts, with a turnover of 581.20 trillion yuan, an increase of 22.13% and 32.84%, respectively, compared to the previous year. The comovement between oil prices and other commodities in China has also been observed. Our research focuses on China's context because of its crucial role on the world commodity and oil market (Zhang et al., 2020). China's industrialization and urbanization have led to a large proportion of the world market being occupied by China's commodity demand.

Furthermore, China is the second-largest consumer of crude oil globally. According to The Blue Book on Oil and Gas Industry Development Analysis and Outlook of China (2018–2019), China imported 462 million tonnes of crude oil in 2018, with a year-on-year increase of 10.1%, and has a high degree of dependence on the international market, up to 70.8%. China is devoted to integration into the world oil market, especially after the increased trading activity in Shanghai crude oil futures (Song et al., 2019). Consequently, both information flows and price linkages between China's and world commodity markets have strengthened.

The economic linkages among commodities connect the price dynamics of different commodity markets and are strengthened by joint production, consumption, or interchange. Financialization is considered the most important determinant of these linkages, with scholars highlighting its relatively prominent financial attributes (Adams et al., 2020). In recent years, commodity cycles have also caused price linkages among various commodities, likely due to deepening financialization (Adams and Glück, 2015; Basak and Pavlova, 2016). The global mechanism of commodity price changes (Kilian, 2009) and the price impact between world crude oil and commodities (Paris, 2018) have been widely studied. However, research into China's commodity market has mainly focused on the impact of world crude oil and agricultural product prices or risk spillovers (Zhang and Qu, 2015; Zhang et al., 2018), although crude oil is the lifeblood of modern industrial development. As such, different mechanisms could affect China's economic growth and development on the commodity market. From a global economic or sector-specific perspective in China, the trend towards linking energy and commodity markets has been increasingly apparent in recent years (Gu et al., 2020; Wu et al., 2020). Therefore, expanding the study of the dependence and tail dependence of various non-energy commodity futures in China on the world crude oil market is necessary.

We empirically investigate the comovement between China's commodity futures and world crude oil prices, using a test of their mutual causality. Although the causal relationship between China's commodity and energy markets has yet to be fully validated, many scholars have focused on the link between a sector of the commodity market and the world crude oil market (Balcilar et al., 2021; Guhathakurta et al., 2020; Mo et al., 2021). In contrast, others have shown that a sector of the commodity market in China and the international energy market are uncorrelated or weakly correlated (Ma et al., 2015). To develop a more in-depth and comprehensive study of the relationship between the various sectors of China's commodity market and the world crude oil market, we utilize the GAS model, which better captures the dynamic characteristics of time-varying commodity series in combination with the copula model. Furthermore, we assess the interdependence between commodity and world crude oil markets with tail dependence, allowing us to quantify comovement when commodity market returns have extraordinarily high or low values. Exploring the comovement between China's commodity futures and world crude oil prices is crucial for portfolio reallocation and risk hedging, benefiting cross-border and cross-market investors, industry policymakers and regulators.

To the best of our knowledge, this paper makes several meaningful contributions. Firstly, most existing empirical research into the oil-commodity nexus examines the relationship from a global perspective or focuses on the nexus between oil and a specific commodity (Kang et al., 2017). In contrast, the linkages between the world crude oil market and regional commodity market sectors have been studied less frequently. Previous empirical results cannot be easily applied to understanding the linkages between China and world commodities in constant flux. In the past decade, China has become one of the largest importers of crude oil in the world. As the China's economic and trade market grows in importance and becomes more integrated with the global economy, the dynamic correlation between China's commodities and the world oil market becomes increasingly relevant and worthy of study.

Secondly, conventional market linkages measure only average deviations from the mean without considering upper and lower tail dependence (Patton, 2013). This linear framework is unsuitable for describing the correlation of commodity price sequences, as these sequences are rarely normally distributed in financial time series. To overcome this limitation, we adopt copula functions, which have technical advantages over linear measures in model fit. Using copula functions, we can transform the commodity return series into the marginal distribution of a dependent structure, more accurately characterizing the distribution characteristics and time series properties of each return series. Furthermore, this approach enables us to describe the dependence of the commodity return series from the structure, leading to a more accurate description of the joint distribution of commodities. Additionally, we analyse the dynamic changes to deepen our understanding of the linkage characteristics between China's commodity futures and the world crude oil market. Tail dependence provides a more accurate prediction of extreme events. Thus, based on the copula function framework, we study the tail dependence of world crude oil prices and China's commodity futures and analyse their dynamics to help us understand the interdependence between the extreme price changes of China's commodity futures and the world crude oil market.

Thirdly, this paper employs the GAS model as a marginal distribution model to obtain standardized residuals of the commodity return series. This approach is preferable over the traditional GARCH family model as it better captures the dynamic volatility characteristics of the asset series (Tomanová and Holý, 2021). The resulting GAS copula dynamic model is expected to provide more accurate estimates of the time-varying linkages between China's commodity and crude oil markets. Additionally, we adopt a nonlinear Granger causality approach to test the causal relationship between these markets before conducting the comovement analysis, which is more reliable and convincing than using the copula model directly to obtain the market linkage analysis.

Finally, some existing studies on China's commodity futures market have relied mainly on the commodity price index. However, compared with the world market, China's commodity futures market is still underdeveloped and lacks commodity index-based trading variety. Moreover, the price information on China's commodity index needs to be more comprehensive

(Yin and Han, 2016). Therefore, we use the daily data for China's representative commodity futures with data available to address these limitations rather than relying on the price index.

The rest of this paper is organized as follows: Section 2 reviews relevant literature. Section 3 outlines the methodology for model setting. Section 4 presents the main empirical research results, and Section 5 is the conclusion.

2. Literature Review

According to previous research, the price elasticity of demand for most global commodities, such as crude oil, steel, titanium, rice and coffee, ranges between 0.1 and 0.5. Gilbert (2010) and Wright (2011) have emphasized that this characteristic is a major factor contributing to their high price volatility. The low price elasticity of demand for world commodities means that if an economy is highly dependent on these commodities, price changes can significantly affect that economy. The historical and international perspectives have also demonstrated the crucial role of world crude oil prices on the global market (Hamilton, 1996) and the substantial effects of oil prices on other commodities (Wu et al., 2020). The interdependence between oil and other commodity prices is essential for macroeconomic stability in countries, including both resource-dependent countries that rely heavily on exports, and manufacturing countries such as China, which depend heavily on imports.

Previous studies have primarily examined the relationship between crude oil and agricultural markets, focusing on the volatility spillover effects. Nazlioglu (2011) found no linear correlation between agricultural products and crude oil prices but did find that crude oil has a one-way nonlinear causal effect on maize and soybean. Du et al. (2011) investigated the volatility spillover effect among crude oil, maize and wheat markets and found that oil price shocks had spillover effects, resulting in significant price changes on agricultural markets, particularly in maize and wheat. Nicola et al. (2016) found a highly correlated relationship between price returns of energy and agricultural commodities, increasing comovement among commodities. Lucotte (2016) analysed the comovement between crude oil and food prices and found evidence of linkages. Paris (2018) used a nonlinear framework to prove the long-term effect of oil prices on agricultural commodity prices. Fretheim (2019) provided evidence of a comovement between crude oil price changes and grain prices after 2006. Dahl et al. (2020) found that the correlation between crude oil and agricultural prices increased during financial and economic turmoil periods.

Some literature has examined the impact of crude oil on other commodities, highlighting the excess comovement hypothesis. Fernandez (2015) investigated the excess price of oil and 11 non-energy commodities and supported this hypothesis, particularly for oil and industrial metals. Kang et al. (2017) studied the spillover effects between crude oil and five other commodity futures and found a positive correlation between commodity futures markets. Umar et al. (2021) examined the response of several industrial and precious metals to crude oil shocks and found that copper, zinc, and platinum were net recipients of crude oil exposure. From a country-specific perspective, Nazlioglu and Soytas (2011) evaluated the effects of world oil prices on commodity prices in Turkey. They found that world crude oil price fluctuations do not significantly influence Turkish agricultural products in the short term and are neutral in the long run. Fowowe (2016) investigated the relationship between oil prices and commodity prices in South Africa and found that South Africa's agricultural prices are neutral to world oil prices. López Cabrera and Schulz (2016) examined volatility risk in linkages between energy and commodity prices in Germany and found simultaneous price changes in the long run.

Focusing on China's commodity markets, several studies have investigated the relationship between world crude oil prices and China's commodity price index. Zhang and Chen (2014) found that China's commodity market is affected by both expected and unexpected world oil price fluctuations, with the response of the petrochemical and oil index being more significant than that of the metal and grain indices. Similarly, Zhang and Qu (2015) found different effects of oil price shocks on six agricultural commodities in China using the GARCH family models. A study conducted by Zhang et al. (2018) examined the relationship between world crude oil prices and China's commodity index. The researchers discovered that anticipated oil price shocks have notable positive effects, which are also asymmetric, at both the overall and industry levels. Building upon this research, Liu et al. (2021) conducted a more recent investigation into the clustering of crude oil price volatility and its dynamic jump characteristics. They employed the ARJI and ARMA-EGARCH models and found that volatility and jumps on the crude oil market specifically affect non-ferrous metals in China.

Current research focusing on the relationship between crude oil and commodities has primarily relied on a restrictive linear assumption, which assumes a normal distribution of commodity prices. However, it is worth noting that asset return series often exhibit skewness and fat-tailed characteristics (Mohammadi and Su, 2010). Attempting to fit a nonlinear structural relationship among commodities using traditional normal distribution assumptions presents a significant challenge. We propose employing empirical research utilizing the copula function to overcome this challenge. Copulas offer a means to capture dependences among variables through marginal distribution, eliminating the need to satisfy normal distribution conditions. Using copula models, we can separately model the marginal distribution of commodity series and the dependence structure, thereby enabling more flexible calculations and a comprehensive study of interdependences (Charfeddine and Benlagha, 2016).

The copula function is increasingly used in financial market research, including its application to linkages and comovement between commodity and capital markets (Mokni, 2020; Reboredo and Rivera-Castro, 2014). Some studies use the elliptical copula function to conduct empirical research into the relationship between crude oil and commodities. For instance, Reboredo (2012) used static Gaussian and Student's t-copulas to study the relationship between crude oil and three agricultural commodities and found that the prices of agricultural commodities are unaffected by crude oil prices. Li and Yang (2013) used static copulas to study the relationship between crude oil prices and natural rubber prices and found that Student's t-copula performs better in describing the correlation between crude oil and natural rubber. Koirala et al. (2015) used the Archimedes copula function to study the relationship between energy products and agricultural product prices and found that the prices of energy and agricultural products are highly positively correlated, with a high correlation in the lower tail. Adhikari and Putnam (2020) studied the excess comovement between energy, grain and livestock under the copula function setting for the regression residuals that exclude macro factors from the rate of return. They found that goods in the same sector are more relevant than those in different sectors, with a weak positive excess between energy and livestock consumption.

Several scholars have studied the interdependence of commodity markets by analysing their variability over time. Ghorbel et al. (2016) utilized a time-varying copula to explore the dynamic relationship between crude oil prices and various commodity prices, such as cotton, rice, wheat, silver, sugar, and coffee. Their findings revealed increased correlation and volatility between crude oil and commodities over the past six years. Similarly, Yahya et al. (2019) employed the DCC t-copula to examine the dependence of agricultural commodities on crude oil prices. Their study indicated that the correlation between these factors tends to escalate during financial and economic turmoil. Taking a different approach, Cai et al. (2019) utilized the wavelet transform and copula function to explore the comovement between different commodity sectors. Their research revealed that the dependence among commodity sectors varies across time and frequency. They observed a strong comovement between energy-livestock and energy-precious metal pairs in the long run. Furthermore, Zhang and Zhao (2021) investigated the dynamic dependence between crude oil and natural gas returns using time-varying copulas, including geometric copulas.

In summary, previous studies have exhibited certain shortcomings. Firstly, some studies have focused solely on the relationship between crude oil and specific sectors of commodity or agricultural markets, lacking comprehensive comparisons across various commodity markets. Secondly, certain studies have predominantly utilized linear methods to examine the interaction between crude oil and commodity prices, assuming symmetric correlations in commodity volatility. Thirdly, when considering nonlinear relationships among commodities, some scholars have only concentrated on static or aggregated correlations over the sample period. Fourthly, certain studies have employed the copula approach to investigate the nonlinear correlation of dynamics. However, the conventional marginal distribution model fitted to commodity series fluctuations lacked a dynamic portrayal and did not sufficiently test the existence of a causal relationship before exploring the linkage relationship.

We overcome these limitations by investigating the relationship between the world oil market and China's commodity market. We utilize a powerful nonlinear Granger causality test for the comovement study. Our analysis considers dynamic fluctuations of the commodity series, time-varying comovement and correlations amidst extreme volatility to provide a comprehensive and exhaustive analysis.

3. Methodology

3.1 Copula function

In recent years, researchers have been using copula-based dependence measures more frequently to study nonlinear effects. It is important to note that the dependence between two or more random variables cannot be determined solely from their individual marginal distributions. However, the copula function provides a way to retrieve the joint distribution by utilizing the marginal distributions. Essentially, a copula function acts as a tool that connects multiple one-dimensional uniform distribution functions to a multivariate cumulative distribution function.

