

**Could COVID-19 induce China's commodity price jumps? An
information spillover and wavelet coherency analysis**

Xingyu Dai

*College of Economics and Management, Nanjing University of Aeronautics and
Astronautics, Nanjing 211106, China*

*Research Center for Soft Energy Science, Nanjing University of Aeronautics and
Astronautics, Nanjing 211106, China*

Matthew C. Li *

(Corresponding author, matthew.li@rhul.ac.uk)

Royal Holloway University of London, Egham TW20 0EX, United Kingdom

Ling Xiao

Royal Holloway University of London, Egham TW20 0EX, United Kingdom

Qunwei Wang

*College of Economics and Management, Nanjing University of Aeronautics and
Astronautics, Nanjing 211106, China*

*Research Center for Soft Energy Science, Nanjing University of Aeronautics and
Astronautics, Nanjing 211106, China*

Abstract: Jumps in commodity prices can make asset risk management challenging. This study explores the influence feature of the COVID-19 epidemic on China's commodity price jumps, using 5-minute intraday high-frequency futures data of three China's commodity markets (energy, chemical, and metal) from January 23, 2020 to June 10, 2022. We find that firstly the information spillover from the COVID-19 spread situation to China's energy price jumps is relatively weak, and the COVID-19 epidemic shows the most substantial jump information spillover pattern to China's chemical price. The information spillover pattern is time-varying across the COVID-19 spread situation phase. Secondly, there are co-movement patterns between China's commodity price and China/global COVID-19 confirmed cases. This co-movement feature mainly occurs at the medium- or long-run time scales and varies across commodities. Thirdly, the demand elasticity for China's commodities and its dependence on imports and exports are the main factors influencing the sensitivity of its price jumps to the COVID-19 outbreak.

Keywords: COVID-19; Commodity market prices; High-frequency data; Price jumps; Information spillover; Wavelet coherency

1. Introduction

Jump processes could be caused by unexpected market information (Pan et al., 2020), which could cause returns and volatility to change rapidly, thus affecting participants' (commodity market investors, exporters, and importers) decisions on portfolio construction and price forecasting (Wang, 2020; Zhou et al., 2019). Such jump risk should be mainly a concern under the "once-in-a-century" COVID-19 pandemic (Gates, 2020). Since the first COVID-related death in January 2020, the Chinese government has taken the strongest and speediest regulatory actions against the outbreak. Nevertheless, commodity price jumps have been observed in the pandemic.¹ This study explores the influence feature of the COVID-19 epidemic on China's commodity price jumps.

The jumping behavior in commodity price follows a different pattern of movement from that based on changes in returns or volatility, and has been widely used in recent years in portfolio construction and risk management. In the general case, the pattern of movement of commodity prices obeys a Geometric Brownian Motion (GBM), *i.e.*, the price of a commodity consists of a drift term reflecting changes in the mean, and a fluctuation term reflecting changes in the variance (Tong et al., 2022). However, some studies have found that the movement pattern of commodity prices is likely to add a jump term to the GBM. This jump term is not reflected in the variance change (Pan et al., 2020; Wang et al., 2020, and also see Appendix A). It implies that the mean term, the variance term, and the jump drive commodity prices simultaneously, while if we ignore the jump term, then we cannot accurately fit the price movement pattern. Indeed, several studies have found that jumps in commodity prices affect changes in the

¹As the pandemic evolved, crude oil prices quickly plummeted from \$65.15 per barrel in January 2020 to a new low of \$24.96 per barrel, even diving into negative prices in March, exhibiting significant price jump risk.

variance and mean of commodity prices (Alqahtani et al., 2021; Bouri et al., 2021; Cao et al., 2018; Liu et al., 2020). Exploring the interaction between the COVID-19 outbreak and the commodity price jumps in China is a thought-provoking topic, and offers market participants a better risk management perspective. Furthermore, being a powerful commodity trading nation (exports and imports), information on China's commodity market movements is highly relevant to market stakeholders worldwide.

Existing studies have documented that pandemics can cause disasters to the financial and commodity markets (Corbet et al., 2020; Baker et al., 2020; Goodell and Huynh, 2020; Ji et al., 2020). However, most of them have focused on the impact of the COVID-19 pandemic on price shocks, yet overlooking price jumps that are genuinely detrimental to risk management work. China is the world's largest consumer and producer of most primary commodities (Fernandes, 2020) and plays a pivotal role in the global economy (Gusarova, 2019). It is beneficial to examine how the COVID-19 outbreak initially started in China has contributed to Chinese commodities' price jumps. This study explores the influence feature of the COVID-19 epidemic on China's commodity price jumps, and provides insights into price forecasting and risk hedging for Chinese commodity market participants by informing them of the attitude with which exogenous shocks to prices should be viewed.

This study adds new insights into the effects of COVID-19 on commodity market price movements, and we make at least three contributions to the subject matter. First, we uncover and depict the jump characteristics in COVID-19 that enhance the understanding of a pandemic's impact on commodity markets. To the best of our knowledge, this is the first paper that examines commodity price jumps in COVID-19 instead of commodity price volatility. We study the interaction between the COVID-19 situation proxy data and three China commodity markets data (energy, chemicals, and

metals) and use the cutting-edge information spillover model and wavelet coherency method to reveal the magnitude and dynamic characteristics of this impact. Our findings help investors enhance their knowledge of risk-hedging and extend existing research (e.g., Yarovaya et al. 2020) from a critical perspective.

Secondly, this paper explores how COVID-19 has impacted the Chinese commodity markets when most of the research has primarily focused on developed markets. Exploring Chinese commodity markets offers us the advantage of further understanding emerging markets' sensitivity to major black swan events such as a pandemic.

Thirdly, using the jump test proposed by Barndorff-Nielsen & Shephard (2006), we identify jump characteristics in high-frequency data, providing more reliable information in understanding market characteristics in a pandemic (Mensi et al., 2020). Although many studies utilize daily data to describe the nature of price movements, the robustness of these results may be affected by empirical analysis based on a relatively small amount of data, as such daily data do not seem to satisfy the "burn period" for which most time series model parameters are fitted. The stability of the jump results generated through high-frequency data overcomes the realistic context of a small sample data.

The rest of this paper is as follows. Section 2 is the literature review. Section 3 introduces the methodology. Section 4 describes data selection. Section 5 discusses our empirical findings, and section 6 concludes the paper.

2. Literature review

The impact of COVID-19 on China's commodity markets has been complex and profound via domestic and worldwide channels. At the beginning of the outbreak, the

Chinese government insisted on a "zero-COVID" policy, such as lockdown or restrictions on population movement, which significantly weakened consumer demand and production incentives for all types of commodities (Deng, 2022; Mensi et al., 2021; Ma et al., 2021; Chen et al., 2022; Umar et al., 2021). China's COVID19-related policy is uncommon in other developed or emerging countries, and it will undoubtedly come at the expense of economic development (Guo et al., 2022). In addition, the global COVID-19 spread trend will also affect Chinese commodity markets due to China's dependence on exports and the fact that Chinese commodity prices are highly influenced by international commodity prices (Ahmed and Huo, 2021). In a word, COVID-19 could influence China's commodities markets via many channels.

Firstly, the lockdown in China's "Zero-COVID" policy will significantly impact the energy market, especially the crude oil market. The significant reduction in the transport of China's goods and people has led directly to a decline in energy consumption (Narayan, 2020; Selmi, 2022), energy supply (Akhtaruzzaman et al., 2021), and China's energy firms (Tong et al., 2022). Especially, crude oil is the blood of the industry, and fluctuations in crude oil prices are easily transmitted to other commodity prices (Kang et al., 2017; Umar et al., 2021). This kind of spillover effect is likely to affect the energy sector from other commodity sectors (Tiwari et al., 2020), eventually allowing the impact of COVID-19 in the energy sector to spread to several commodity sectors in China.

Secondly, the COVID-19 situation in China may directly interrupt Chinese commodities' consumption and production. Fei et al. (2020) states that supply chain disruptions are a major challenge for the food market in China. Further, Li et al. (2021) finds that the COVID-19 outbreak changed the original structure of the industry-related network, directly influencing the consumption and supply of metal and chemical

commodities in China. As mentioned above, movements in the prices of these commodities could still interact with each other in the COVID-19 epidemic to shake up China's commodity markets (Jiang and Chen, 2022).

Last but not least, the macro factors, including the COVID-19 shocks from international commodity prices and China's macro economy, would play an essential role in making waves in China's commodity markets. The prices of China's significant commodities are mainly led by their corresponding futures markets (Chen and Tongurai, 2022). However, prices in China's futures markets are heavily influenced by international commodity futures markets (Kang and Yoon, 2016). Since the outbreak of COVID-19, the impact of the global recession and logistical disruptions on commodity markets has been unprecedented (Farid et al., 2022; Selmi et al., 2022; Tiwari et al., 2022), which could easily lead to variations in China's commodity prices.

