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China’s energy stock market jumps: To what extent does the COVID-19 pandemic play a part?

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ABSTRACT

The price jump behavior may bring tremendous challenges on risk management and asset pricing. This paper uses the BN-S test, the wavelet coherence method, and applies high-frequency data to explore whether and to what extent the COVID-19 pandemic impacts China’s energy stock market jumps and its characteristics. The empirical results uncover the significant and heterogeneous interactions between the COVID-19 pandemic and China’s energy stock market jumps across market specifications, investment horizons, and China/global pandemic tols at different time scales. First, the oil stock market jumps were the most correlated with the pandemic, especially during the peak and re-deterioration phases. The pandemic played a positive and leading role in the short term (1–4 days length period) and long term (over 32 days length period). Second, the coal stock market jumps have similar characteristics to those of oil, but mainly show a negative correlation with the pandemic. Third, renewable energy stock market jumps were the least correlated, mainly showing a positive correlation in the short term and a negative correlation in the long term. In addition, the interaction characteristics of systemic co-jumps in different China’s energy stock markets are also significant.

1. Introduction

China accounts for 26.1% of global primary energy consumption in 2020 and continues to hold the world’s top position for several years (British Petroleum, 2021). The growing importance of China’s energy markets means that they have the potential to shake up global energy markets (Andrews-Speed and Dannreuther, 2011; Ahmed and Huo, 2021). However, since 2020, most energy industries in China have suffered from the severe impact of COVID-19. China’s energy stock prices plunged sharply in a short period of time, and the market continued to be in the doldrums, which has caused widespread concern.

Given this situation, several studies have been conducted from the perspective of market volatility (Mazur et al., 2021; Baek et al., 2020; Gil-Alana and Monge, 2020; Narayan, 2020; Devpura and Narayan, 2020). As a result of unexpected shocks, market volatility would increase rapidly and stock prices would fall wildly for a short time (Eraker et al., 2003). The so-called dramatic discontinuous variations are likely to be jumps (Caporin et al., 2017; Wang et al., 2020a, 2020b; Lu et al., 2021; Roh et al., 2021). The essential difference between price jumps and huge price volatility is the unpredictability of the jumping behavior, which indicate a severe impact on investors’ psychological expectations (Lu et al., 2020). Jumping behavior is always accompanied by a black swan event, and in the context of COVID-19, jumping risk is well worth being considered. Given that a price variation process with jump term is hardly estimated by traditional volatility model, such as GARCH and so on, jumps not only can affect the depiction of the panoramic picture of the variation characteristics (Zhang et al., 2018; Zhou et al., 2020; Semyuvitin et al., 2021; Janda and Kourilek, 2020), but also cause the pricing and risk management work to become invalid (Dutta et al., 2021; Guo and Lin, 2020), bringing incalculable losses to large number of China’s energy market investors worldwide. This study will directly reveal how COVID-19 triggers the jumps component in the price movement pattern of China’s energy stocks.

For investors with different investment horizons, the effects of jumps with multi-time scales may be not the same due to the heterogenous investment horizon (Dai et al., 2020; Wang et al., 2020b; Dai et al., 2021b; Miao et al., 2022). For investors with short investment horizons, the short-term effects of stock price jumps will bring the most intuitive

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** China’s GDP shrank by 6.8% compared to the previous year in the first quarter of 2020. The decline in the energy sector exceeded 20% from January 13, 2020, to February 2, 2020, and from March 5, 2020, to March 23, 2020.

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and significant losses (Erdemlioglu and Gradojevic, 2021). Conversely, for investors with long investment horizons, long-term effects may change the fundamentals of the industries and impact the adjustments to their investment strategies (Yang et al., 2016; Jorion, 2000; Bakshi et al., 2000). More seriously, the associated markets could show a co-movement of prices (also called co-jumps) in the face of the same shock, thus affecting the strategy of investors with both short and long investment horizons, and even impacting China’s entire energy stock market.

In response to this situation, this study focuses on China’s energy stock markets and aims to explore whether and to what extent the COVID-19 pandemic will impact jumps; their interaction characteristics in different time and frequency domains are investigated as a focus. China’s energy stock market would be first divided into three categories (oil, coal, and renewable energy). Then, 5-min high-frequency price data were selected for three leading stocks with the largest trading volume in each market, in order to detect jumps with a BN-S test. Then, new confirmed cases were used as the proxy of the COVID-19 pandemic. Thus, the impact patterns of the pandemic could be distinguished from a Chinese and global perspective, owing to their distinct characteristics. After obtaining both pandemic and jump sequence data, the wavelet coherence method was used to explore the interaction relationship between China’s energy stock market jumps and the COVID-19 pandemic in different time-frequency domains. Finally, several practical implications for subsequent research are put forward, based on this study’s empirical evidence.