We define a random vector sequence of commodity price returns $X = (X_1, \cdots, X_d)'$, and its corresponding value is $(x_1, \cdots, x_d)$. To simplify the analysis, we assume that the marginal distribution of the commodity return series is a continuous increasing function. A dimensional copula function C is assumed to be a d-dimensional standard uniform marginal distribution $[0.1]^d$ link function. According to the Sklar theorem (Sklar, 1959), a d-dimensional distribution function F can be obtained, and the related marginal distributions are $F_1, \cdots, F_d$ .The copula function meets the following condition: $F(x_1, \cdots, x_d) = C(F_1(x_1), \cdots, F_d(x_d))$ and that of the joint distribution function can be defined as follows: $F\left(x_1, \ldots, x_d\right) = C\left(u_1, \ldots, u_d\right) = \varphi\left(\varphi_1^{-1}(u_1), \ldots, \varphi_d^{-1}(u_d)\right)$, where $u_i = F_i(x_i)$ denotes the cumulative distribution function of the marginal function X_i, and φ_i^{-1} is the quantile function for the marginal distribution x_i.

The occurrence of extreme events on multiple commodity markets simultaneously raises concerns among investors and policymakers regarding their strong comovement during such events. A copula function is a valuable tool to accurately characterize extreme correlations between variables, such as tail dependence, which signifies the dependence structure between extreme cases. Our study employs a two-dimensional distribution copula model to investigate the comovement between global crude oil and China's commodities. The copula function, known as $C(u_1, u_2)$, helps us express the tail dependence between two variables.

$$\lambda_U = \lim_{u\to 1} P(u_1 > u \mid u_2 > u) = \lim_{u\to 1}\frac{1-2u+C(u,u)}{1-u} \tag{1}$$

$$\lambda_L = \lim_{u\to 0} P(u_1 \le u \mid u_2 \le u) = \lim_{u\to 0}\frac{C(u,u)}{u} \tag{2}$$

where $\lambda_U \in [0.1]$, $\lambda_L \in [0.1]$. When λ_U or $\lambda_L = 0$, there is no upper or lower tail correlation between the two variables. If $\lambda_U > 0$, upper tail dependence is present, indicating that positive extreme values can occur concurrently. If $\lambda_L > 0$, there is a presence of lower tail dependence, indicating that negative extreme values may occur concurrently.

For the conditional copula function, the conditional event is assumed to be w, and then the copula function is $F_{X_1\ldots X_d|w}(x_1, \ldots, x_d) = \mathrm{C}(F_{X_1|w}(x_1 \mid w), \ldots, F_{X_d|w}(x_d \mid w) \mid w)$. In order to use the conditional copula function, the marginal distribution and conditional events of the copula function must be the same. However, if the conditional events of each marginal distribution do not affect other distributions or copula functions, the conditional events can differ (Patton, 2006). In this study, we employ several copula models to estimate the correlation between global crude oil and China's commodities. The optimal copula estimation model is determined using the Akaike information criterion (AIC) as follows: $AIC = -2\sum_{i=1}^{N}\ln[c(u_1,u_2 \mid \theta)] + 2z$, where z is the number of estimated parameters. When selecting a model, a smaller value of AIC indicates a better model. We employ the two-step estimation method that Joe and Xu (1996) proposed to estimate the specific parameter values. In the first step, we derive the marginal distribution parameters, and in the second step, we utilize maximum likelihood estimation to obtain the copula function parameters. The estimation equation is given by $\hat{\theta} = \arg\max \sum_{t=1}^{T}\ln c(\hat{u}_1,\hat{u}_2;\theta)$, where $\hat{u}_2 = F_2(x_2;\hat{\alpha})$ and $\hat{u}_2 = F_2(x_2;\hat{\beta})$ are the pseudo-sample observations from the copula.

3.2 Marginal distribution model

Return series for financial and commodity assets tend to show serial autocorrelation and volatility aggregation. Their probability distribution is often characterized by excess kurtosis and heavy tails. In this paper, we utilize an observation-driven model based on the score function as the marginal distribution, specifically the generalized autoregressive score (GAS) model proposed by Creal et al. (2013). The GAS model combines the technical strengths of several other observation-driven models, including generalized autoregressive conditional heteroskedasticity, autoregressive conditional duration, autoregressive conditional intensity, and Poisson count models with time-varying mean. The model is expressed as follows:

$$y_t \mid y_{1:t-1} \sim C(y_t;\, \theta_t) \tag{3}$$

$$\theta_{t+1} = k + \sum\nolimits_{i=1}^{p} A_i s_{t-i+1} + \sum\nolimits_{j=1}^{q} B_j \theta_{t-j+1} \tag{4}$$

where y_t denotes the commodity returns subject to the observed density function in Equation (3), $y_{1:1-t}$ indicates the set information contained by the time $t-1$. θ_t is a time-varying variable driven by the score of the conditional distribution defined in Equation (3), which satisfies the autoregressive equation in Equation (4). k is a constant vector, A_i and B_j are coefficient matrices of a particular dimension, where $i = 1, \ldots, p$, $j = 1, \ldots, q$. s_t is the positive definite matrix related to θ_t, and satisfies Equation (5):

$$s_t = S_t(\theta_t)\nabla_t(y_t,\, \theta_t) \tag{5}$$

$$\nabla_t(y_t,\, \theta_t) = \frac{\partial lnC(y_t;\, \theta_t)}{\partial \theta_t} \tag{6}$$

where $S_t(\theta_t)$ is a positive scaling matrix at the time t, $\nabla_t(y_t, \theta_t)$ is the fraction of density function at θ_t and $S_t(\theta_t)$ can be defined as the inverse power of the information matrix θ_t, where $\gamma > 0$, that is:

$$S_t(\theta_t) = N_t(\theta_t)^{-\gamma} \tag{7}$$

$$N_t(\theta_t) = E_{t-1}[\nabla_t(y_t,\, \theta_t)\nabla_t(y_t,\, \theta_t)^T] \tag{8}$$

In the parameter model of marginal distributions, we assume that the standard deviation of the model has a constant conditional probability distribution. It has a mean of 0 and a variance of 1. When selecting the distribution model for the parametric method, we compared the skewed normal distribution, Student's t- distribution, and the skewed Student's t-distribution. The optimal parameter distribution model was determined using the CVM test.

3.3 Static copula function

We use different copula functions for empirical fitting, including the normal copula, Student's t-copula, Clayton copula, Gumbel copula, Frank copula, Joe copula, BB1 copula, BB6 copula and BB7 copula. However, due to space limitations, we will only show examples of Student's t-copula, Clayton copula, BB1 copula and BB7 copula used for empirical study by model comparison in the next section.

3.3.1 Student's t-copula

Student's t-copula setting not only accounts for fat tails in the returns but also captures the structural characteristics of dependence during extreme events. The mathematical expression is as follows:

$$C(u_1,u_2;\rho,\nu)=\int_{-\infty}^{T_\nu^{-1}(u_1)}\int_{-\infty}^{T_\nu^{-1}(u_2)}\frac{1}{2\pi\sqrt{1-\rho^2}}\left[1+\frac{t^2+s^2-2\rho st}{\nu(1-\rho^2)}\right]^{-\frac{\nu+2}{\nu}}d_s d_t \tag{9}$$

where u_1 and u_2 represent the sequences of the cumulative distribution function for the world crude oil prices and China's commodity return series under the conditional marginal distribution. These sequences are transformed into a uniform distribution for convenience. Besides, ρ and ν respectively represent the parameters of the copula function; $T_\nu^{-1}(u)$ is the inverse of the standard Student's t-distribution with a degree of freedom of υ. When the parameter υ is increased, the tail dependence between sequences also increases, resulting in a higher likelihood of extreme events occurring. The upper tail correlation coefficient and the lower tail correlation coefficient are calculated as $\lambda_L=\lambda_U=2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{1-\rho}\sqrt{1+\rho})$.

3.3.2 Clayton copula

The Clayton copula is classified as an Archimedean copula function, known for its asymmetric nature. It provides a direct representation of lower tail dependence, while the upper tail dependence of the Clayton copula is zero. The mathematical expression is:

$$C(u_1,u_2;\theta)=(u_1^{-\theta}+u_2^{-\theta}-1)^{-1/\theta} \tag{10}$$

where θ is a parameter of the copula function, which satisfies $\theta > 0$. Kendall correlation coefficient is calculated as $\tau=\theta/(\theta+2)$.The upper tail correlation coefficient $\lambda_u = 0$. The lower tail correlation coefficient $\lambda_L=2^{-1/\theta}$

3.3.3 BB1 copula

The BB1 copula stands apart from the single-parameter Archimedes copula model as a representative two-parameter model that effectively captures the structural properties of upper and lower tail dependence. Its mathematical expression is:

$$C(u_1,u_2;\theta,\delta)=\left\{1+[(u_1^{-\theta}-1)^{\delta}+(u_2^{-\theta}-1)^{\delta}]^{1/\delta}\right\}^{-1/\theta} \tag{11}$$

where the parameters meet the following requirements: $\theta > 0$, $\delta > 1$. The Kendall correlation coefficient expression is $\tau = 1-2/\delta(\theta+2)$. The upper tail correlation coefficient is $\lambda_u = 2-2^{-1/\delta}$, and the lower correlation coefficient is $\lambda_L = 2^{-1/(\delta\theta)}$.

3.3.4 BB7 copula

The BB7 copula function is a two-parameter model that represents the correlation between the upper and lower tails. Its mathematical expression is:

$$C(u_1,u_2;\theta,\delta) = 1-(1-[(1-(1-u_1)^{\theta})^{-\delta}+(1-(1-u_2)^{\theta})^{-\delta}-1]^{-1/\delta})^{1/\theta} \tag{12}$$

where the parameters meet the following requirements: $\theta > 1$, $\delta > 0$. The upper tail correlation coefficient is $\lambda_U = 2-2^{-1/\theta}$, and the lower correlation coefficient is $\lambda_L = 2^{-1/\delta}$.

3.4 Time-varying copula

Static copula models can represent the comovement between crude oil returns and commodity futures. However, it is essential to note that their relationship might be subject to time-dependent changes. More than a static copula model is needed to capture the daily varying correlation characteristics adequately. Therefore, in this study, we utilize the Student's t GAS copula model and the rotated Gumbel GAS copula model proposed by Patton (2013) to fit the time-varying properties of the joint function, as follows:

$$\delta_t = \frac{1-\exp\{-f_t\}}{1+\exp\{-f_t\}} \tag{13}$$

$$f_{t+1} = \omega + \beta f_t + \alpha I_t^{-1/2} h_t \tag{14}$$

$$h_t = \tfrac{\partial}{\partial\delta}\log c\left(u_{1t},u_{2t};\delta_t\right) \tag{15}$$

$$I_t = E_{t-1}[\mathrm{s}_t \mathrm{s}_t'] = I(\delta_t) \tag{16}$$

In Equation (13), the static parameter δ_t of the copula is related to the parameters of the previous phase and the time-varying parameter of the score change of the copula likelihood function, and the parameter δ_t is converted into the parameter f_t in the range $(-1,1)$. In this paper, we employ Student's t GAS copula and the rotated Gumbel GAS copula to effectively capture the time-varying dependence in the return series, considering their fat tail and the possibility of an asymmetric linkage structure. The rotated copula function incorporates a 180-degree rotation, enabling a more accurate representation of the tail distribution in specific asymmetric copula functions. This approach helps us capture essential characteristics of the joint distribution.

4. Empirical Results

4.1 Data

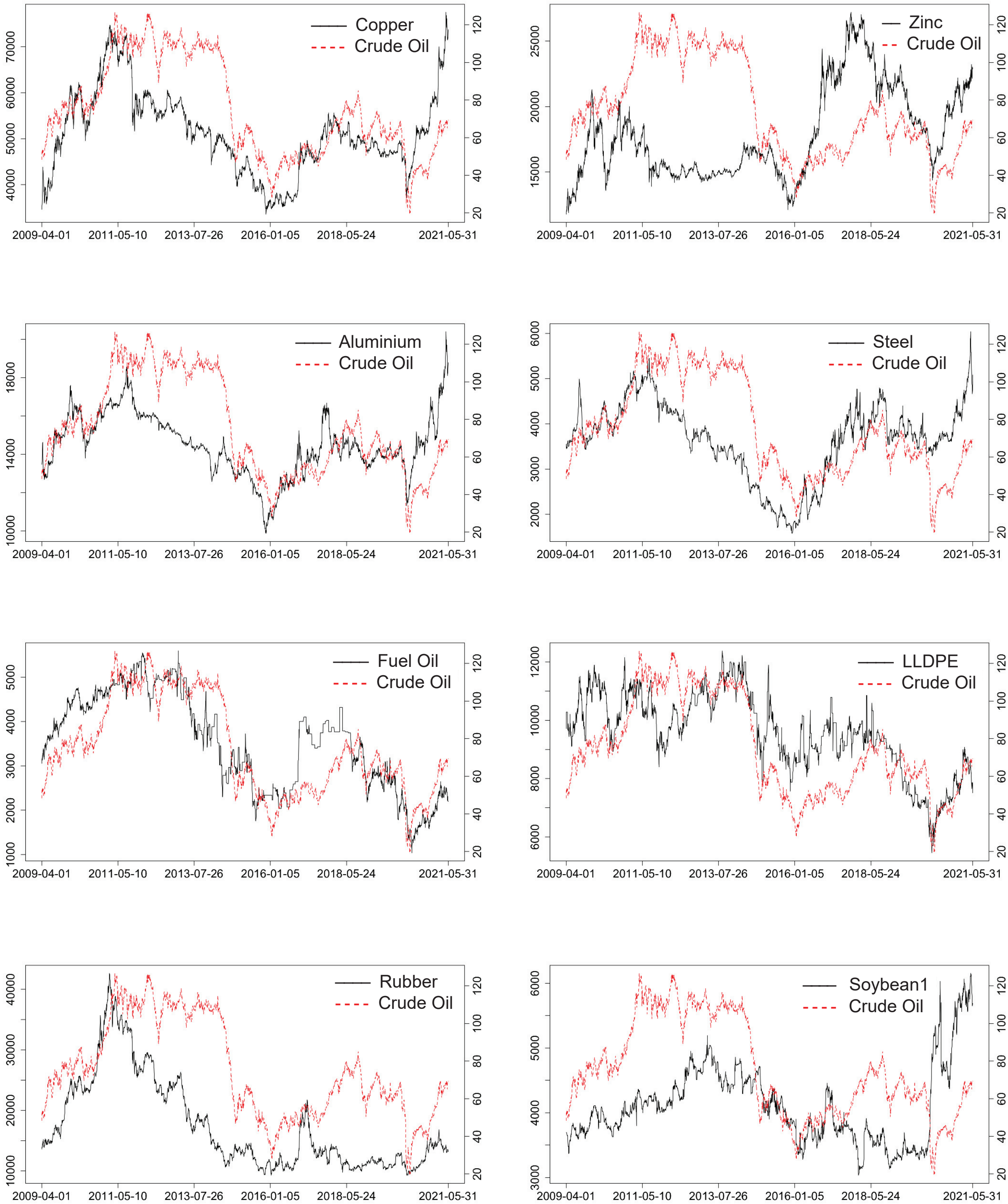
The dataset utilized in this paper comprises global crude oil and China's commodity data, covering the period from 1 April 2009 to 31 May 2021. Brent crude oil serves as the internationally recognized benchmark for crude oil, and in China, oil prices are predominantly determined using a pricing formula linked to Brent crude oil (Zavadska et al., 2020). Therefore, we use Brent crude oil futures to represent the global crude oil price. Regarding China's commodity futures trading, we have selected relevant futures contracts listed on the market for over ten years. Our focus is on seven significant categories, encompassing 13 commodity futures varieties. These categories include non-ferrous metals (cathode copper, zinc, and aluminium), coal/coke/steel, energy (fuel oil), chemicals (LLDPE and natural rubber), vegetable oils and oilseeds (yellow soybean no. 1, soybean oil and soybean meal), grain (yellow maize) and soft commodities (cotton and white sugar).