The above studies show evidence that global and China's COVID-19 epidemic could significantly impact the price of China's commodities. However, they have two shortcomings: firstly, they do not systematically portray the panoramic view of the impact of COVID-19 on the overall commodity market in China, and secondly, they focus only on the movement of China's or global commodities in terms of returns and volatilities. Cao et al. (2018) reveals that more than 30% variation of oil and natural gas returns is in a jump form. Liu et al. (2020) shows that global oil price jumps could influence China's oil commodities' returns and volatility. Zhang et al. (2022) finds that oil price jumps have negative shocks on China's industrial sector returns and positive spillovers on its volatility. Evidence from Alqahtani et al. (2021), Bouri et al. (2021), Liu et al. (2021), and Semeyutin et al. (2021) shows that jumps in commodity prices may also happen, and even the characteristics of price jumps among different commodities may be contagious. Jump risk has become a factor in commodity price

risk management that cannot be ignored. The rapid outbreak and spread of the COVID-19 outbreak are likely to trigger a jump in Chinese commodity prices as the price jump originates from investors receiving information far from expectations. In this study, we seek to uncover the overall picture of how the COVID-19 epidemic affected the jump in commodity prices in China.

3. Methodology

3.1. BNS jump test

Following Barndorff-Nielsen and Shephard (2006) (BNS) and Tong et al. (2022), an assumption is that the price of a China's commodity (log-price) follows an Ito semi-martingale process with jumps components, which can be described as,

$$P_t^{jump} = P_{t-1}^{jump} + \underbrace{\int_{t-1}^t \mu(s) ds + \int_{t-1}^t \sigma(s) dB_s}_{\text{Continuous Component}} \quad (1)$$

versus non-jump component model

$$P_t^{\text{non-jump}} = P_{t-1}^{\text{non-jump}} + \underbrace{\int_{t-1}^t \mu(s) ds + \int_{t-1}^t \sigma(s) dB_s}_{\text{Continuous Component}} + \underbrace{\int_{t-1}^t \kappa(s) dJ_s}_{\text{Jump Component}} \quad (2)$$

where B_s obeys a standard Brownian motion, J_s is a counting process with intensity λ_s , and $\kappa(s)$ is the intensity of the jump equal to $P_s - P_{s-}$. The jump component in Eq.(2) is what we want to reveal the price jumps of one commodity. Using intraday high-frequency data, the price process could be calculated by realized measures, that is Realized Variation (RV) and Realized Bipower Variation (BPV) (see BNS (2006)),

$$RV_t^{[2]} = \lim_{\delta \rightarrow 0} \sum_{i=1}^{\lfloor N_t/\delta \rfloor} \Delta P_{t,i}^2 \xrightarrow{\mathbb{P}} P_t^{jump}. \quad (3)$$

N_t is the transaction hours and δ is the high-frequency price interval in day t , and

$$BPV_t^{[1,1]} = \lim_{\delta \rightarrow 0} \left(\frac{\sqrt{\pi}}{2} \right)^{-2} \left(\frac{1}{\lfloor N_t/\delta \rfloor} \right)^{1-\frac{r+s}{2}} \sum_{i=1}^{\lfloor N_t/\delta \rfloor - 1} |\Delta P_i| |\Delta P_{i+1}| \xrightarrow{\mathbb{P}} P_t^{\text{non-jump}}. \quad (4)$$

Thus the jump intensity of one commodity at day t could be calculated by $J_t = \max(RV_t^{[2]} - BPV_t^{[1,1]}, 0)$. A statistical significance of J_t are given in BNS (2006),

$$Z(\delta) = \lim_{\delta \rightarrow 0} [N_t/\delta]^{-2} \frac{RV_t^{[2]} - BPV_t^{[1,1]}}{\left(\left(\frac{\pi}{2}\right)^{-4} + 2\left(\frac{\pi}{2}\right)^{-2} - 5\right) \int_{t-1}^t \sigma(s) ds} \xrightarrow{D} \mathcal{N}(0,1). \quad (5)$$

It is imperative to note that a significant price movement does not always mean that a jump has occurred. In this study, only jump points at the 95% significance level or above are classified as jump components.

3.2. DY's information spillover index

After computing the jump component in one commodity price movement process, we compute how much jump information COVID-19 confirmed cases contribute to one commodity price jump or the information spillover from COVID-19 to price jumps. A classical method is to use DY's information spillover model proposed by Diebold and Yilmaz (2012) and widely used in Dai et al. (2021) and Dai et al. (2022).

Taking China's energy commodity markets as an example, in this study, we select 4 commodities: crude oil futures, coking coal futures, coke futures, and steaming coal futures. We note the price jumps of above assets as $\{J_{1,t}, J_{2,t}, J_{3,t}, J_{4,t}\}$. We use China's and global daily new confirmed cases ($\{C_{\text{China},t}, C_{\text{Global},t}\}$) as the proxy of COVID-19 spread situation. We could then construct a six-element vector or multivariate time series, as $\mathbf{x}_t = (J_{1,t}, J_{2,t}, J_{3,t}, J_{4,t}, C_{\text{China},t}, C_{\text{Global},t})$. This time series could be expressed in a VMA(∞) structure, $\mathbf{x}_t = \mathbf{C}(L)\boldsymbol{\epsilon}_t$. Then, information spillover index from the element $x_{j,t}$ to the element $x_{i,t}$ in \mathbf{x}_t is given as,

$$\tilde{\theta}_{i,j}^{DY}(H) = \frac{\theta_{i,j}^{DY}(H)}{\sum_k (\theta_{j,k}^{DY}(H))}, \quad (6)$$

where $\theta_{i,j}^{DY}(H) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} (e_i' C_k \Sigma e_j)^2}{\sum_{k=0}^{H-1} (e_i' C_k \Sigma C_k' e_i)}$, and H is the forecast step which is selected as 100 in this paper. Readers could refer to Diebold and Yilmaz (2012), Dai et al. (2021), and Dai et al. (2022) for more information about DY's information spillover index.

3.3 Wavelet coherency method

This paper aims to uncover the linear co-movement pattern between COVID-19 tolls and Chinese commodity price jumps and their characteristics at different time scales.² This study applies the wavelet method to reveal the multi-scale interplay between COVID-19 and price jumps.

In wavelet theory, in order to reflect the variations of COVID-19 tolls in the time and frequency domains $T(t)$, we assemble wavelet self-power spectra for the analysis, that is,³

$$\sigma_T^2 = \frac{1}{c_\varphi} \int_0^{+\infty} \int_{-\infty}^{+\infty} |W_T(a, b)|^2. \quad (7)$$

Further, the cross wavelet transformation of COVID-19 tolls $T(t)$ and China commodity price jumps $J(t)$ could be defined as $W_{T,J}(a, b) = W_T(a, b) \overline{W_J(a, b)}$, and their cross-wavelet power spectrum could be defined as $|W_{T,J}(a, b)|^2 = |W_T(a, b)|^2 |\overline{W_J(a, b)}|^2$. Following Dai et al. (2020), Goodell and Goutte (2020), and Tong et al. (2022), the cross-wavelet correlation between COVID-19 tolls and China commodity jumps is,

$$R_{T,J}^2(a, b) = \frac{|b(b^{-1}W_{T,J}(a,b))|^2}{b(b^{-1}|W_T(a,b)|^2)b(b^{-1}|W_J(a,b)|^2)}. \quad (8)$$

²The "time scale" is the length of the period in which the event occurs. For example, if a causal relationship between two variates occurs at a short-run or a long-run period (Dai et al., 2020; Mensi et al., 2020).

³where $c_\varphi = \int_0^{+\infty} \frac{|\hat{\varphi}(\omega)|^2}{\omega} dt$ and a, b refer to locationship and scale parameters.

The value of $R_{T,J}^2(a,b)$ that gets closer to 1 indicates a higher correlation between $T(t)$ and $J(t)$; whereas, the closer to 0, the lower the correlation between COVID-19 tolls and price jumps. The phase difference is defined as the ratio of imaginary \Im and real parts \Re wavelet cross power spectrum,

$$\phi_{T,J}(a,b) = \tan^{-1}\left(\frac{\Im(W_{T,J}(a,b))}{\Re(W_{T,J}(a,b))}\right) \quad (9)$$

where the $\phi_{T,J}(a,b)$ is in $[-\pi, \pi]$. In the empirical analysis section, we use the black arrows to indicate the quadrant where the phase difference is located. If the arrow points north-west, it means that the change in the number of COVID-19 infections is currently leading to the change in the commodity price jump and that the two variables are in reverse motion. If the arrow points south-east, the change in the number of COVID-19 infections leads to the change in the commodity price jump, and the two variables are moving in the same direction.

4. Data

Following Goodell and Goutte (2020), we choose the confirmed cases of COVID-19 as the proxy of the COVID-19 spread situation. As mentioned in the introduction section, the possible impact of the global and Chinese COVID-19 diffusion scenarios on the price jumps of China's commodities may vary. Therefore, this study selects daily China's and global confirmed cases, which is vividly shown in Figure 3.

The full sample period in this paper is from January 23, 2020 to June 10, 2022, where the COVID-19 confirmed cases data is available from the World Health Organization (WHO) and the National Health Commission of the People's Republic of China (NHCPRC). From Figure 3, we find that the dynamic characteristics of the spread of the COVID-19 epidemic, both globally and in China, have undergone different

development phases. Following Rouatbi et al. (2021), this study wanted to look at the impact of COVID-19 on commodity price jumps in China under different time periods, so we first needed to delineate the epidemic development phases.