This study makes at least two contributions, as follows: First, it initially examines the jumps and systemic co-jumps of China’s energy stock markets under the COVID-19 pandemic. Thus, it fills the gap of the empirical literature on the COVID-19 pandemic, which to date has mainly focused on the impact from the perspective of price or price volatility (Devpura and Narayan, 2020; Salisu and Adediran, 2020; Gil-Alana and Monge, 2020), stock returns (Prabheesh et al., 2020; Liu et al., 2020a, 2020b; Iyke, 2020), firm performance (Fu and Shen, 2020; Shen et al., 2020) and so on. Second, this study dynamically reveals the interaction relationship between the COVID-19 pandemic and China’s energy stock market jumps across market specifications, investment horizons, and China/global pandemic tolls at different timescales, thereby enriching the limitations of correlation analyses that focus on a single time or frequency domain (Mensi et al., 2017a; Gil-Alana and Monge, 2020; Salisu et al., 2020).

The remainder of this paper is organized as follows: Section 2 elaborates the transmission mechanism of COVID-19 to the energy market. Section 3 describes the research methodology. Section 4 offers the studied dataset. Section 5 discusses the empirical results, and Section 6 provides the concluding remarks.

2. Transmission mechanism behind China’s energy stock market jumps

Understanding the transmission mechanism of the COVID-19 pandemic to China’s energy stock market jumps is important for market participants attempting to manage the fluctuation risks associated with energy stock prices. Fig. 1 presents the impact transmission paths; this study will also shed light on the mechanism in the following section.

The COVID-19 pandemic has had a detrimental effect on global healthcare systems and has also caused fears to investors in financial markets (Açikgöz and Günay, 2020; He et al., 2020a; Bambrà et al., 2020; McKibbin and Fernando, 2020). Faced with the high infection rate of the virus, governments have enforced border closures, business lockdowns, and self-isolation to contain the spread of the pandemic (Wang and Su, 2020; Chen et al., 2020; Whitworth, 2020; Sim, 2020; Chatterjee, 2020; Chang et al., 2020). The pandemic has hit the energy market mainly through three specific measures.

First, many countries have set border closures to restrict unnecessary travel under the COVID-19 pandemic. For instance, the US has banned all foreigners from China, Iran, and certain European countries from entering the country (Baker et al., 2020; Nicole et al., 2020). Such a restriction leads directly to a significant drop in travel activities. Naturally, this decreases energy consumption, since there is less need for aviation and other forms of traffic; therefore, the demand for energy is reduced accordingly (Klemes et al., 2020; Sharif et al., 2020; Gillingham et al., 2020; Qin et al., 2020). Additionally, the travel constraints could also slow down the transmission of energy (Nicole et al., 2020). In this sensitive situation, if a political event acts as a catalyst, the fluctuations of energy supply will drastically increase (Aloui et al., 2020; Kuzemko et al., 2020; Sovacool et al., 2020; Gozgor et al., 2021). For instance, due to the spat between Saudi Arabia and Russia, OPEC failed to reach a

![Fig. 1. Transmission mechanism of COVID-19 to energy market jumps.](image_url)
production quota agreement that would regulate the supply of oil (Bouri et al., 2020; Qin et al., 2020).

Second, widespread business lockdowns have not only reduced industrial production, but they have also disrupted the supply chain (Nicolé et al., 2020; Mofijur et al., 2021; Salisu et al., 2020; Fernandes, 2020; Baker et al., 2020). The disruption to supply chains and the resulting decreased demand for raw materials due to the decrease in production have also decreased energy consumption, thus reducing the demand for energy (Remko, 2020; Baldwin and Di Mauro, 2020; Sharma et al., 2020; Ivanov and Dolgui, 2020). The fundamental driver of price in any market is supply and demand. As a result, both the reduced demand for energy and the fluctuation of energy supply have created an additional risk to the energy market, thus causing energy price jumps (Abouti et al., 2020).

Third, self-isolation has limited the mobility of populations. Self-isolation also inhibits people’s consumption activities and forces the working class to suffer job losses (Nasr et al., 2020; Chen et al., 2020; Sarkis et al., 2020). Since the energy industry is characterized by heavy assets and high energy consumption, it is more vulnerable to market risks. The decreasing revenue caused by reduced demand, the constraints on production caused by staff deficiencies, and the increasing cost of high fixed assets all enhance the uncertainty of operations. This results in poor performances on the part of these companies and is reflected in the fall in equity prices, thus directly increasing the volatility of the financial market (Fu and Shen, 2020; Shen et al., 2020; Ding et al., 2021; Dai et al., 2021).