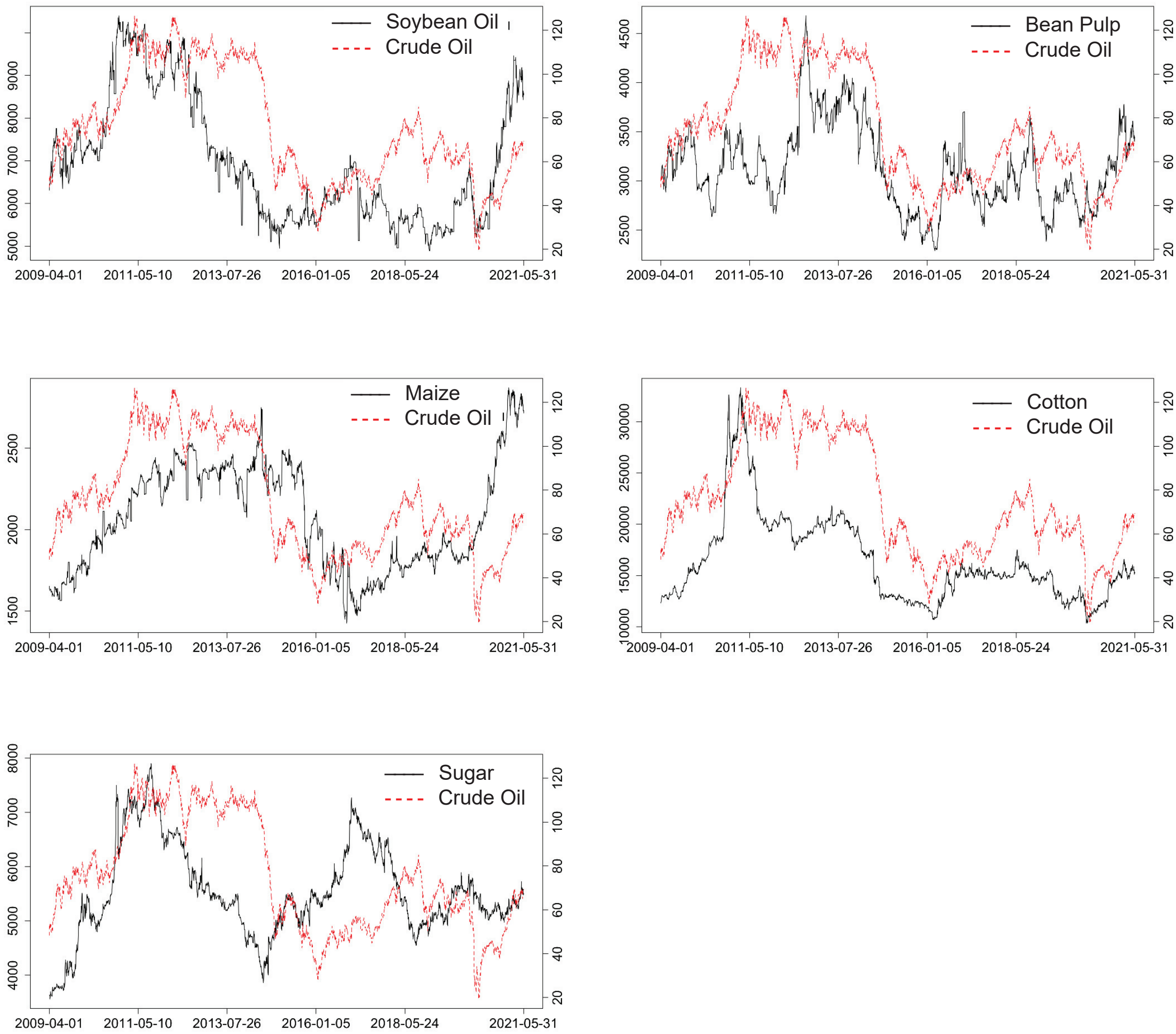
We obtained the sample data from the WIND commodity database, which is widely used by academics as a reliable source of commodity market information (Huang and Huang, 2020; Liu et al., 2019).

The chart in Figure 1 shows the daily returns of different commodity futures over time. China's commodity futures and international crude oil futures have similar trends of going up and down during specific periods. After the global financial crisis in 2008, there was a significant increase in commodity futures prices that dropped after peaking in 2011–2012. Then, starting in 2016, there was a new phase of price increases after a period of decline. Recently, from the start of 2021 to May 2021, these commodity futures have experienced a significant increase and reached record highs.

Figure 1 shows that China's commodity futures correlate with global crude oil prices, albeit with certain commodities either lagging or leading the peak of international crude oil prices. Notably, non-ferrous metals display higher volatility than crude oil. In contrast, the price fluctuations of vegetable oil and other agricultural commodity futures tend to trail behind the changes in international crude oil prices. China's fuel oil price trend aligns relatively closely with global crude oil.

Figure 1: Time series chart of daily closing prices of different commodities and global crude oil





Notes: From left to right, and from top to bottom daily closing prices for copper, zinc, aluminium, steel, fuel oil, LLDPE, rubber, soybean no. 1, soybean oil, bean pulp, maize, cotton, and sugar for the whole sample.
Source: authors' calculations

Table 1 presents the descriptive statistics for the return series of global crude oil and China's commodity futures. Most return series exhibit a negative skewness, indicating a tendency towards lower returns. Additionally, the kurtosis value for all commodities series is greater than 3, suggesting sharp peaks and fat tails in the distribution. It is worth noting that agricultural product futures demonstrate more pronounced characteristics of fat tails compared to non-ferrous metal commodity futures. Therefore, none of the return series adhere to a normal distribution, and significant tail distribution is evident.

In Table 2, the Jarque-Bera statistical test is employed to evaluate the normality assumption of the data. Based on the reported descriptive statistics, the test results reject the null hypothesis of normal distribution at the 1% significance level.

Table 1: Summary statistics of daily returns for entire sample

	Mean	Minimum	Maximum	St. dev.	Skewness	Kurtosis
Crude oil	0.013	–27.976	19.077	2.449	–0.602	18.687
Copper	0.028	–11.245	10.298	1.325	–0.208	6.569
Zinc	0.025	–11.702	5.958	1.451	–0.433	4.282
Aluminium	0.012	–6.942	4.991	0.972	–0.423	5.630
Steel	0.013	–19.746	10.382	1.860	–0.791	12.505
Fuel oil	–0.012	–22.461	19.075	2.523	–0.510	16.392
LLDPE	–0.010	–13.823	13.951	1.779	–0.577	12.529
Rubber	–0.001	–10.090	19.571	2.007	0.435	8.101
Soybean no. 1	0.016	–17.770	11.950	1.314	–0.678	22.526
Soybean oil	0.011	–25.348	21.335	1.688	0.494	42.366
Bean pulp	0.005	–14.652	16.008	1.566	–0.609	18.033
Maize	0.019	–19.089	13.565	1.367	–0.936	36.875
Cotton	0.008	–17.362	8.376	1.274	–1.059	17.829
Sugar	0.016	–15.002	12.300	1.161	–0.320	20.685

Source: authors' calculations

In Table 2, we also conducted Augmented Dickey-Fuller (ADF) tests to examine the presence of unit roots and determine the stationarity of the sequences. The null hypothesis of the ADF test assumes the existence of a unit root. According to the tests presented in Table 2, the ADF tests reject the null hypothesis at the 1% significance level. This rejection suggests that the commodity sequences are stationary and not random walks. Additionally, we observed significant sequence correlation based on the Q(10) and $Q(10)^2$ statistics in the Ljung-Box test. Moreover, the ARCH statistic test confirmed the presence of significant conditional heteroscedasticity. Consequently, employing the generalized autoregressive score (GAS) model to fit each return series is appropriate.

Table 2: Statistical tests of daily returns for entire sample

	ADF	J-B	Q(10)	Q(10)²	ARCH
Crude oil	−14.548***	39017.735***	21.591***	537.480***	327.260***
Copper	−13.691***	4822.843***	9.483	328.990***	187.540***
Zinc	−13.677***	2125.271***	17.3*	241.040***	131.230***
Aluminium	−12.208***	3608.436***	11.819	475.210***	211.340***
Steel	−13.674***	17680.688***	6.344	58.251***	47.215***
Fuel oil	−15.398***	30015.002***	5.937	34.548***	30.332***
LLDPE	−51.767***	17618.390***	25.893***	33.452***	30.701***
Rubber	−13.136***	7388.641***	12.356	35.369***	27.961***
Soybean no. 1	−13.604***	56664.944***	37.731***	61.154***	52.775***
Soybean oil	−14.858***	199811.823***	42.731***	274.410***	299.900***
Bean pulp	−13.878***	36350.748***	7.644	26.564***	26.135***
Maize	−15.259***	151685.802***	64.637***	26.922***	24.917***
Cotton	−13.201***	35869.972***	32.904***	61.016***	44.474***
Sugar	−13.850***	47654.684***	22.561***	45.668***	38.562***

Notes: ADF is the Augmented Dickey-Fuller unit root test. J-B is the Jarque-Bera test. L-B is the Ljung-Box test. ARCH LM is the ARCH Lagrange Multiplier test. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Source: authors' calculations

4.2 Marginal distribution

We utilized the GAS model to precisely capture the distribution of commodity future return sequences. This model is essential for integrating time-varying parameters into a variety of nonlinear models, which helped us in identifying the volatility characteristics in commodity futures. Our analysis of different commodity futures revealed the presence of skewness and kurtosis, which indicated that a normal distribution would not be appropriate for our model. The GAS (p, q) model allowed us to fine-tune the parameters to meet our requirements, and we compared different models to identify the best one. In our paper, we refer to these models as GAS skewed normal, GAS Student's t, and GAS skewed Student's t.

To fit the marginal distribution of the return series of the commodity futures and global crude oil using the GAS (p, q) model, we compared the four different probability distributions, namely skewed normal distribution, Student's t-distribution, and skewed Student's t-distribution using the CVM (Cramer–von Mises) test. Our findings indicate that the test statistics of Student's t-distribution for most of the return series were the smallest, with the skewed Student's t-distribution ranking second in Table 3. Therefore, we ultimately used Student's t-distribution to fit the marginal distribution for our comparison.

Table 3: Model fitting under alternative distributions

CVM	Skewed normal	Student's t	Skewed Student's t
Crude oil	6.5421	0.46665	6.0718
Copper	6.4265	0.45621	6.7287
Zinc	11.065	0.22423	7.5611
Aluminium	10.998	0.68902	8.5571
Steel	21.85	5.2007	12.956
Fuel oil	52.356	22.466	35.449
LLDPE	42.931	19.851	28.655
Rubber	12.483	1.272	8.6017
Soybean no. 1	22.68	3.5429	11.697
Soybean oil	51.664	24.602	33.082
Bean pulp	35.887	6.6175	15.8
Maize	42.757	4.6111	11.169
Cotton	16.765	1.1115	7.7871
Sugar	13.871	1.3905	9.1985

Notes: the Cramer-von Mises test is based on the exact and asymptotic distributions proposed by Csörgő and Faraway (1996) to test the goodness of fit of a single sample.
Source: authors' calculations

Based on formal statistical tests, we have identified the GAS Student's t model as the optimal choice for capturing the marginal distribution of each commodity. The corresponding results for each model parameter are presented in Table 4. These parameter results align with the vectors in Equation (4), where k_1, k_2 and k_3 constitute the K-vector, a_1, a_2 and a_3 form the A-matrices, and b_1, b_2 and b_3 form the B-matrices. It is worth noting that the dimensions of the constant vector K and the coefficient matrices A and B differ.