The COVID-19 epidemic first experienced a period of outbreak, mainly in mainland China. The lack of awareness of the new coronavirus induces its rapid spread. Under the very strict control of the Chinese government, the number of infections began to fall after March. However, since the WHO declared COVID-19 as a global pandemic on March 11, 2020, the number of confirmed cases has increased exponentially. Figure 3 shows a deviation in the trajectory of the number of confirmed cases globally and in China before March 19. The number of confirmed diagnoses worldwide spiked rapidly in late February. This study defines this period as *Phase I (2020/1/23-2020/5/5)*, whereby a rapid outbreak of COVID-19 is in China and the world.

With the development of vaccine technology and herd immunity, the COVID-19 epidemic entered a plateau between May 2020 and December 2021, a notable feature of which is that there is no longer an exponential trend in the number of new infections per day. This study defines this period as *Phase II (2020/5/5-2021/12/27)*.

The Omicron strain differs significantly from previous strains of the new coronavirus in that it is less harmful but more transmissible and infectious, and immune breakthroughs have occurred in many countries and regions. In Figure 3, There is an exponential increase in infections globally and in China after 2022, which could create a huge panic in China's commodity market. This study defines this period as *Phase III (2021/12/27-2022/6/10)*. This study reveals the impact pattern of China and global COVID-19 on China's commodities price across different phases.

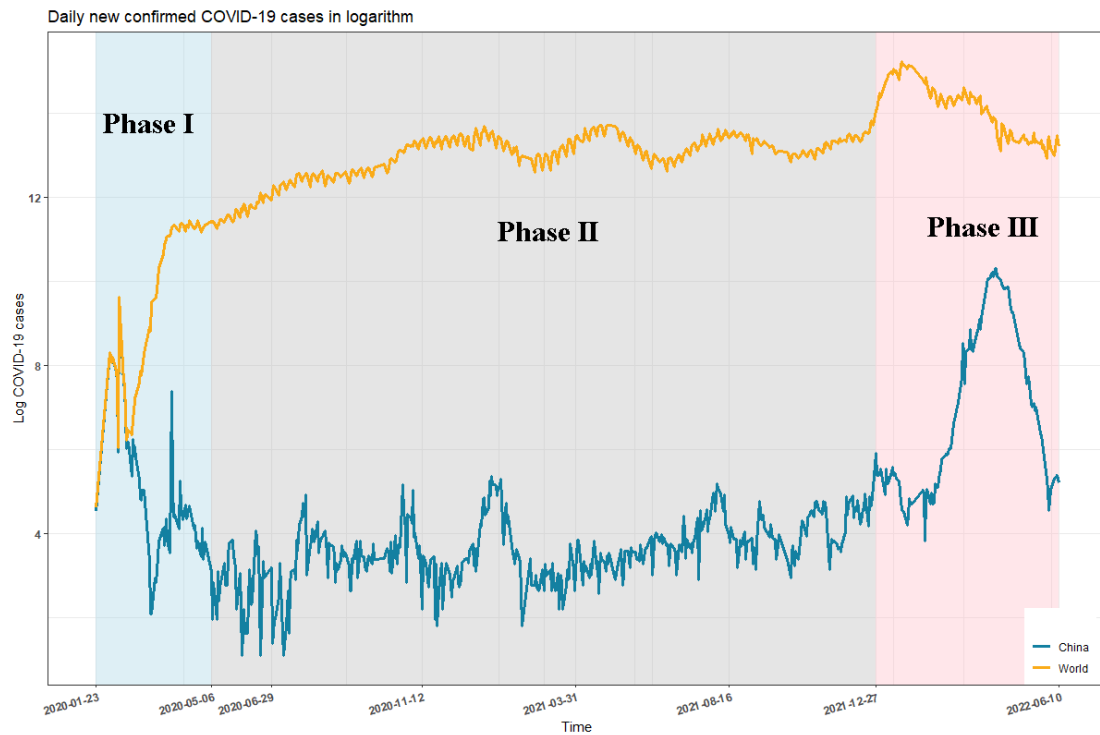


Figure 1. Confirmed cases of COVID-19 in China and worldwide.

Note: we plot the logarithm of China's and the world's daily new confirmed COVID-19 cases in Figure 3. In this study, the Phase I COVID-19 spread period is from 2020-01-23 to 2020-05-06, which is tied in the blue shadow in Figure 3. The Phase II COVID-19 spread period is from 2020-05-06 to 2021-12-27, which is tied in grey shadow in Figure 3. The Phase III COVID-19 spread period is from 2021-12-27 to 2020-06-10, which is tied in the red shadow in Figure 3. Since the Chinese commodity market is relatively unaffected by the Hong Kong, Macau, and Taiwan pandemic, only COVID-19 confirmed case/death toll data from mainland China are counted in this study. In addition, COVID-19 confirmed tolls do not include asymptomatic infected individuals.

This study selects three major commodity markets: energy, chemical, and metal commodities, which have been widely noted for their performance (Mensi et al., 2020) and price jump behavior (Todorova et al., 2014). The commodity choice reflects the heterogeneity of price jump characteristics in China, whose timespan is from January 23, 2020, to June 10, 2022. We collect well-performed five-minute high-frequency futures closed price data from the *Wind* database to compute the jump component of price movement (Wang et al., 2020). All critical dates since the outbreak of COVID-19 are included in the sample period (Corbet et al., 2020). Details of the data source can be found in Table 1. We select daily futures data, given that commodity futures is the price leader of China's commodities prices and fully reflect the balance between supply

and demand.

Table 1

The Commodities futures varieties list

Energy	<u>Steaming coal</u>	<u>Crude oil</u>	<u>Coke</u>	<u>Coking Coal</u>
Exchange	CZCE	INE	DCE	DCE
Chemical	<u>Polypropylene</u>	<u>Soda</u>	<u>Rubber</u>	<u>PVC</u>
Exchange	CZCE	CZCE	SHFE	DCE
Metal	<u>Iron Ore</u>	<u>Copper</u>	<u>Lead</u>	<u>Gold</u>
Exchange	DCE	SHFE	SHFE	SHFE

Note: INE: Shanghai International Energy Exchange. CZCE: Zhengzhou Commodity Exchange. DCE: Dalian Commodity Exchange. SHFE: Shanghai Futures Exchange.

5. Empirical analysis

5.1. Influence of COVID-19 on China's energy price jumps

Due to restrictions on transportation activities and a lockdown on economic activities, China's energy market would be struck by COVID-19. We first compute the DY's spillover index model by Eq. (6) and show the histogram result in Figure 2. Among China's steaming coal, crude oil, coke, and coking coal prices, we find that the global COVID-19 situation contributes to more jump occurrence of China's crude oil price, which is vividly shown in Figure 2, especially in Phase III. China is very dependent on imports for its crude oil consumption, and China's crude oil price is highly led by international oil futures (Dai et al., 2022). In Phase I and Phase III period of global COVID-19 spread situation, the sudden increase in the number of infections could very easily trigger irrational expectations among consumers in the China's crude oil market, thus inducing a jump in crude oil prices. Compared to crude oil, China is rich in coal resources and has a smaller external dependence. We could find that the information spillover index from global COVID-19 confirmed cases has fewer magnitude to China's steaming coal, coke, and coking coal price jumps than that to China's crude oil price jumps, which is shown in Figure 2.

In terms of the Phase of the epidemic diffusion process, the length of time of Phase I and Phase III was short, but the degree of information spillover contribution of COVID-19 to the jump in China's energy price was higher than that of Phase II. This is mainly because China's energy commodity investors have adapted to the new normal of epidemic development during Phase II. Although the number of Chinese and global infections continued to be added during Phase II, the information contributed to the jump in Chinese energy commodities has been weaker. Looking into the fourth sub-figure of Figure 2, we find that the information spillover from the global and China's COVID-19 epidemic to China's coking coal price jumps is only 0.24% and 0.04%, which implies that there is little information spillover effect on price jumps.

To some extent, we find that the information spillover from the COVID-19 spread situation to China's energy price jumps is not that high, which could explain that China's energy commodity has relatively low demand elasticity. Many participants in the energy market are constantly watching the epidemic's impact on energy prices overall, and the COVID-19 spread situation did not give these investors much in the way of unexpected expectations. As mentioned earlier, price jumps come mainly from irrational expectations.