After analysing the coefficient matrices A and B, some interesting observations can be made. Specifically, the coefficient a_1 appears to have a weaker influence in the overall dynamics as it tends to approach zero. In addition, when comparing rubber and cotton to other commodities, the coefficients a_2 and a_3 tend to be closer to zero, indicating a lower degree of time variability. On the other hand, the coefficients of the B matrix for all commodity futures returns converge towards unity, suggesting a significant accumulation in the fluctuation process of the models. These coefficients also suggest a weaker tendency for mean reversion in commodity futures returns.

Table 4: Parameter estimation of marginal distribution model

	k_1	k_2	k_3	a_1	a_2	a_3	b_1	b_2	b_3
Crude oil	0.0003 (0.0003)	0.0199 (0.0064)	−0.1810 (0.0928)	0.0069 (0.0053)	0.2424 (0.0317)	9.9743 (0.0000)	0.9974 (0.0024)	0.9786 (0.0064)	0.9645 (0.0196)
Copper	0.0007 (0.0004)	−0.2432 (0.0371)	−1.0487 (0.0000)	0.0000 (0.0000)	—	5.5005 (0.0000)	0.9801 (0.0000)	—	0.9831 (0.0000)
Zinc	0.0003 (0.0002)	0.0028 (0.0016)	−0.6428 (0.3104)	0.0000 (0.0000)	0.1709 (0.0258)	9.8636 (0.0011)	0.9911 (0.0000)	0.9955 (0.0008)	0.8468 (0.0820)
Aluminium	0.0000 (0.0001)	−0.0155 (0.0078)	−5.1807 (0.0000)	0.0007 (0.0000)	0.3221 (0.0398)	0.1898 (0.0000)	0.9969 (0.0000)	0.9824 (0.0059)	0.6118 (0.0000)
Steel	0.0001 (0.0002)	0.0014 (0.0048)	−0.4126 (0.0000)	0.0059 (0.0039)	0.3039 (0.0749)	5.5000 (0.0000)	0.9964 (0.0040)	0.9507 (0.0235)	0.9811 (0.0000)
Fuel oil	0.0025 (0.0071)	0.1273 (0.0459)	−1.3849 (0.0000)	0.0000 (0.0000)	—	5.5001 (0.0000)	0.6890 (0.0000)	—	0.9847 (0.0000)
LLDPE	0.0010 (0.0029)	−0.0755 (0.0211)	−0.2343 (2.3519)	0.0000 (0.0000)	0.7040 (0.0831)	5.4949 (0.0000)	0.7821 (0.0000)	0.8364 (0.0343)	0.9878 (0.0061)
Rubber	0.0004 (0.0005)	0.0173 (0.0060)	−0.3136 (2.5713)	0.0000 (0.0000)	0.2096 (0.0324)	0.1898 (0.0000)	0.9801 (0.0000)	0.9696 (0.0096)	0.9806 (0.0141)
Soybean no. 1	0.0001 (0.0002)	−0.6649 (0.0395)	−0.4830 (0.0000)	0.0018 (0.0023)	—	5.5000 (0.0000)	0.9874 (0.0095)	—	0.9811 (0.0000)
Soybean oil	0.0001 (0.0003)	−0.1959 (0.0417)	−0.4730 (0.0000)	0.0000 (0.0000)	0.5492 (0.0636)	5.5000 (0.0000)	0.9802 (0.0000)	0.7644 (0.0458)	0.9810 (0.0000)
Bean pulp	0.0157 (0.0144)	−0.4680 (0.0400)	−0.4283 (19.7299)	0.1032 (0.0192)	—	5.5000 (0.0000)	0.3361 (0.1773)	—	0.9807 (0.1493)
Maize	0.0001 (0.0002)	−0.2915 (0.0640)	−0.4735 (0.0000)	0.0018 (0.0012)	0.7248 (0.0730)	5.5000 (0.0000)	0.9884 (0.0031)	0.7583 (0.0508)	0.9810 (0.0000)
Cotton	0.0002 (0.0003)	−0.0316 (0.0103)	−0.3616 (0.0000)	0.0000 (0.0000)	0.4112 (0.0536)	0.1898 (0.0000)	0.9798 (0.0000)	0.9498 (0.0135)	0.9805 (0.0000)
Sugar	0.0000 (0.0003)	−0.0328 (0.0093)	−0.3550 (0.0000)	0.0000 (0.0000)	0.2807 (0.0362)	5.500 (0.0000)	0.9794 (0.0000)	0.9519 (0.0119)	0.9805 (0.0000)

Notes: The parameters in brackets are standard errors.
Source: authors' calculations

4.3 Nonlinear causality test

To investigate the comovement relationship between world crude oil prices and China's commodities, we first test for causality between the two markets. We use standardized residual series of crude oil and various commodities and employ a nonlinear causality test that utilizes an artificial neural network. This test constructs two models, one with a sequence of X and another with two sequences of X and Y, to assess any differences between them. We compare the sum of squared residuals of Model 1 and Model 2 to test the original hypothesis that X is not a nonlinear Granger causal cause of Y. The lag period is set to 1 to test the causal impact in the current period. This study focuses on nonlinear relationships when exploring the relationship between markets.

Table 5 presents the test results, which reveal a significant nonlinear causal impact of world crude oil prices on each category of China's commodities throughout the sample period at a 1% significance level. However, commodities such as steel, bean pulp, maize and cotton do not exhibit a significant nonlinear causal impact on crude oil. These results align with previous studies indicating that world crude oil prices have an impact on various commodity markets in China (Liu et al., 2021; Zhang and Qu, 2015). Crude oil plays a crucial role as a raw material for the production of different commodities, resulting in changes in world crude oil prices that affect the markets of various standardized commodity categories through input cost variations. Non-energy commodities are indirectly affected by fluctuations on international crude oil markets because crude oil is an essential input in producing many non-energy commodities (Ahmadi et al., 2016; Hammoudeh and Yuan, 2008). As our primary objective is to investigate the evolving process of interaction between world crude oil and China's commodity markets, we will further explore market comovement. In addition, transportation costs and their impact on commodity market prices are closely linked to crude oil, especially when settling non-energy commodities.

Table 5: Nonlinear Granger causality testing based on artificial neural networks

	Original hypothesis: no nonlinear Granger causality effect of each commodity on world crude oil prices	Original hypothesis: no nonlinear Granger causality effect of world crude oil prices on each commodity
Copper	0.0233***	0.0071**
Zinc	0.0239***	0.0124***
Aluminium	0.0251***	0.0292***
Steel	0.0224***	0.0000
Fuel oil	0.0244***	0.0258***
LLDPE	0.0272***	0.2299***
Rubber	0.0197***	0.0251***
Soybean no. 1	0.0276***	0.2065***
Soybean oil	0.0288***	0.3220***
Bean pulp	0.0212***	0.0000
Maize	0.0216***	0.0000
Cotton	0.0226***	0.0000
Sugar	0.0248***	0.0373***

Notes: ***, **, * denote rejection of the original hypothesis of "no nonlinear Granger causality" at the 1%, 5% and 10% significance levels respectively.
Source: authors' calculations

4.4 Copula estimation

Based on the standardized residual sequences of the conditional marginal model, we utilize the static copula function to analyse the overall correlation between world crude oil prices and China's commodity futures. We compare the normal copula, Student's t-copula, Clayton copula, Gumbel copula, Frank copula, Joe copula, BB1 copula, BB6 copula and BB7 copula function models based on the AIC to find the most optimal copula function model. The estimation of copula parameters is done using the nonparametric method of marginal distribution. Based on the principle that a smaller AIC value indicates better model estimation, Table 6 shows the optimal copula estimation models and reports the parameter values and AIC values of each optimal model.

Our analysis reveals a positive relationship between the return series of China's commodity futures and world crude oil prices. Specifically, we observe that the non-ferrous metal-oil pair and rubber-oil pair exhibit a dependence of approximately 0.1. Conversely, agricultural products, steel, and crude oil display relatively lower dependence. These findings suggest a dependence relationship between China's commodity futures and world crude oil prices, with potential implications for investors and operators. Therefore, it is crucial to discuss the significance of the dependences obtained through the static copula approach.

The following economic reasons can explain the empirical results: (1) China's manufacturing industry exhibits a high demand for non-ferrous metals and relies heavily on imports when local supplies are insufficient. Compared to other metals, China has a relatively lower share of global copper reserves, making it susceptible to pricing influences from international markets. Additionally, world crude oil prices play a crucial role as a cost input for extracting, smelting, and transporting non-ferrous metals, establishing a link between the two markets. (2) China is the largest importer of natural rubber, thus creating a dependence on the foreign natural rubber market. It heightens reliance and increases the interconnection between the rubber and world oil markets. (3) The domestic production of steel in China is substantial, and its development is significantly influenced by the demand side, particularly by the real estate industry. (4) Agricultural commodities are closely related to the consumer goods basket, and their price stability holds significant importance for the sustainable development of the macroeconomy. China's governments can utilize interventions such as inventory management to stabilize domestic prices.

By considering these economic factors, we can gain insights into the empirical results and better understand the relationship between China's commodity markets and world crude oil prices.

The BB7 copula is determined to be the optimal copula function for the non-ferrous metal-oil pair, as it exhibits higher upper tail dependence. This finding suggests that the impact of crude oil on non-ferrous metals will be more pronounced during rising yields. As for the chemical and natural oil pair, both the BB7 copula and BB1 copula are identified as optimal copula functions. For the remaining commodities and crude oils, Student's t-copula is the optimal choice, indicating symmetrical tail dependence between most commodities and crude oil. Moreover, the results indicate a stronger comovement between China's chemical commodity futures and crude oil than agricultural commodity futures and crude oil.

Table 6: Static copula parameter results

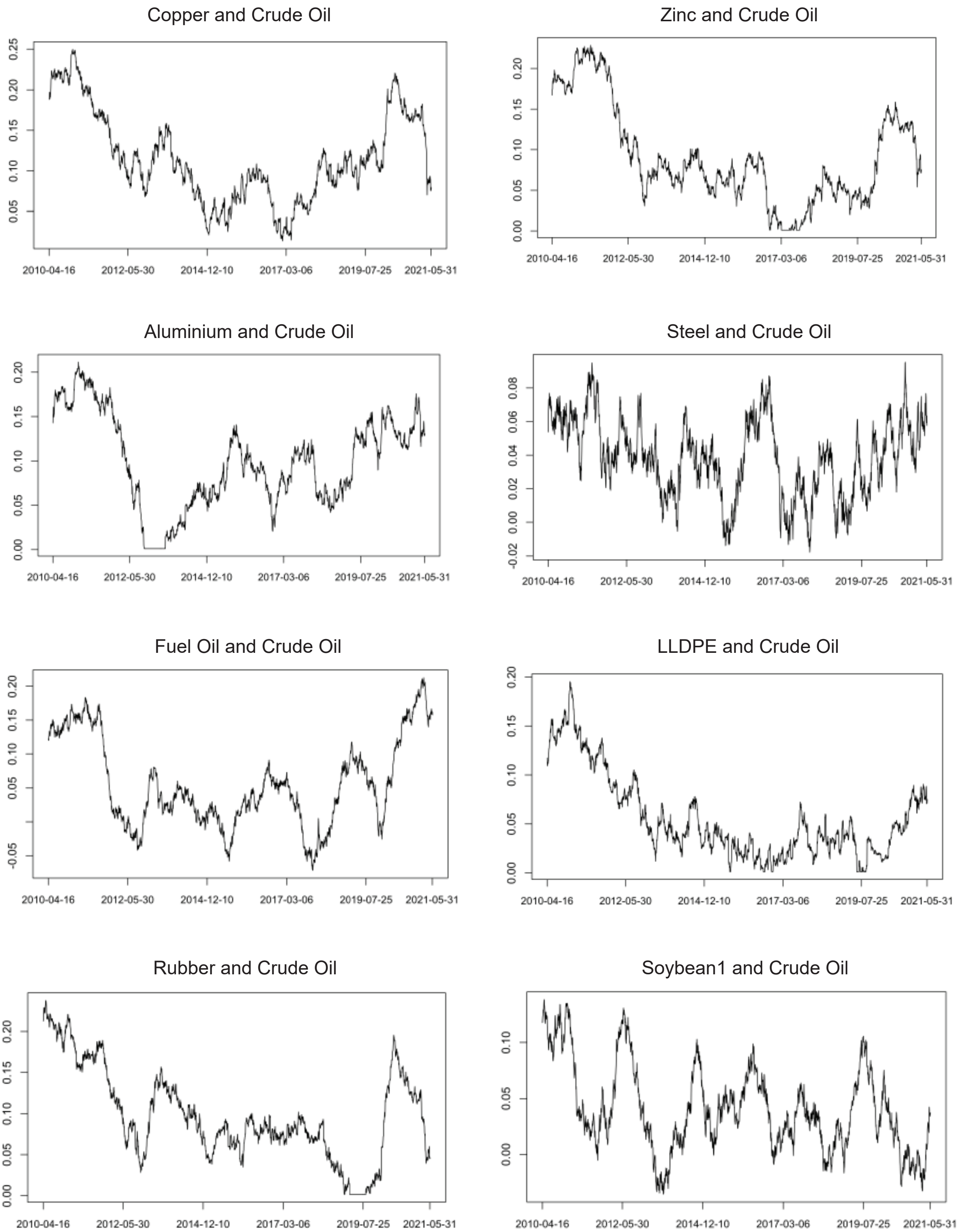
	Copula	Par_1	Par_2	Tau	Upper	Lower	AIC
Copper	BB7	1.05 (0.02)	0.19 (0.03)	0.11^{***}	0.07	0.03	–102.93
Zinc	BB7	1.03 (0.01)	0.17 (0.03)	0.09^{***}	0.04	0.02	–76.33
Aluminium	BB7	1.03 (0.02)	0.18 (0.03)	0.1^{***}	0.04	0.02	–79.62
Steel	Student's t	0.07 (0.02)	15.96 (5.77)	0.04^{**}	0.001	0.001	–16.47
Fuel oil	Student's t	0.11 (0.02)	13.25 (3.92)	0.07^{***}	0.004	0.004	–43.73
LLDPE	BB7	1.04 (0.02)	0.07 (0.02)	0.05^{***}	0.05	0.000	–21.6
Rubber	BB1	0.13 (0.03)	1.04 (0.02)	0.09^{***}	0.05	0.01	–66.73
Soybean no. 1	Student's t	0.06 (0.02)	10.8 (2.64)	0.04^{***}	0.01	0.01	–24.94
Soybean oil	Student's t	0.03 (0.02)	28.15 (16.61)	0.02	0.000	0.000	–1.1
Bean pulp	Student's t	0.05 (0.02)	9.95 (2.31)	0.03^{***}	0.01	0.01	–24.88
Maize	Student's t	0.04 (0.02)	14.79 (4.83)	0.03^{**}	0.002	0.002	–10.67
Sugar	Student's t	0.07 (0.02)	17.45 (6.61)	0.04^{***}	0.0008	0.0008	–16.51
Cotton	Student's t	0.07 (0.02)	21.47 (9.89)	0.04^{***}	0.0002	0.0002	–13.34

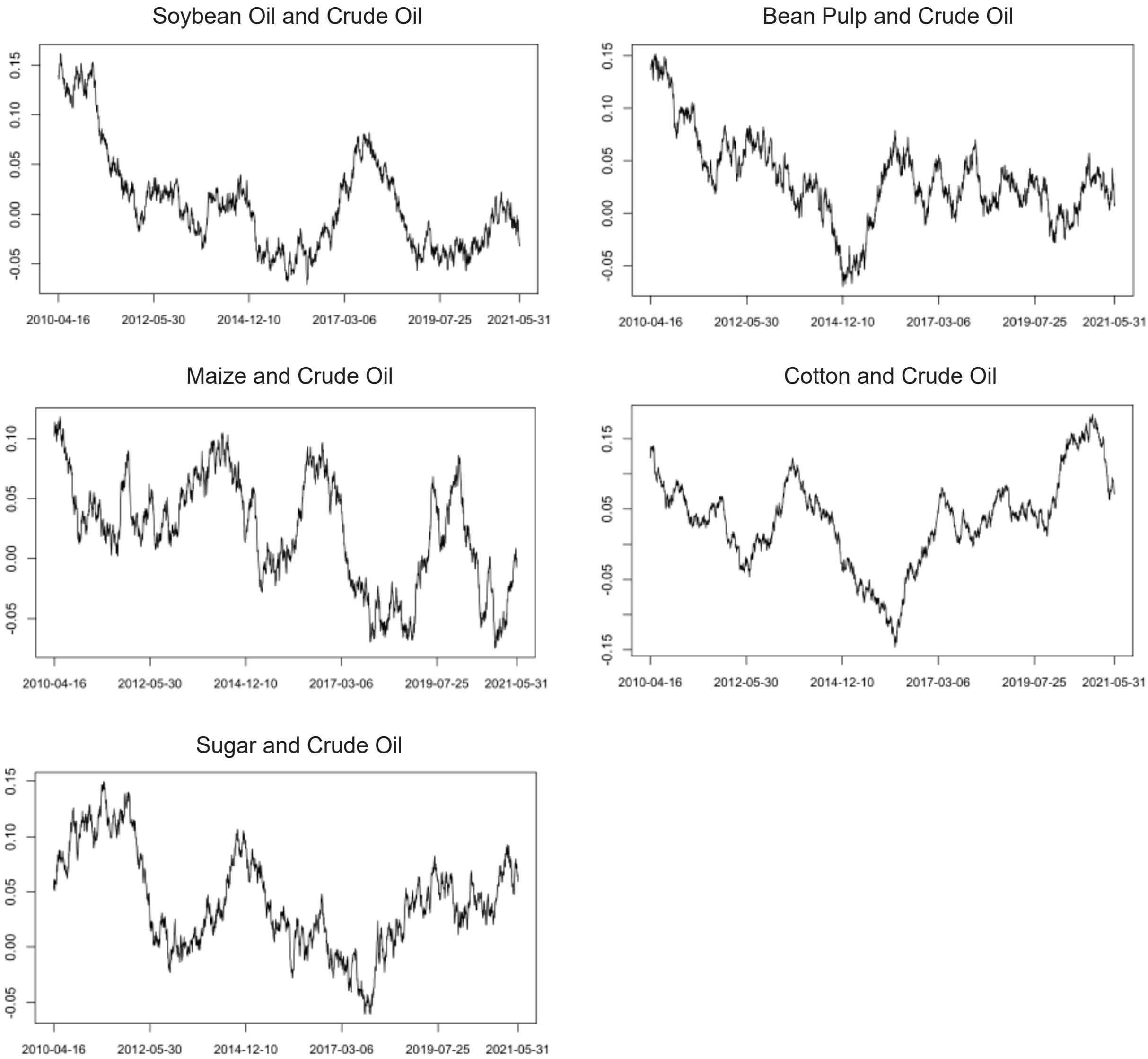
Notes: Upper and Lower represent λ_U and λ_L respectively. Tau is calculated as $\tau = 4\int_0^1\int_0^1 C(u,v)dC(u,v)-1$.
The parameters Par_1 and Par_2 in Student's t-copula function represent ρ and υ in the methodology section respectively. The parameters Par_1 and Par_2 in the BB1 copula function represent θ and δ respectively.
The parameters Par_1 and Par_2 in the BB7 copula function represent θ and δ respectively.
Source: authors' calculations

Furthermore, we investigate the comovement between various commodity futures and crude oil prices during different periods. We utilize the optimal copula function and employ a rolling window approach with a window period of 250 working days to fit the static copula function of each return series (Engle, 2009). As shown in Figure 2, the correlation between China's commodity futures and crude oil prices has been decreasing since 2010. This decline could be attributed to the reduced correlation between China's commodity prices and external oil price fluctuations following the 2008 global financial crisis. Moreover, the effects of world crude oil prices on China's commodities have steadily decreased since the crisis. However, after some fluctuations, the correlation between certain commodities and world crude oil prices has exhibited an upward trend since 2018, possibly due to the price effect caused by the increased global economic recovery demand. Since 2020, the comovement has shown both upward and downward trends. This is because China has implemented internal price controls when its commodity prices are driven by the rising global commodity prices since 2020. Overall, the comovement between China's commodity futures and the world crude oil prices has deepened.

The dependence coefficient between prices of non-ferrous metals and world crude oil is approximately 0.25. In contrast, agricultural commodity futures, such as cotton, soybean meal and soybean oil, exhibit a lower dependence on world crude oil prices, around 0.15. Regarding classification: (1) Non-ferrous metals: China's zinc production has steadily increased in recent years, making it the largest producer globally. Therefore, the comovement between zinc and world crude oil prices is lower than the other two non-ferrous metal futures. Conversely, the production of copper and aluminium is relatively low, and there is a higher dependence on the foreign market. Therefore, the comovement of copper and aluminium with world crude oil prices fluctuates widely. (2) Steel has always been supplied by China's domestic market, resulting in the lowest comovement with the world crude oil prices among all the commodities in the sample. (3) Fuel oil: As a downstream product of crude oil, fuel oil has a strong comovement with the world crude oil, especially in Southeast Asia, which shows an increasing trend. Under the reform of the price formation mechanism for refined oil products in China in 1998, crude oil prices are set based on international crude oil prices (An et al., 2018). This is one of the primary reasons for the close relationship between China's oil commodities and world crude oil. The dependence of LLDPE on international crude oil prices has increased in recent years, but the overall trend is declining due to the replacement of crude oil with natural gas and coal. (4) Natural rubber: Since China has been promoting the cultivation of domestic natural rubber in recent years, which helps establish a stable supply, the comovement between natural rubber and world crude oil prices has declined rapidly since 2013. Nevertheless, it maintained half the highest level from 2014 to 2018. (5) Agricultural commodities: The overall comovement of agricultural commodities, especially soft commodities, with crude oil, has fallen since 2015. Since soybean no. 1 is consumed on China's domestic market, and the output is limited, the global soybean market relies mainly on supplies from the United States and Brazil. Therefore, the influence of international soybean prices will also pass through China's domestic soybeans market. The comovement between soybean no. 1 and crude oil prices is larger than for the other two kinds of vegetable oils in recent years.

Figure 2: Dynamic copula correlation between different commodities and global crude oil





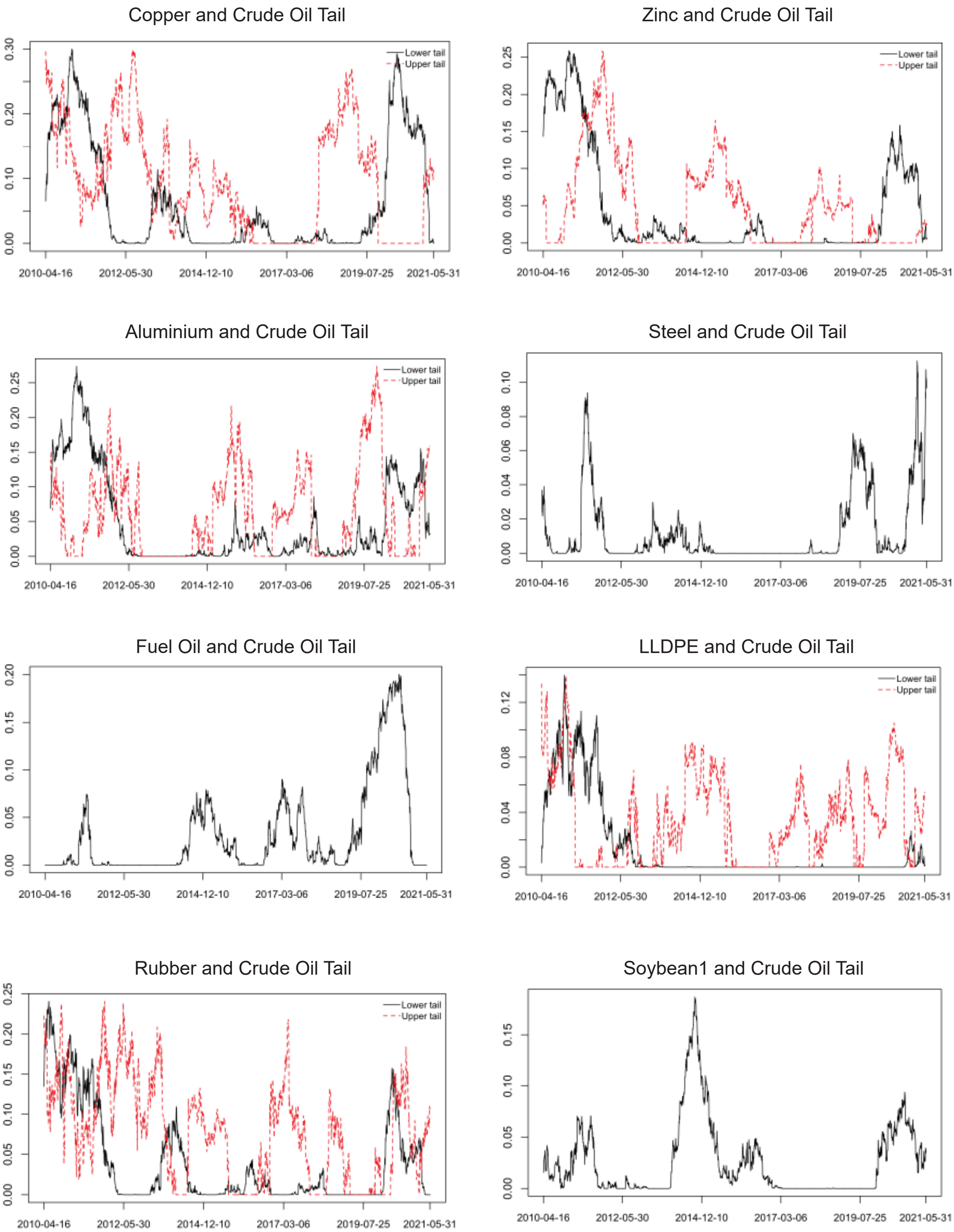
Notes: from left to right, and from top to bottom daily returns for copper, zinc, aluminium, steel, fuel oil, LLDPE, rubber, soybean no. 1, soybean oil, bean pulp, maize, cotton and sugar for the whole sample.
Source: authors' calculations