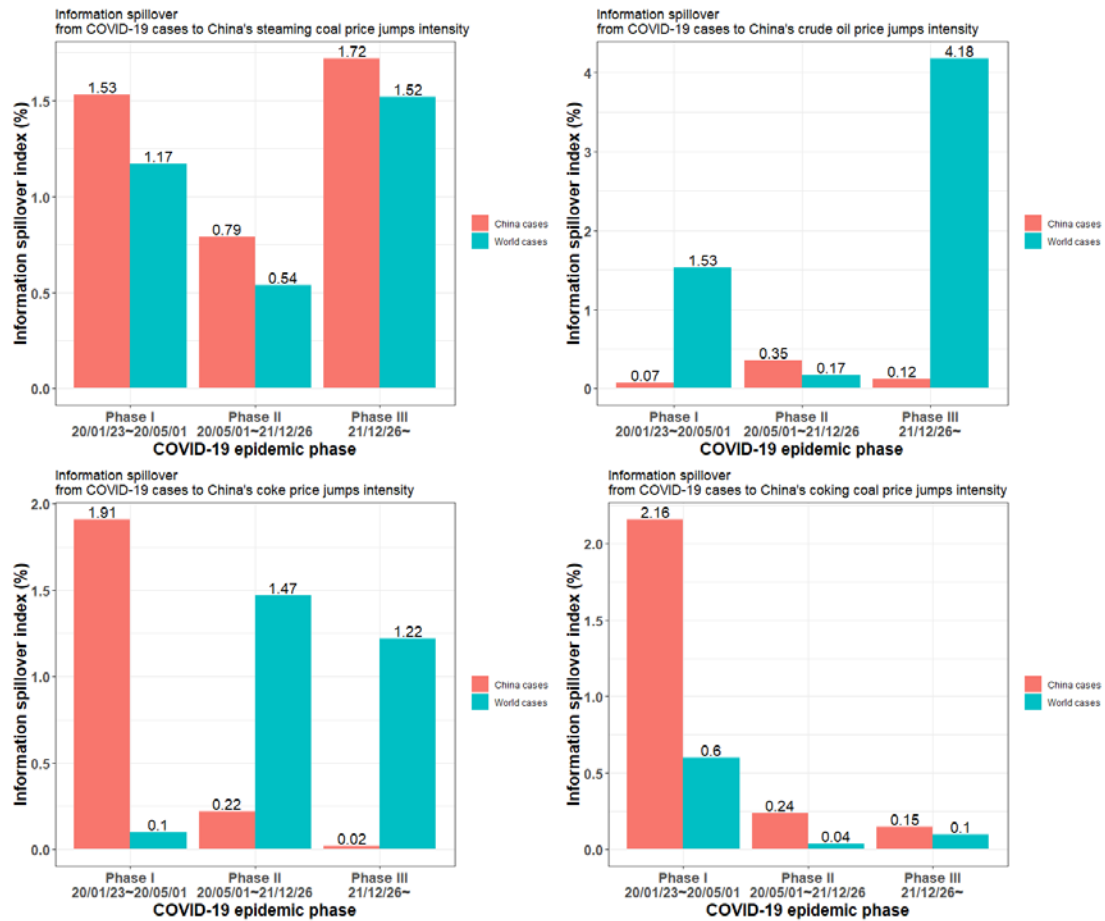


Figure 2. The information spillover from COVID-19 tolls to China's energy price jump

Note: The height of each bar represents the magnitude of the information spillover of the COVID-19 epidemic on the price jumps of China's commodities computed by Eq. (6) in sub-section 3.2. The red bars represent the information spillover from the number of people infected with COVID-19 in China to the jump in commodity prices, and the blue bars represent the spillover from the number of people infected with COVID-19 globally.

We then consider the lead-lag co-movement pattern between the COVID-19 spread situation and China's energy commodity price jumps, which is vividly shown in Figure 3. The white vertical line in each sub-figure cuts the full sample period into Phase I, II, and III. Figure 3 shows that the COVID-19 confirmed cases and the Chinese energy commodity price jumps tend to move together. However, this co-movement occurs at certain specific time scales.

In Phase I, the area of red islands in the sub-figures in the left column is smaller than those in the right column, which implies that the co-movement pattern between China's confirmed cases and energy price jumps is weaker than that between world

confirmed cases and energy price jumps. Moreover, we could find that the co-movement mainly occurs at 16-32 days-length time scales. It indicates that the panic created by COVID-19 for energy commodity investors did not occur at the short-run time scale, but at the longer-run time scale. When looking into the direction of the arrows in Phase I, we could find many arrows pointing to north-west, suggesting that the COVID-19 confirmed cases co-move with energy price jumps in the opposite direction.

When the number of infections spikes during Phase I, the impact on the degree of jump in energy prices becomes smaller over time, which is mainly explained by the fact that during Phase I, energy price investors have quickly prepared themselves for the continued spread of the epidemic, resulting in steady changes in energy prices rather than jumps.

In Phase II of each sub-figure in Figure 3, the red islands are predominantly distributed at the time scales greater than 128 days (Y-axis greater than 128). The red islands are larger in the sub-figures of the wavelet coherency between global COVID-19 and energy price jumps than those in the wavelet coherency between China COVID-19 and energy price jumps. It suggests that the global epidemic largely influenced the jump in Chinese energy commodity prices during Phase II and that this impact occurred over a very long-run time scale. The epidemic's impact on the irrational expectations of energy commodity investors is long-term.

Going into Phase III, the co-movement between the COVID-19 spread situation and China's energy price jumps is stronger than the situation in Phase II, especially for China's crude oil price jumps. Most arrows in Phase III point to the north-west direction. There is no doubt that during Phase III, the number of infections is surging globally and in China due to the Omicron strain. The epidemic also affected the irrational

expectations of energy commodity investors. The arrow's direction suggests that as the number of infections rises, the strength of the jump caused by the epidemic slowly decreases.

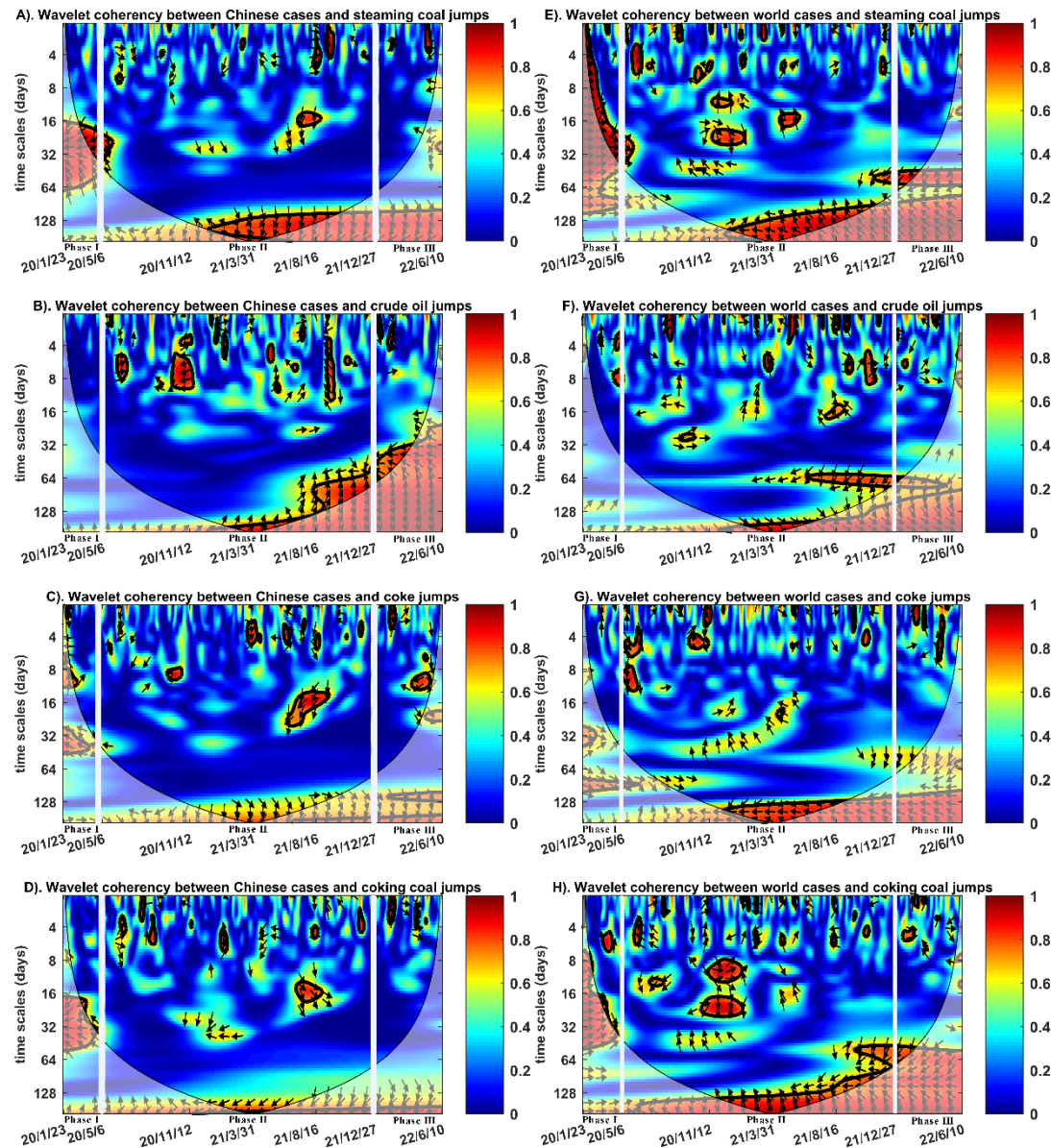


Figure 3. The wavelet coherency between China's energy price jumps and COVID-19 cases tolls

Note: The two vertical white lines in each sub-figures divide the full sample period into Phase I, Phase II and Phase III. The X-axis represents time and the Y-axis represents the time scale (which means short-, medium-, or long-run time scale). The red islands represent a co-movement trend between the intensity of the commodity price jumps and the number of COVID-19 infections at a given time and time scale according to the islands' X-axis and Y-axis values. If the arrow points north-west, it means that the change in the number of COVID-19 infections is leading the change in the commodity price jump currently and that the two variables are in reverse motion. If the arrow is pointing south-east, the change in the number of COVID-19 infections is leading the change in the commodity price jump and the two variables are moving in the same direction.