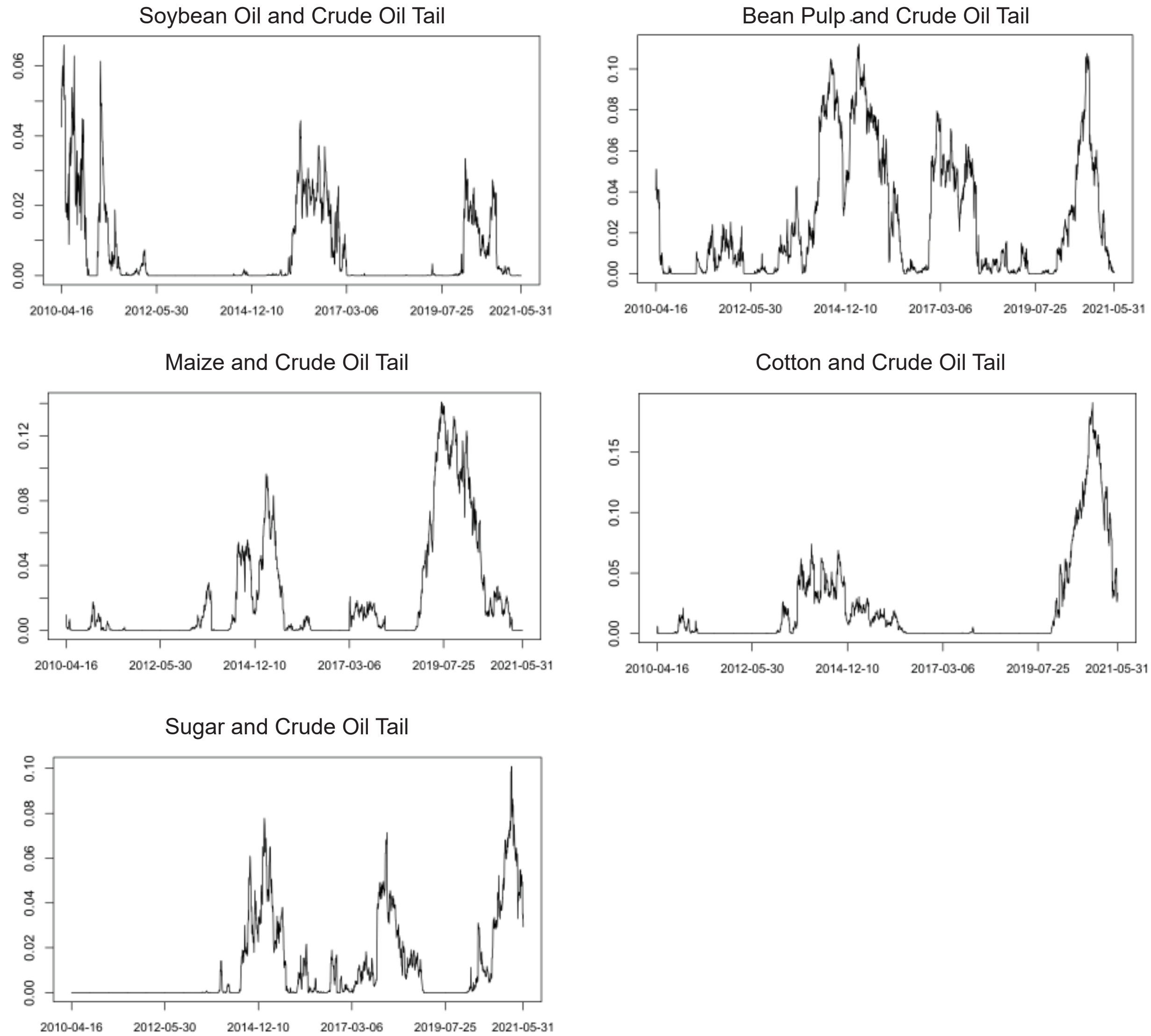
The relationships between China's various commodities and world crude oil prices are illustrated in Figure 3, with a focus on their tail dependences. Non-ferrous metals displayed high volatility in their upper tail dependence, while the lower tail dependence peaked between 2011 and 2012. Copper exhibited a wider range of fluctuations among non-ferrous metals, with a peak of 0.30. Its dependence on world crude oil prices reached its highest point between 2011 and 2012, while the other two non-ferrous metals showed a decreased dependence on crude oil, almost reaching zero between 2013 and 2014. Zinc's upper and lower tail dependences remained close to zero for a long time, indicating its average sensitivity to crude oil price changes. The increase in crude oil prices had a more significant impact on non-ferrous metal commodities than the decrease. LLDPE and rubber also showed a higher dependence on crude oil price increases. The lower tail dependence of LLDPE remained close to zero for a long time, indicating that the systemic risk of extreme price drops in chemical and non-ferrous metal commodities was low. However, the dependence on the upper tail showed an upward trend, emphasizing the need to take the significant rise in world oil prices seriously. The expansion of the crude oil derivatives market and the increasing financialization of crude oil have made energy futures crucial in hedging and speculative trading (Umar et al., 2023). As a result, various linkages between China's specific commodities and world crude oil prices exist during both upward and downward movements.

Additionally, we have examined the symmetric tail-dependent situation over time. The tail dependence of steel remained stable at around zero between 2015 and 2019 but exhibited significant fluctuations from 2019 to 2020. There has been a notable increase in tail dependence on fuel oil in recent years, indicating a higher vulnerability to the transmission of global crude oil risks. Downstream crude oil products have shown a significant rise in tail dependence on crude oil in recent years. Among the three vegetable oil commodities, soybean no. 1 has experienced higher fluctuations in tail dependence, influenced by demand factors. The extreme price movements of these commodities in relation to world crude oil prices have shown higher values in recent years. The tail dependence of agricultural commodities and crude oil remains consistently low, indicating the greater adaptability of China's agricultural product market.

In summary, world crude oil and China's various commodities are critical in portfolio diversification as an asset class (Wang et al., 2022). Commodity types with more stable linkages to world crude oil can be considered risk-hedging assets. In comparison, commodities with stronger linkages to world crude oil can be reasonably risk-averse through inverse operations during rallies and falls.

Figure 3: Tail dependences of dynamic copula between different commodities and global crude oil





Notes: from left to right, and from top to bottom daily returns for copper, zinc, aluminium, steel, fuel oil, LLDPE, rubber, soybean no. 1, soybean oil, bean pulp, maize, cotton and sugar for the whole sample.
Source: authors' calculations

4.5 Time-varying copula estimation

While the non-parametric copula estimation method is convenient, it may face criticisms when estimating static and dynamic copula models, as it is evaluated based on a specific period and may not account for daily changes in dependence. To overcome this limitation, we utilize the parameter method. We apply the GAS copula model to estimate the time variation between the return series of China's commodities and world crude oil prices.

In the first step, we estimate the parameters of the GAS copula to model the relationship between commodity futures and crude oil. The rotated Gumbel and Student's t GAS copula show similar AIC values. According to the AIC, a smaller value indicates better model estimation. Therefore, the Gumbel GAS copula model is suitable for capturing the correlation between zinc, aluminium, rubber, sugar, cotton, and crude oil futures. On the other hand, Student's t GAS copula model is more appropriate for the remaining commodities. The parameter results show that the β values of zinc, aluminium, steel, fuel oil, soybean oil, bean pulp, maize and crude oil under both time-varying models are above 0.9. It suggests that the relationship between zinc and aluminium on the one hand and crude oil on the other is highly influenced by the previous day's values, indicating a strong time-varying effect.

Table 7: Time-varying copula parameter results

	Rotated Gumbel GAS copula				Student's t GAS copula				
	ω	α	β	AIC	ω	α	β	v^{-1}	AIC
Copper	−0.0163 (0.0068)	0.0308 (0.0143)	0.9926 (0.0033)	−85.6408	0.1193 (0.0196)	0.0396 (0.0132)	0.6536 (0.0729)	0.0818 (0.0196)	−87.8073
Zinc	−0.0053 (0.0000)	0.0291 (0.0000)	0.9980 (0.0004)	−77.3424	0.0005 (0.0001)	0.0091 (0.0018)	0.9977 (0.0000)	0.0785 (0.0234)	−69.2400
Aluminium	−0.0116 (0.0007)	0.0323 (0.0148)	0.9950 (0.0004)	−77.9619	0.0019 (0.0003)	0.0103 (0.0069)	0.9937 (0.0000)	0.0524 (0.0145)	−70.1901
Steel	−0.2502 (0.4130)	−0.1155 (0.0996)	0.9203 (0.1384)	−9.6883	0.0025 (0.0009)	−0.0203 (0.0029)	0.9796 (0.0000)	0.0635 (0.0724)	−16.9973
Fuel oil	−0.0409 (0.0059)	0.0647 (0.0254)	0.9832 (0.0029)	−68.6710	0.0120 (0.0024)	0.0391 (0.0104)	0.9514 (0.0000)	0.1147 (0.0181)	−80.4023
LLDPE	−0.4886 (0.5747)	0.2041 (0.3853)	0.8480 (0.1585)	−14.9572	0.0269 (0.0179)	0.0293 (0.0175)	0.8190 (0.1257)	0.0503 (0.0481)	−17.2987
Rubber	−0.0133 (0.0014)	0.0553 (0.0278)	0.9946 (0.0009)	−79.6846	0.2976 (0.0412)	−0.0550 (0.0163)	0.0000 (0.0000)	0.0631 (0.0108)	−64.3619
Soybean no. 1	−0.1226 (0.0000)	0.1154 (0.0406)	0.9599 (0.0040)	−14.9188	0.0811 (0.0315)	0.0153 (0.0052)	0.3400 (0.0952)	0.0929 (0.0255)	−19.7814
Soybean oil	−0.2012 (0.1573)	−0.0285 (0.0733)	0.9499 (0.0411)	1.3541	0.0040 (0.0004)	−0.0237 (0.0028)	0.9094 (0.0447)	0.0340 (0.0027)	0.9067
Bean pulp	−0.0038 (0.0006)	−0.0225 (0.0137)	0.9990 (0.0002)	−11.1035	0.0092 (0.4092)	−0.0262 (0.3752)	0.9134 (2.8206)	0.1031 (0.4268)	−24.3104
Maize	−0.1162 (0.5559)	0.1107 (0.2683)	0.9695 (0.1476)	−0.2513	0.0073 (0.0077)	0.0193 (0.0167)	0.9124 (0.0864)	0.0687 (0.0232)	−7.8500
Sugar	−0.0147 (0.0115)	0.0261 (0.0173)	0.9954 (0.0037)	−21.5206	0.1283 (0.0229)	−0.0421 (0.0094)	0.0000 (0.0000)	0.0589 (0.0184)	−13.8893
Cotton	−0.0151 (0.0136)	0.0362 (0.0244)	0.9953 (0.0043)	−21.3637	0.1279 (0.0356)	−0.0475 (0.0230)	0.0000 (0.0000)	0.0594 (0.0184)	−13.6096

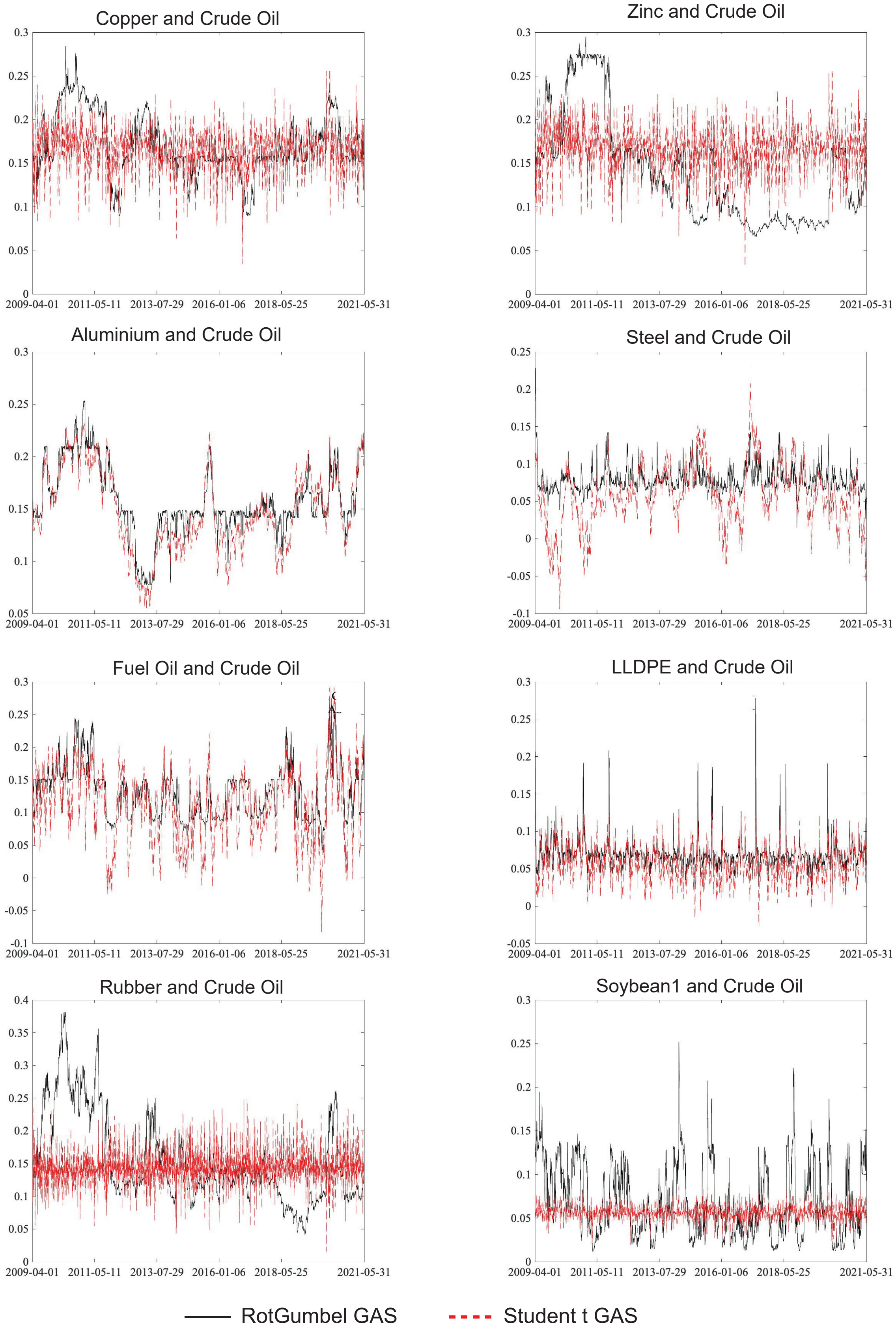
Source: authors' calculations

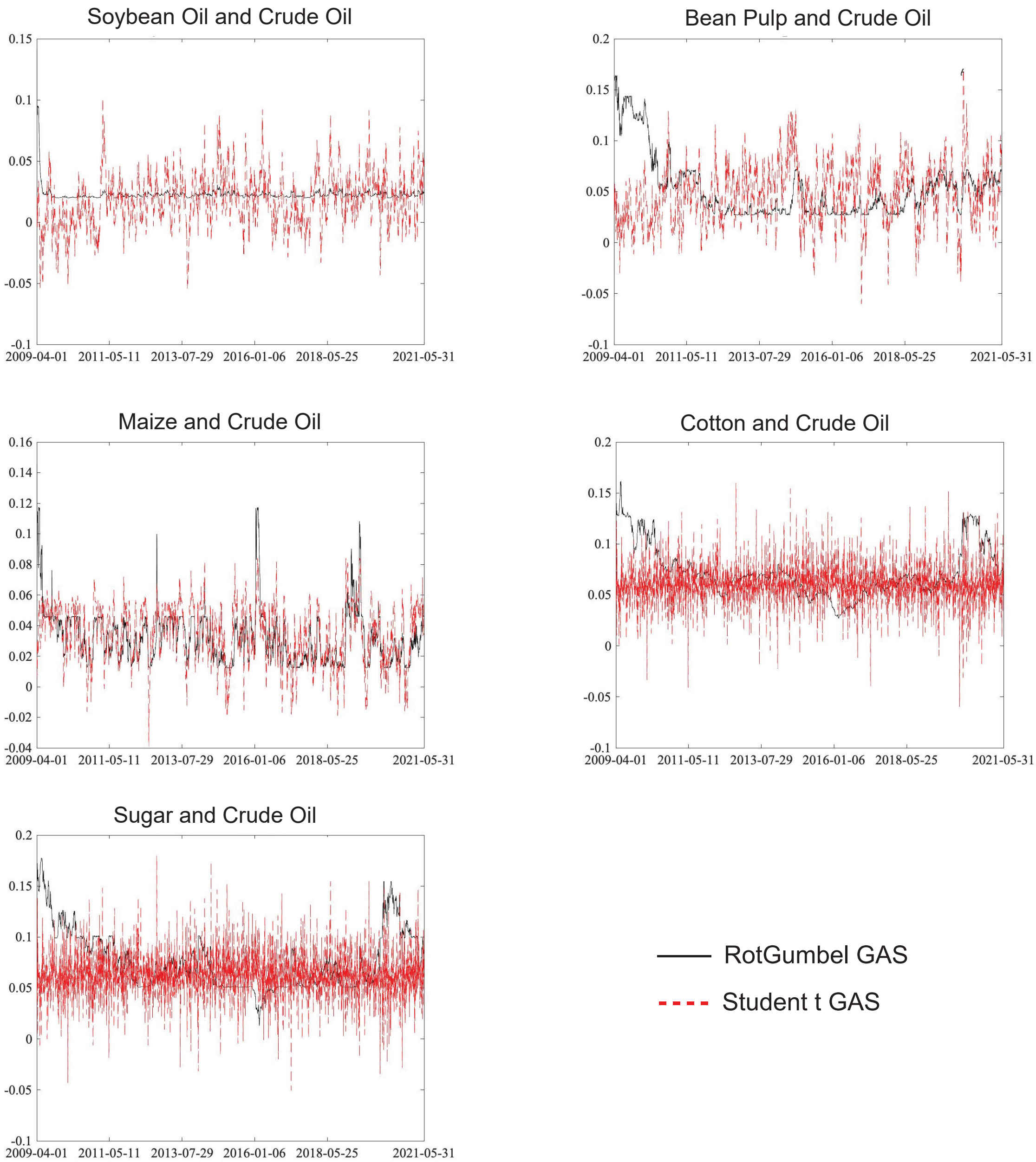
Figure 4 illustrates the time-varying correlation between China's commodities and world crude oil prices. The fitted results of the two models reveal that the fluctuations of the Gumbel GAS copula are smoother compared to those of Student's t GAS copula. The activity associated with Student's t GAS copula oscillates up and down. For instance, the comovement between copper and world crude oil prices peaked at 0.25 to 0.3 in 2010, declined in 2011, and remained around 0.15 after that. Conversely, zinc exhibited little change, staying between 0.10 and 0.15 for an extended period. The comovement of aluminium under both models declined from 2010 to 2013, experienced a rebound in 2013, and fluctuated around 0.15. Notably, since 2021, it has shown a significant increase.

The dependence parameter between steel and crude oil exhibited an oscillation around 0.07, while the dependence parameter between fuel oil and crude oil peaked between 0.25 and 0.3, with fluctuations around 0.1. The dependence between LLDPE and crude oil was particularly susceptible to extreme events, reaching as high as 0.28 at very few time points. The dependence parameter between rubber and crude oil showed significant variations under the two fitted models. The optimal Gumbel GAS copula model revealed a high dependence parameter from 2010 to 2011, reaching up to 0.38, and a stable dependence parameter of around 0.10 since 2020. Compared to non-ferrous metals and chemical products, the correlation between the three vegetable oils and crude oil was relatively lower, hovering around 0.05. The correlation between agricultural commodities and world crude oil prices also remained low, declining from the peak of 0.12 to 0.15 in 2009 to a range between 0.02 and 0.05, indicating a relatively stable reaction to crude oil price changes.

In summary, commodities for which China is more involved in foreign trade tended to exhibit stronger time-varying comovement with crude oil prices. Furthermore, crude oil shocks can affect the exchange rate market between the US dollar and other currency countries, as linkages are observed over time between crude oil prices and exchange rates (Yang et al., 2017). These factors can further influence the price changes of China's foreign trade commodities.

Figure 4: Time-varying copula dependence parameters





Notes: From left to right, and from top to bottom daily returns for copper, zinc, aluminium, steel, fuel oil, LLDPE, rubber, soybean no. 1, soybean oil, bean pulp, maize, cotton and sugar for the whole sample.

Source: authors' calculations

5. Conclusions and policy recommendations

The purpose of this paper was to analyse how China's commodities and world crude oil prices are related in terms of their comovement. The return series of China's commodities show weak autocorrelation, asymmetric leverage, and significant conditional heteroscedasticity.

Additionally, the distribution of these returns indicates non-normality due to excess kurtosis and heavy tails. To effectively capture these characteristics, we used GAS models, which are suitable for modelling nonlinear and time-varying relationships. We also employed nonlinear Granger causality analysis to examine the causal relationship between world crude oil prices and China's commodities. To measure the comovement and dependences between these variables, we used various copula models, including static, dynamic, and time-varying copulas. This comprehensive approach helped us understand the interdependence and transmission dynamics between world crude oil prices and China's commodities.

The study's results indicate that world crude oil prices have a significant impact on China's commodities in a nonlinear fashion. China's commodities and world crude oil prices exhibit a positive correlation, but the strength of this dependence varies among different commodities. Commodities that rely heavily on imports, such as non-ferrous metals and natural rubber, have a stronger correlation with world crude oil prices due to the impact of international market pricing on foreign trade commodities and the crucial role of crude oil prices in the production and transportation of industrial commodities. Additionally, the world crude oil price has a strong association with the US dollar exchange rate, which can affect the settlement price fluctuations of industrial commodities. However, the correlation between China's other agricultural commodities and world crude oil prices is relatively limited, as domestic market factors have a more significant influence. It is noteworthy that white sugar shows weak lower tail dependence on world crude oil prices, thanks to China's effective regulatory measures on agricultural commodity prices.

From a dynamic perspective, the comovement between China's commodities and world crude oil prices has declined during the early sample period, followed by an increase since the 2008 global financial crisis. This trend can be attributed to the price linkage effect resulting from the subsequent global economic recovery. In terms of tail dependence, there are significant variations in the overall linkage between China's commodities and extreme price movements of crude oil, as indicated by the characteristics of the optimal copula function.

The analysis revealed interesting findings regarding the tail dependence of non-ferrous metals, LLDPE, rubber and other commodities on world crude oil prices. Specifically, the lower tail dependence of non-ferrous metals, LLDPE and rubber has declined, indicating a reduced risk associated with extreme declines in global crude oil prices. However, the upper tail dependence exhibited an upward trend, highlighting the need to consider the potential risks of sharp increases in world crude oil prices. Non-ferrous metals showed significant upper tail linkages with world crude oil prices, indicating a stronger comovement driven by higher prices. It can be attributed to the financialization of China's commodity markets and the cross-market capital flows, which have facilitated the integration of energy and other markets. These factors have contributed to changes in tail linkages that are more sensitive to price increases (Hau et al., 2020).

Regarding symmetrical tail dependence, fuel oil has experienced a notable increase in recent years, indicating its vulnerability to the transmission of risk from world crude oil prices and its susceptibility to the import scale. Additionally, the range of tail dependence for soybean no. 1 is higher than for the other two vegetable oil commodities. Nevertheless, the tail dependence between each agricultural commodity and world crude oil prices remains consistent. Overall, these findings shed light on the complex dynamics of tail dependence and highlight the interplay between commodities and international crude oil prices on the global market.

This study utilized time-varying copulas to analyse the relationship between China's commodities and world crude oil prices. The Gumbel GAS copula demonstrated smoother fluctuations than Student's t-GAS copula, indicating more volatile connections. The dependence between non-ferrous metals and crude oil fluctuates around 0.15, peaking between 0.25 and 0.3 after the financial crisis. The growing popularity of derivatives and index investment products has amplified cross-market speculation and portfolio adjustment, potentially intensifying inter-market interactions on commodity markets (Zhang and Broadstock, 2020). Since 2021, there has been a notable increase in the correlation between aluminium and crude oil, while the comovement between fuel oil and crude oil has reached its highest point at 0.25–0.3. The dependence of the LLDPE-oil pair is sensitive to extreme events. Comparatively, the comovement between vegetable oils and crude oil is lower than that for non-ferrous metals and chemical commodities. On the other hand, the linkage reaction of agricultural futures to crude oil prices remains relatively stable.

Investors and policymakers can gain valuable insights from these findings regarding market management and investment. While allocating assets across different markets, it is important to consider the ever-changing correlation between world crude oil prices and China's various commodity types. The disproportionate impact of upward volatility in world crude oil prices should also be kept in mind. In addition, the ripple effects of external crisis events should be closely monitored. Policy regulators should implement and maintain real-time monitoring of inter-market linkages and take proactive measures to stabilize diverse commodity markets, thus mitigating market shocks stemming from excessive speculation. As China's commodity markets continue to develop, their interdependence with global markets will remain susceptible to persistent volatility.

References

Adams, Z., Collot, S., Kartsakli, M. (2020). Have Commodities Become a Financial Asset? Evidence from Ten Years of Financialization. *Energy Economics*, 89, 104769. https://doi.org/10.1016/j.eneco.2020.104769

Adams, Z., Glück, T. (2015). Financialization in Commodity Markets: A Passing Trend or the New Normal? *Journal of Banking & Finance*, 60, 93–111. https://doi.org/10.1016/j.jbankfin.2015.07.008

Adhikari, R., Putnam, K. J. (2020). Comovement in the Commodity Futures Markets: An Analysis of the Energy, Grains, and Livestock Sectors. *Journal of Commodity Markets*, 18, 100090. https://doi.org/10.1016/j.jcomm.2019.04.002

Ahmadi, M., Bashiri Behmiri, N., Manera, M. (2016). How is Volatility in Commodity Markets Linked to Oil Price Shocks? *Energy Economics*, 59, 11–23. https://doi.org/10.1016/j.eneco.2016.07.006

Alquist, R., Bhattarai, S., Coibion, O. (2020). Commodity-price Comovement and Global Economic Activity. *Journal of Monetary Economics*, 112, 41–56. https://doi.org/10.1016/j.jmoneco.2019.02.004

An, Y., Sun, M., Gao, C., Han, D., Li, X. (2018). Analysis of the Impact of Crude Oil Price Fluctuations on China's Stock Market in Different Periods – Based on Time Series Network Model. *Physica A: Statistical Mechanics and its Applications*, 492, 1016–1031. https://doi.org/10.1016/j.physa.2017.11.032

Balcilar, M., Gabauer, D., Umar, Z. (2021). Crude Oil Futures Contracts and Commodity Markets: New Evidence from a tvp-var Extended Joint Connectedness Approach. *Resources Policy*, 73, 102219. https://doi.org/10.1016/j.resourpol.2021.102219

Basak, S., Pavlova, A. (2016). A Model of Financialization of Commodities. *The Journal of Finance*, 71, 1511–1556. https://doi.org/10.1111/jofi.12408

Cai, G., Zhang, H., Chen, Z. (2019). Comovement between Commodity Sectors. *Physica A: Statistical Mechanics and its Applications*, 525, 1247–1258. https://doi.org/10.1016/j.physa.2019.04.116

Charfeddine, L., Benlagha, N. (2016). A Time-varying Copula Approach for Modelling Dependency: New Evidence from Commodity and Stock Markets. *Journal of Multinational Financial Management*, 37–38, 168–189. https://doi.org/10.1016/j.mulfin.2016.10.003

Creal, D., Koopman, S. J., Lucas, A. (2013). Generalized Autoregressive Score Models with Applications. *Journal of Applied Econometrics*, 28, 777–795. https://doi.org/10.1002/jae.1279

Csörgő, S., Faraway, J. J. (1996). The Exact and Asymptotic Distributions of Cramér-von Mises Statistics. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58, 221–234. https://doi.org/10.1111/j.2517-6161.1996.tb02077.x

Dahl, R. E., Oglend, A., Yahya, M. (2020). Dynamics of Volatility Spillover in Commodity Markets: Linking Crude Oil to Agriculture. *Journal of Commodity Markets*, 20, 100111. https://doi.org/10.1016/j.jcomm.2019.100111

Du, X., Yu, C. L., Hayes, D. J. (2011). Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis. *Energy Economics*, 33, 497–503. https://doi.org/10.1016/j.eneco.2010.12.015

Engle, R. (2009) *Anticipating Correlations: A New Paradigm for Risk Management*. Princeton University Press.