5.2. Influence of COVID-19 on China's chemical price jumps

Chemical commodities are closely linked to energy and industry, and changes in energy prices can also easily trigger chemical price changes.

We first compute the information spillover from COVID-19 confirmed cases to China's chemical commodity price jumps, which is shown in Figure 4. We see numerically that, overall, COVID-19 has a higher information spillover to China's chemical commodity price jumps than it does to China's energy price jumps. In addition, the global COVID-19 spread situation has a relatively strong information spillover effect. Especially for polypropylene, the global COVID-19 confirmed cases contribute 10.41% information spillover to China's polypropylene price jumps.

Looking at different Phases, we found that the information spillover of COVID-19 on chemical prices was more substantial in Phase I and III. During Phase II, however, the global COVID-19 confirmed case also contribute 2.28% information spillover to China's soda price jumps and 1.69% information spillover to China's PVC price jumps, as shown in Figure 4.

The contribution of the COVID-19 pandemic to the price jump of China's chemical commodity depends on the elasticity of demand. The impact on chemicals with low elasticity of demand, such as polypropylene, was relatively small. On the other hand, polypropylene is mainly produced from both coal and oil. The flexibility of the production methods makes it less likely that price changes will occur in the form of "jump" and more likely to be "fluctuation." Chemical commodities have a slightly more elastic demand than energy commodities, so their prices are prone to jumps triggered by COVID-19.

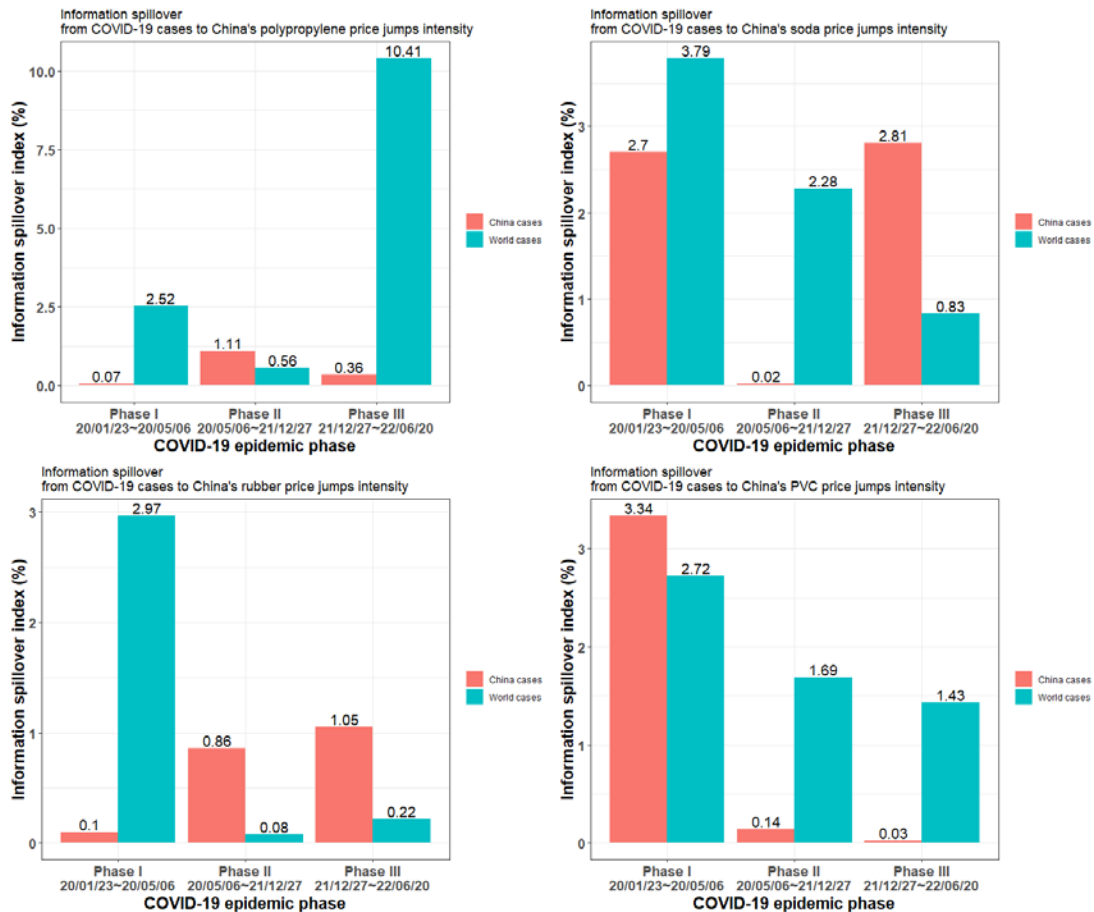


Figure 4. The information spillover from COVID-19 tolls to China's chemical price jump

Note: See Figure 2.

Figure 5 shows the wavelet coherency between COVID-19 confirmed cases and China's chemical commodity price jumps. In Phase I, we find that the red islands are not very large in the area compared to the case in China's energy commodity markets. The linear co-movement between COVID-19 confirmed cases and the chemical price jumps mainly at the 32-64 days-length time scale. It suggests that in Phase I, the linear correlation between confirmed cases and the chemical price jumps in China is not that strong. Moreover, China's confirmed cases mainly co-move in the opposite direction with the chemical price jumps intensity, while the global confirmed cases co-move in the same direction.

In Phase II, there are few red islands in sub-figures of wavelet coherency between

China's confirmed cases and chemical price jumps, while global confirmed cases have a strong linear co-movement pattern with China's polypropylene price jumps at 64 days-length time scale, which could be found in the sub-figure E of Figure 5. In Phase II of sub-figure E of Figure 5, most arrows point to the south-east, indicating that a global increase in the number of daily infections would also increase the strength of the jump in polypropylene prices linearly in the same direction. This fact also confirms what we found in Figure 4. This kind of linear co-movement pattern occurs at 32-64 days-length time scales. Apart from sub-figure E and sub-figure H of Figure 5, we do not find large red islands in Phase II of the other sub-figures.

Compared to the case in China's energy price jumps, in Phase III, there are also few red islands in sub-figure A, B, C, and D. Although there was a massive increase in the number of infections in China during Phase III, the linear correlation between COVID-19 and chemical price jumps was not too strong. In construct, in sub-figure E of Figure 5, there is a big area of red island where the arrows point to south-east. There is a positive linear correlation between the growth of the global epidemic and the jump in Chinese polypropylene prices, and the global epidemic guides the jump in Chinese polypropylene prices. From the evidence in Figure 5, we find a strong linkage between China's chemical commodity price jumps and global epidemic dynamics, mainly occurring over 32 days-length time scales.

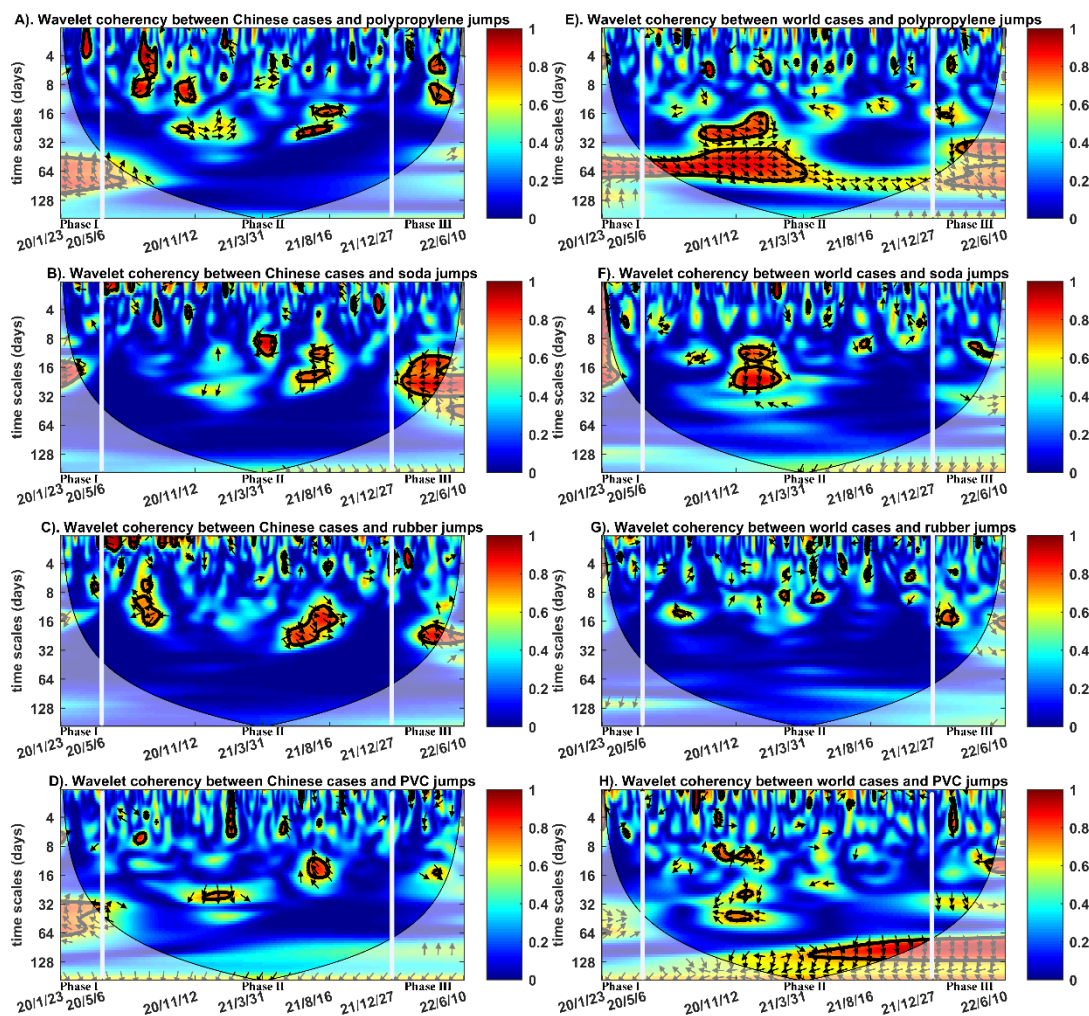


Figure 5. The wavelet coherency between China's chemical price jumps and COVID-19 cases tolls

Note: See Figure 3.

5.3. Influence of COVID-19 on China's metal price jumps

The price jumps in the Chinese metal market were closely linked to the epidemic that hit the entire industrial production sector. From the evidence in Figure 6, the information spillover from the COVID-19 confirmed cases to the price jumps of metal commodities is not high. Both the global and Chinese epidemics contributed information spillovers to price jumps, whether in Phase I, Phase II, or Phase III, with no significant time-varying characteristics. Through Figure 6, we could find that the contribution of daily COVID-19 confirmed cases to China's metal price jumps is higher

from that of China than from that of global. This feature occurs particularly in Phase II and Phase III. The overall import dependence of China's metallurgical industry is high, but it is mainly the extent of China's infrastructure development that affects the metal industry. In 2020, China proposed a new infrastructure plan to build extra-high voltage and other infrastructure. Coupled with China's better economic recovery during Phase II compared to the world, the global epidemic will not trigger undue panic among China's metal commodity investors. However, the domestic epidemic in China could create irrational expectations for metal commodity investors, thereby inducing a jump in China's metal prices.

We find that the information spillover from the global epidemic to China's gold price jump is always higher than the information spillover from the Chinese epidemic, as shown in the third sub-figure of Figure 6. Gold has solid financial attributes, it is a good hedge, and its price is very much influenced by the appreciation and depreciation of the US dollar (Dai et al., 2020). Changes in the global epidemic will give more information on the jump in gold prices in China.

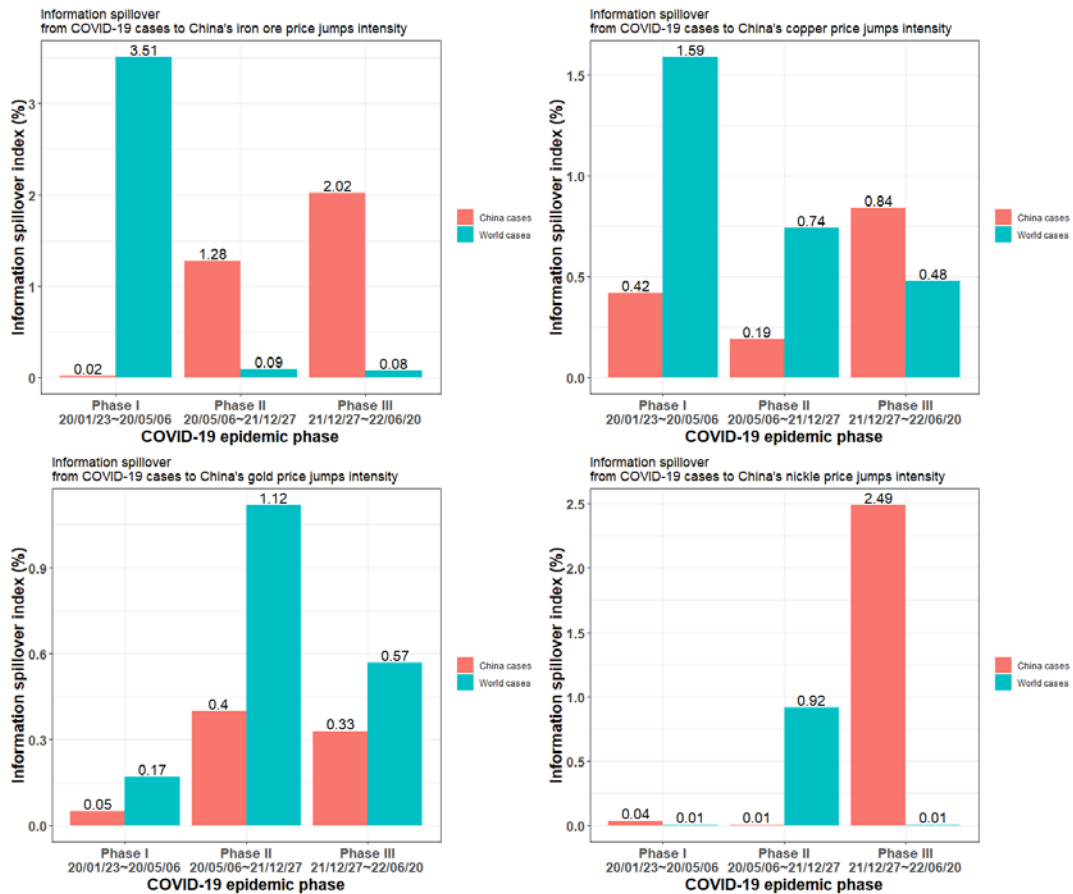


Figure 6. The information spillover from COVID-19 tolls to China's metal price jump

Note: See Figure 2.

Looking into the linear co-movement between COVID-19 confirmed cases and China's metal price jumps, Figure 7 shows that there is almost no red island in Phase I, indicating that both China's and global epidemic have little co-movement patterns with China's metal price jumps. Moreover, in Phase II, there are many red islands below 16 days-length time scale. The distribution of these red islands on the X-axis (time axis) is very short in length. In the sub-figures C, D, G and H of Figure 7, there are huge red islands over the 128 days-length time scale. Significantly, most arrows in sub-figure G and H in Phase II point to the south-east, which indicates that the global COVID-19 confirmed cases co-move with and lead to the change in China's gold and nickel price jumps in the same direction.

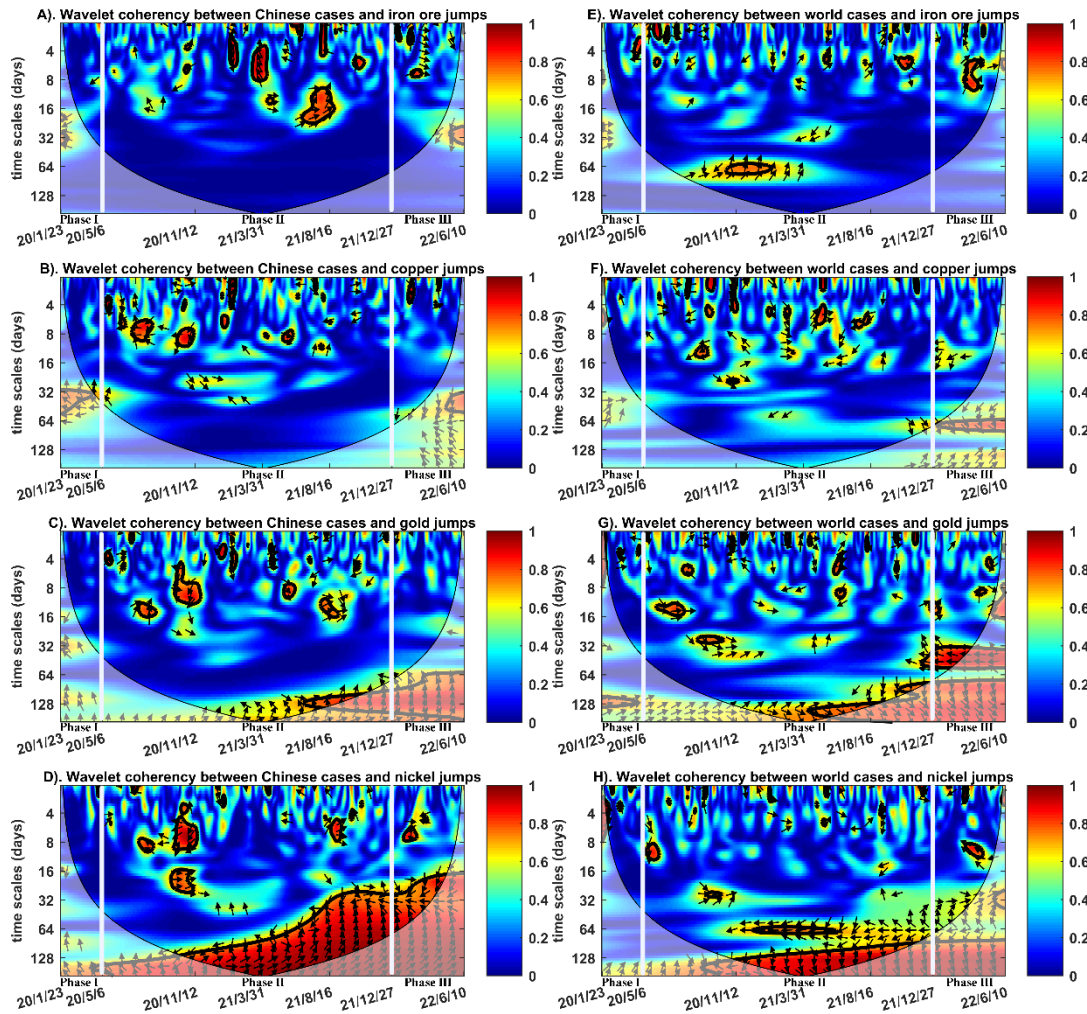


Figure 7. The wavelet coherency between China's metal price jumps and COVID-19 confirmed cases

Note: See Figure 3.