Fernandez, V. (2015). Commodity Price Excess Co-movement From a Historical Perspective: 1900–2010. *Energy Economics*, 49, 698–710. https://doi.org/10.1016/j.eneco.2015.04.003

Fowowe, B. (2016). Do Oil Prices Drive Agricultural Commodity Prices? Evidence from South Africa. *Energy*, 104, 149–157. https://doi.org/10.1016/j.energy.2016.03.101

Fretheim, T. (2019). An Empirical Analysis of the Correlation between Large Daily Changes in Grain and Oil Futures Prices. *Journal of Commodity Markets*, 14, 66–75. https://doi.org/10.1016/j.jcomm.2018.07.002

Ghorbel, A., Hamma, W., Jarboui, A. (2016). Dependence between Oil and Commodities Markets using Time-varying Archimedean Copulas and Effectiveness of Hedging Strategies. *Journal of Applied Statistics*, 44, 1509–1542. https://doi.org/10.1080/02664763.2016.1155107

Gilbert, C. L. (2010). How to Understand High Food Prices. *Journal of Agricultural Economics*, 61, 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x

Gu, F., Wang, J. Q., Guo, J. F., Fan, Y. (2020). Dynamic Linkages between International Oil Price, Plastic Stock Index and Recycle Plastic Markets in China. *International Review of Economics & Finance*, 68, 167–179. https://doi.org/10.1016/j.iref.2020.03.015

Guhathakurta, K., Dash, S. R., Maitra, D. (2020). Period Specific Volatility Spillover Based Connectedness between Oil and Other Commodity Prices and Their Portfolio Implications. *Energy Economics*, 85, 104566. https://doi.org/10.1016/j.eneco.2019.104566

Hamilton, J. D. (1996). This Is What Happened to the Oil Price Macroeconomy Relationship. *Journal of Monetary Economics*, 38, 215–220. https://doi.org/10.1016/S0304-3932(96)01282-2

Hammoudeh, S., Yuan, Y. (2008). Metal Volatility in Presence of Oil and Interest Rate Shocks. *Energy Economics*, 30, 606–620. https://doi.org/10.1016/j.eneco.2007.09.004

Hau, L., Zhu, H., Huang, R., Ma, X. (2020). Heterogeneous Dependence between Crude Oil Price Volatility and China's Agriculture Commodity Futures: Evidence from Quantile-on-Quantile Regression. *Energy*, 213, 118781. https://doi.org/10.1016/j.energy.2020.118781

Huang, X., Huang, S. (2020). Identifying the Comovement of Price between China's and International Crude Oil Futures: A Time-frequency Perspective. *International Review of Financial Analysis*, 72, 101562. https://doi.org/10.1016/j.irfa.2020.101562

Joe, H., Xu, J. J. (1996) The Estimation Method of Inference Functions for Margins for Multivariate Models. http://dx.doi.org/10.14288/1.0225985.

Kang, S. H., McIver, R., Yoon, S.-M. (2017). Dynamic Spillover Effects among Crude Oil, Precious Metal, and Agricultural Commodity Futures Markets. *Energy Economics*, 62, 19–32. https://doi.org/10.1016/j.eneco.2016.12.011

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, 99, 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Koirala, K. H., Mishra, A. K., D'Antoni, J. M., Mehlhorn, J. E. (2015). Energy Prices and Agricultural Commodity Prices: Testing Correlation Using Copulas Method. *Energy*, 81, 430–436. https://doi.org/10.1016/j.energy.2014.12.055

Li, M., Yang, L. (2013). Modeling the Volatility of Futures Return in Rubber and Oil – a Copula-Based GARCH Model Approach. *Economic Modelling*, 35, 576–581. https://doi.org/10.1016/j.econmod.2013.07.016

Liu, F., Zhang, C., Tang, M. (2021). The Impacts of Oil Price Shocks and Jumps on China's Nonferrous Metal Markets. *Resources Policy*, 73, 102228. https://doi.org/10.1016/j.resourpol.2021.102228

Liu, S., Fang, W., Gao, X., An, F., Jiang, M., Li, Y. (2019). Long-term Memory Dynamics of Crude Oil Price Spread in Non-dollar Countries under the Influence of Exchange Rates. *Energy*, 182, 753–764. https://doi.org/10.1016/j.energy.2019.06.072

López Cabrera, B., Schulz, F. (2016). Volatility Linkages between Energy and Agricultural Commodity Prices. *Energy Economics*, 54, 190–203. https://doi.org/10.1016/j.eneco.2015.11.018

Lucotte, Y. (2016). Co-Movements between Crude Oil and Food Prices: a Post-Commodity Boom Perspective. *Economics Letters*, 147, 142–147. https://doi.org/10.1016/j.econlet.2016.08.032

Ma, Z., Xu, R., Dong, X. (2015). World Oil Prices and Agricultural Commodity Prices: the Evidence from China. *Agricultural Economics (Zemědělská ekonomika)*, 61, 564–576. https://doi.org/10.17221/6/2015-AGRICECON

Mo, K., Suvankulov, F., Griffiths, S. (2021). Financial Distress and Commodity Hedging: Evidence from Canadian Oil Firms. *Energy Economics*, 97, 105162. https://doi.org/10.1016/j.eneco.2021.105162

Mohammadi, H., Su, L. (2010). International Evidence on Crude Oil Price Dynamics: Applications of ARIMA-GARCH Models. *Energy Economics*, 32, 1001–1008. https://doi.org/10.1016/j.eneco.2010.04.009

Mokni, K. (2020). A Dynamic Quantile Regression Model for the Relationship Between Oil Price and Stock Markets in Oil-Importing and Oil-Exporting Countries. *Energy*, 213, 118–639. https://doi.org/10.1016/j.energy.2020.118639

Nazlioglu, S. (2011). World Oil and Agricultural Commodity Prices: Evidence from Nonlinear Causality. *Energy Policy*, 39, 2935–2943. https://doi.org/10.1016/j.enpol.2011.03.001

Nazlioglu, S., Soytas, U. (2011). World Oil Prices and Agricultural Commodity Prices: Evidence from an Emerging Market. *Energy Economics*, 33, 488–496. https://doi.org/10.1016/j.eneco.2010.11.012

Nicola, F. d., De Pace, P., Hernandez, M. A. (2016). Co-Movement of Major Energy, Agricultural, and Food Commodity Price Returns: a Time-Series Assessment. *Energy Economics*, 57, 28–41. https://doi.org/10.1016/j.eneco.2016.04.012

Paris, A. (2018). On the Link Between Oil and Agricultural Commodity Prices: Do Biofuels Matter? *International Economics*, 155, 48–60. https://doi.org/10.1016/j.inteco.2017.12.003

Patton, A. (2013) Chapter 16 - Copula Methods for Forecasting Multivariate Time Series. In: Elliott, G. and Timmermann, A., (eds.) *Handbook of economic forecasting*, Elsevier.

Patton, A. J. (2006). Modelling Asymmetric Exchange Rate Dependence. *International Economic Review*, 47, 527–556. https://doi.org/10.1111/j.1468-2354.2006.00387.x

Pindyck, R. S., Rotemberg, J. J. (1990). The Excess Co-Movement of Commodity Prices. *The Economic Journal*, 100, 1173–1189. https://doi.org/10.2307/2233966

Qian, C., Zhang, T., Li, J. (2023). The Impact of International Commodity Price Shocks on Macroeconomic Fundamentals: Evidence From the US and China. *Resources Policy*, 85, 103904. https://doi.org/10.1016/j.resourpol.2023.103904

Rafiq, S., Bloch, H. (2016). Explaining Commodity Prices Through Asymmetric Oil Shocks: Evidence from Nonlinear Models. *Resources Policy*, 50, 34–48. https://doi.org/10.1016/j.resourpol.2016.08.005

Reboredo, J. C. (2012). Do Food and Oil Prices Co-Move? *Energy Policy*, 49, 456–467. https://doi.org/10.1016/j.enpol.2012.06.035

Reboredo, J. C., Rivera-Castro, M. A. (2014). Wavelet-Based Evidence of the Impact of Oil Prices on Stock Returns. *International Review of Economics & Finance*, 29, 145–176. https://doi.org/10.1016/j.iref.2013.05.014

Sklar, M. (1959). Fonctions de Répartition À n Dimensions et Leurs Marges. *Publications de l'Institut Statistique de l'Université de Paris*, 8, 3.

Song, M. L., Fang, K. N., Zhang, J., Wu, J. B. (2019). The Co-Movement between Chinese Oil Market and Other Main International Oil Markets: a DCC-MGARCH Approach. *Computational Economics*, 54, 1303–1318. https://doi.org/10.1007/s10614-016-9564-5

Tomanová, P., Holý, V. (2021). Clustering of Arrivals in Queueing Systems: Autoregressive Conditional Duration Approach. *Central European Journal of Operations Research*, 29, 859–874. https://doi.org/10.1007/s10100-021-00744-7

Uebele, M. (2013). What Drives Commodity Market Integration? Evidence from the 1800s. *CESifo Economic Studies*, 59, 412–442. https://doi.org/.10.1093/cesifo/ifs009

Umar, M., Mirza, N., Rizvi, S. K. A., Furqan, M. (2023). Asymmetric Volatility Structure of Equity Returns: Evidence from an Emerging Market. *The Quarterly Review of Economics and Finance*, 87, 330–336. https://doi.org/10.1016/j.qref.2021.04.016

Umar, Z., Jareño, F., Escribano, A. (2021). Oil Price Shocks and the Return and Volatility Spillover between Industrial and Precious Metals. *Energy Economics*, 99, 105–291. https://doi.org/10.1016/j.eneco.2021.105291

Wang, L., Ahmad, F., Luo, G.-l., Umar, M., Kirikkaleli, D. (2022). Portfolio Optimization of Financial Commodities with Energy Futures. *Annals of Operations Research*, 313, 401–439. https://doi.org/10.1007/s10479-021-04283-x

Wright, B. D. (2011). The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy*, 33, 32–58. https://doi.org/10.1093/aepp/ppq033

Wu, F., Zhao, W. L., Ji, Q., Zhang, D. Y. (2020). Dependency, Centrality and Dynamic Networks for International Commodity Futures Prices. *International Review of Economics & Finance*, 67, 118–132. https://doi.org/10.1016/j.iref.2020.01.004

Yahya, M., Oglend, A., Dahl, R. E. (2019). Temporal and Spectral Dependence between Crude Oil and Agricultural Commodities: a Wavelet-Based Copula Approach. *Energy Economics*, 80, 277–296. https://doi.org/10.1016/j.eneco.2019.01.011

Yang, L., Cai, X. J., Hamori, S. (2017). Does the Crude Oil Price Influence the Exchange Rates of Oil-Importing and Oil-Exporting Countries Differently? A Wavelet Coherence Analysis. *International Review of Economics & Finance*, 49, 536–547. https://doi.org/10.1016/j.iref.2017.03.015

Yin, L., Han, L. (2016). Macroeconomic Impacts on Commodity Prices: China Vs. The United States. *Quantitative Finance*, 16, 489–500. https://doi.org/10.1080/14697688.2015.1018308

Zavadska, M., Morales, L., Coughlan, J. (2020). Brent Crude Oil Prices Volatility During Major Crises. *Finance Research Letters*, 32, 101078. https://doi.org/10.1016/j.frl.2018.12.026

Zhang, C., Chen, X. (2014). The Impact of Global Oil Price Shocks on China's Bulk Commodity Markets and Fundamental Industries. *Energy Policy*, 66, 32–41. https://doi.org/10.1016/j.enpol.2013.09.067

Zhang, C., Qu, X. (2015). The Effect of Global Oil Price Shocks on China's Agricultural Commodities. *Energy Economics*, 51, 354–364. https://doi.org/10.1016/j.eneco.2015.07.012

Zhang, C., Shi, X., Yu, D. (2018). The Effect of Global Oil Price Shocks on China's Precious Metals Market: a Comparative Analysis of Gold and Platinum. *Journal of Cleaner Production*, 186, 652–661. https://doi.org/10.1016/j.jclepro.2018.03.154

Zhang, D., Broadstock, D. C. (2020). Global Financial Crisis and Rising Connectedness in the International Commodity Markets. *International Review of Financial Analysis*, 68, 101239. https://doi.org/10.1016/j.irfa.2018.08.003

Zhang, K.-S., Zhao, Y.-Y. (2021). Modeling Dynamic Dependence Between Crude Oil and Natural Gas Return Rates: a Time-Varying Geometric Copula Approach. *Journal of Computational and Applied Mathematics*, 386, 113243. https://doi.org/10.1016/j.cam.2020.113243

Zhang, X., Xiao, J., Zhang, Z. (2020). An Anatomy of Commodity Futures Returns in China. *Pacific-Basin Finance Journal*, 62, 101366. https://doi.org/10.1016/j.pacfin.2020.101366