In Phase III, we conclude that there is almost no linear co-movement between COVID-19 confirmed cases and China's iron ore price jumps and between confirmed cases and China's copper price jumps. The main reason is that the demand for iron ore and copper is very inelastic, and their use is irreplaceable. Many market participants watch the epidemic's impact on iron ore and copper so that every step of the epidemic does not become an utterly unexpected expectation. In construct, the COVID-19 confirmed cases co-move with China's gold and nickel price jumps at the time scale

over 64 days-length time scale.

6. Conclusion

Commodity price jumps are a pattern of movement distinct from general dynamic mean changes and distinct from dynamic variance changes, and it is highly likely that the COVID-19 epidemic influences the characteristics of such jumps. Commodity price jumps can directly impact commodity pricing and price forecasting, creating many challenges for risk management. This study explores the characteristics of the impact of the COVID-19 epidemic on China's commodity price jumps. We use 5 min high-frequency futures closing price data of three commodity markets (energy, chemical, and metal) to compute the jump intensity of China's commodity. The full sample period in this paper is from January 23, 2020, to June 10, 2022, and we divide the time span into three COVID-19 spread situation Phases, *i.e.*, ***Phase I (2020/1/23-2020/5/5)***, ***Phase II (2020/5/5-2021/12/27)***, and ***Phase III (2021/12/27-2022/6/10)***. Our findings are as follows.

Firstly, the information spillover from the COVID-19 spread situation to China's energy price jumps is relatively weak. The jump information spillover mainly occurs at Phase I and Phase III. In Phase I, the COVID-19 confirmed cases co-move with China's energy price jumps mainly at the 16-32 days-length time scale, while co-moving with China's energy price jumps mainly at the time scales over 128 days-length in Phase II and Phase III.

Secondly, the jump information spillover from the COVID-19 spread situation to China's chemical price jumps is very strong, especially the information from global COVID-19 spread situation. Similar to the cases in China's energy price, the jump information spillover mainly occurs in Phase I and III. The linear co-movement

between COVID-19 confirmed cases and the chemical price jumps mainly at the 32-64 days-length time scale in Phase I, while there is little linear co-movement pattern in Phase II and III.

Thirdly, the contribution of daily COVID-19 confirmed cases to China's metal commodity price jumps is higher from that of China than from that of global. This feature occurs particularly in Phase II and Phase III. There are almost no linear co-movement between COVID-19 confirmed cases and China's metal commodity price jumps in Phase I and III, while the co-movement pattern occurs at a time scale over 128 days-length.

Our findings extend the existing literature on commodity price movements in the COVID-19 epidemic and raise awareness of the resilience of China's commodity markets. Not all markets react to black swan events identically, and jumps in individual markets should be assessed carefully and appropriately by market participants when formulating hedging strategies. This study provides insights into commodity market risk management under significant public health events that may arise in the future.

Appendix A An example of the jumping process

In addition, in order to illustrate the harmfulness of jump term more vividly to price modelling, we further explain the process with Figure. A1. As is shown in Figure. A1, the red solid line is a Geometric Brownian Motion (GBM) and black dotted line is a GBM with a Poisson jump term. Both they have the same volatility in their Brownian motion term and have the same mean in their draft motion term. If a GBM contains a Poisson jump term, it will deviate from the underlying GBM, and investors will mistake this deviation for a volatility component that can be obtained using historical information.

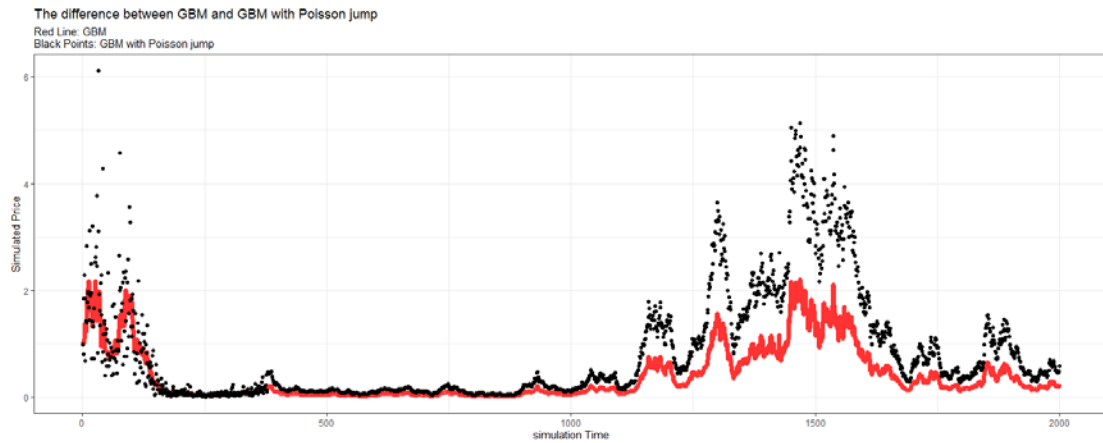


Figure A1. The simulation of the harmfulness of jump term in standard Geometric Brownian Motion (GBM) pricing process.

Note: We simulated a realized GBM $\log P(t) = \log P(t-1) + \int_0^t \left(\mu - \frac{1}{2}\sigma^2\right) dt + \int_0^t \sigma dB_t$ and a realized GBM with jump term process $\log P(t) = \log P(t-1) + \int_0^t \left(\mu - \frac{1}{2}\sigma^2\right) dt + \int_0^t \sigma dB_t + \Delta \sum_{0 < s \leq t} J(s)$, where J_t is a compound Poisson process with $J(t) = \sum_{i=1}^{N(t)} Y_i$, $Y_i \sim \Phi(\mu_Y, \sigma_Y)$ and $N(t) \sim \text{Poisson Process}(\lambda)$. In simulation, we set $\mu = \mu_Y = 0$, $\sigma = 0.1$, $\lambda = 5$ and $\sigma_Y = 0.5$. The realized GBM with jump term would show the same volatility σ with realized GBM under GARCH or other volatility estimation model, while the trajectories of black dotted and red solid line vary and investors would not be aware of the difference if they ignore the price jump behavior.

Reference

- Ahmed, A. D., & Huo, R. (2021). Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China. *Energy Economics*, *93*, 104741.
- Akhtaruzzaman, M., Boubaker, S., Chiah, M., & Zhong, A. (2021). COVID-19 and oil price risk exposure. *Finance research letters*, *42*, 101882.
- Alqahtani, A., Selmi, R., & Hongbing, O. (2021). The financial impacts of jump processes in the crude oil price: Evidence from G20 countries in the pre-and post-COVID-19. *Resources Policy*, *72*, 102075.
- Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742-758.
- Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). *How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic* (No. w26949). National Bureau of Economic Research.
- Barndorff-Nielsen, O. E., & Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, *4*(1), 1-30.
- Bloch, H., Rafiq, S., & Salim, R. (2015). Economic growth with coal, oil and renewable energy consumption in China: Prospects for fuel substitution. *Economic Modelling*, *44*, 104-115.
- Bouri, E., Lei, X., Jalkh, N., Xu, Y., & Zhang, H. (2021). Spillovers in higher moments and jumps across US stock and strategic commodity markets. *Resources Policy*, *72*, 102060.
- Cao, W., Guernsey, S. B., & Linn, S. C. (2018). Evidence of infinite and finite jump processes in commodity futures prices: Crude oil and natural gas. *Physica A: Statistical Mechanics and its Applications*, *502*, 629-641.
- Chen, X., & Tongurai, J. (2022). Spillovers and interdependency across base metals: Evidence from China's futures and spot markets. *Resources Policy*, *75*, 102479.
- Chen, H., Xu, C., & Peng, Y. (2022). Time-frequency connectedness between energy and nonenergy commodity markets during COVID-19: Evidence from China. *Resources Policy*, *78*, 102874.
- Cheong, T. S., Li, V. J., & Shi, X. (2019). Regional disparity and convergence of

- electricity consumption in China: A distribution dynamics approach. *China Economic Review*, 58, 101154.
- Corbet, S., Hou, Y., Hu, Y., Lucey, B., & Oxley, L. (2020). Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic. *Finance Research Letters*, 101591.
- Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the covid-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, 101554.
- Dai, X., Xiao, L., Li, M. C., & Wang, Q. (2022). Toward energy finance market transition: Does China's oil futures shake up global spots market?. *Frontiers of Engineering Management*, 1-16.
- Dai, X., Wang, Q., Zha, D., & Zhou, D. (2020). Multi-scale dependence structure and risk contagion between oil, gold, and US exchange rate: A wavelet-based vine-copula approach. *Energy Economics*, 104774.
- Deng, M. (2022). China economic performance and natural resources commodity prices volatility: Evidence from China in COVID-19. *Resources Policy*, 75, 102525.
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57-66.
- Evans, K. P. (2011). Intraday jumps and US macroeconomic news announcements. *Journal of Banking & Finance*, 35(10), 2511-2527.
- Farid, S., Naeem, M. A., Paltrinieri, A., & Nepal, R. (2022). Impact of COVID-19 on the quantile connectedness between energy, metals and agriculture commodities. *Energy economics*, 109, 105962.
- Fernandes, N. (2020). Economic effects of coronavirus outbreak (COVID-19) on the world economy. *Available at SSRN 3557504*.
- Fei, S., Ni, J., & Santini, G. (2020). Local food systems and COVID-19: an insight from China. *Resources, Conservation, and Recycling*, 162, 105022.
- Gates, B. (2020). Responding to Covid-19—a once-in-a-century pandemic?. *New England Journal of Medicine*, 382(18), 1677-1679.
- Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 101512.
- Goodell, J. W., & Goutte, S. (2020). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters*, 101625.

- Goodell, J. W., & Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters*, 101578.
- Gormsen, N. J., & Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-22).
- Guo, F., Huang, Y., Wang, J., & Wang, X. (2022). The informal economy at times of COVID-19 pandemic. *China Economic Review*, 71, 101722.
- Gusarova, S. (2019). Role of China in the development of trade and FDI cooperation with BRICS countries. *China Economic Review*, 57, 101271.
- Huang, F., Zhou, D., Wang, Q., & Hang, Y. (2019). Decomposition and attribution analysis of the transport sector's carbon dioxide intensity change in China. *Transportation Research Part A: Policy and Practice*, 119, 343-358.
- Ichev, R., & Marinč, M. (2018). Stock prices and geographic proximity of information: Evidence from the Ebola outbreak. *International Review of Financial Analysis*, 56, 153-166.
- Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, 101526.
- Jiang, W., & Chen, Y. (2022). The time-frequency connectedness among metal, energy and carbon markets pre and during COVID-19 outbreak. *Resources Policy*, 102763.
- 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.
- Kang, S. H., & Yoon, S. M. (2016). Dynamic spillovers between Shanghai and London nonferrous metal futures markets. *Finance Research Letters*, 19, 181-188.
- Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, 26(6), 893-921.
- Li, Z. F., Zhou, Q., Chen, M., & Liu, Q. (2021). The impact of COVID-19 on industry-related characteristics and risk contagion. *Finance research letters*, 39, 101931.
- Liu, X., Hang, Y., Wang, Q., & Zhou, D. (2020). Flying into the future: A scenario-based analysis of carbon emissions from China's civil aviation. *Journal of Air Transport Management*, 85, 101793.
- Liu, F., Shao, S., & Zhang, C. (2020). How do China's petrochemical markets react to oil price jumps? A comparative analysis of stocks and commodities. *Energy*

Economics, 92, 104979.

- 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.
- Liu, X., Zhou, D., Zhou, P., & Wang, Q. (2017). What drives CO₂ emissions from China's civil aviation? An exploration using a new generalized PDA method. *Transportation Research Part A: Policy and Practice*, 99, 30-45.
- Ma, Q., Zhang, M., Ali, S., Kirikkaleli, D., & Khan, Z. (2021). Natural resources commodity prices volatility and economic performance: evidence from China pre and post COVID-19. *Resources Policy*, 74, 102338.
- Mann, C. L. (2020). 8 Real and financial lenses to assess the economic consequences of COVID-19. *Economics in the Time of COVID-19*, 81.
- Mensi, W., Reboredo, J. C., & Ugolini, A. (2021). Price-switching spillovers between gold, oil, and stock markets: Evidence from the USA and China during the COVID-19 pandemic. *Resources Policy*, 73, 102217.
- Mensi, W., Sensoy, A., Vo, X. V., & Kang, S. H. (2020). Impact of COVID-19 outbreak on asymmetric multifractality of gold and oil prices. *Resources Policy*, 101829.
- Narayan, P. K. (2020). Oil price news and COVID-19—Is there any connection?. *Energy Research Letters*, 1(1), 13176.
- Ozili, P. K., & Arun, T. (2020). Spillover of COVID-19: impact on the Global Economy. Available at SSRN 3562570.
- Pan, Z., Bu, R., Liu, L., & Wang, Y. (2020). Macroeconomic fundamentals, jump dynamics and expected volatility. *Quantitative Finance*, 1-27.
- Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to covid-19.
- Rajput, H., Changotra, R., Rajput, P., Gautam, S., Gollakota, A. R., & Arora, A. S. (2020). A shock like no other: coronavirus rattles commodity markets. *Environment, Development and Sustainability*, 1-12.
- Rangel, J. G. (2011). Macroeconomic news, announcements, and stock market jump intensity dynamics. *Journal of Banking & Finance*, 35(5), 1263-1276.
- Rouatbi, W., Demir, E., Kizys, R., & Zaremba, A. (2021). Immunizing markets against the pandemic: COVID-19 vaccinations and stock volatility around the world. *International Review of Financial Analysis*, 77, 101819.
- Selmi, R., Hammoudeh, S., Kasmaoui, K., Sousa, R. M., & Errami, Y. (2022). The dual shocks of the COVID-19 and the oil price collapse: A spark or a setback for the circular economy?. *Energy Economics*, 109, 105913.

- Semeyutin, A., Gozgor, G., Lau, C. K. M., & Xu, B. (2021). Effects of idiosyncratic jumps and co-jumps on oil, gold, and copper markets. *Energy Economics*, *104*, 105660.
- Tiwari, A. K., Abakah, E. J. A., Adewuyi, A. O., & Lee, C. C. (2022). Quantile risk spillovers between energy and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Energy Economics*, 106235.
- Tiwari, A. K., Nasreen, S., Shahbaz, M., & Hammoudeh, S. (2020). Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. *Energy Economics*, *85*, 104529.
- Todorov, V., & Bollerslev, T. (2010). Jumps and betas: A new framework for disentangling and estimating systematic risks. *Journal of Econometrics*, *157*(2), 220-235.
- Todorova, N., Worthington, A., & Souček, M. (2014). Realized volatility spillovers in the non-ferrous metal futures market. *Resources Policy*, *39*, 21-31.
- Tong, Y., Wan, N., Dai, X., Bi, X., & Wang, Q. (2022). China's energy stock market jumps: To what extent does the COVID-19 pandemic play a part?. *Energy Economics*, *109*, 105937.
- Umar, Z., Gubareva, M., Naeem, M., & Akhter, A. (2021). Return and volatility transmission between oil price shocks and agricultural commodities. *Plos one*, *16*(2), e0246886.
- Umar, Z., Gubareva, M., & Teplova, T. (2021). The impact of Covid-19 on commodity markets volatility: Analyzing time-frequency relations between commodity prices and coronavirus panic levels. *Resources Policy*, *73*, 102164.
- Wang, X. (2020). Pricing options on the maximum or minimum of multi-assets under jump-diffusion processes. *International Review of Economics & Finance*, *70*, 16-26.
- Wang, Y., & Liu, L. (2010). Is WTI crude oil market becoming weakly efficient over time?: New evidence from multi-scale analysis based on detrended fluctuation analysis. *Energy Economics*, *32*(5), 987-992.
- Wang, J., Huang, Y., Ma, F., & Chevallier, J. (2020). Does high-frequency crude oil futures data contain useful information for predicting volatility in the US stock market? New evidence. *Energy Economics*, *91*, 104897.
- World Bank. (2020). "Three Imperatives to Keep Food Moving in a Time of Fear and Confusion." World Bank blog. Retrieved September 24r 24, 2020 from

<https://blogs.worldbank.org/voices/three-imperatives-keep-foodmoving-time-fear-and-confusion>.

- Yarovaya, L., Brzeszczynski, J., Goodell, J. W., Lucey, B. M., & Lau, C. K. (2020). Rethinking Financial Contagion: Information Transmission Mechanism During the COVID-19 Pandemic. *Available at SSRN 3602973*.
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528.
- Zhang, H., Zhu, X., Guo, Y., & Liu, H. (2018). A separate reduced-form volatility forecasting model for non-ferrous metal market: Evidence from copper and aluminum. *Journal of Forecasting*, 37(7), 754-766.
- Zhao, B. (2020). COVID-19 pandemic, health risks, and economic consequences: Evidence from China. *China Economic Review*, 64, 101561.
- Zhang, C., Mou, X., & Ye, S. (2022). How do dynamic jumps in global crude oil prices impact China's industrial sector?. *Energy*, 249, 123605.
- Zhou, C., Wu, C., & Wang, Y. (2019). Dynamic portfolio allocation with time-varying jump risk. *Journal of Empirical Finance*, 50, 113-124.
- Zhang, Y. J., Chevallier, J., & Guesmi, K. (2017). "De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets. *Energy Economics*, 68, 228-239.