However, all three of the abovementioned measures have, in turn, intensified fears of an impending economic crisis (Nicolé et al., 2020). Investors generally hold pessimistic attitudes concerning the outlook of markets, thus increasing their aversion to risk when dealing with any uncertainty (Chang et al., 2020; Fu and Shen, 2020). In this situation, investors are more likely to display herdish behaviors, mimicking the actions of other investors. This behavior contributes to broad-based selling and deferred investments (Wagner, 2020; Mazur et al., 2021; He et al., 2020; Ashraf, 2020). One of the consequences is the fall in stock prices, which creates high volatility and uncertainty in the financial market and exacerbates the risk aversion rate (Cont and Bouchaud, 2000; Roos, 2006; Zheng et al., 2015; Liu et al., 2021). Thus, a severe and vicious circle is formed. Since there is a strong cointegration relationship between the stock market and the energy market, any stock market risk could spill over into the energy market, leading to increased volatility (Prabheesh et al., 2020). Since the stock price acts as a barometer of the market and most price jumps are followed by increased volatility (Joulin et al., 2008; Jacob and Todorov, 2010; Todorov and Tauchen, 2011), the energy stock market has witnessed large and discontinuous changes during the pandemic, known as jumps.

Although the fossil fuel (oil and coal) industry and the renewable energy industry have great differences in production methods and raw material sources, they share the same economic environment and are therefore interrelated with each other. Once a risk appears in one market, it is easy for that risk to transcend borders and form a systemic co-movement (Mensi et al., 2017b; Wang et al., 2018; Gupta et al., 2020; Yarowaya et al., 2020).

Existing studies mainly focus on the volatility spillover effect between energy commodities, and particularly oil products (Corbet et al., 2020; Bouri et al., 2020; Aloui et al., 2020; Mensi et al., 2021a). Otherwise, the studies analyze co-movement in the international energy stock market (Wu et al., 2020; Prabheesh et al., 2020). Few studies examine time-frequency interactions between the COVID-19 pandemic and different China’s energy stock market jumps. This study contributes to the limited research by focusing on China’s energy stock market jumps under the COVID-19 pandemic and the jumps’ interaction relationships in different time-frequency domains, providing new empirical evidence to the existing research on the impact of the COVID-19 pandemic.

3. Methodology

3.1. Jump and co-jump detection

To explore whether jumps occur in different China’s energy stock markets during the COVID-19 pandemic and to characterize those jumps accordingly, the first thing that is needed is the identification and detection of market jumps. For different stock markets, the leading stocks with the highest trading volume during the sample period were selected to represent the fluctuation trend of each different China’s energy stock markets. The BN-S test method identifies jumps by decomposing the total variance of asset returns into continuous and discontinuous components. This method has the advantages of being model-free, easy to compute, and more accurate in depicting financial market volatility from the high-frequency data (Andersen and Bollerslev, 1998).

This study uses the intraday returns of energy stocks to construct the daily realized variance (RV), which represents the total variation (Andersen et al., 2007), as follows:

\[ RV_{t+1}(\Delta) = \sum_{j=1}^{n} n_{j} r_{t,j} \Delta^2 \]

where \( r_{t,j} \) represents day \( t \) of the input intraday return, which is calculated from the logarithmic asset price. Also, the realized bi-power variation (BPV) is the continuous part, which can be calculated as:

\[ BPV_{t+1}(\Delta) = \mu_1^2 \sum_{j=2}^{n} |r_{t,j-1} \Delta| \]

where \( \mu_1^2 = \sqrt{2/\pi} \). Then, the difference of RV and BPV is just the discontinuous portion and is called a jump component when \( \Delta = 0 \); that is:

\[ J_{t+1}(\Delta) = RV_{t+1}(\Delta) - BPV_{t+1}(\Delta). \]

As mentioned above, stock prices can fluctuate slightly within the normal range. This makes it a little difficult to test whether jumps are significant, depending on one’s feelings. To detect the significant jumps, this study follows the Z-ratio test proposed by Barndoff-Nielsen and Shephard (2006). Meanwhile, high-frequency data are more useful for detecting slight changes in the stock market. However, the data may be heavily contaminated by market microstructure noise, leading to detection bias (Bandi and Russell, 2006; Barndoff-Nielsen et al., 2008). We thus refer to the suggestion made by Andersen et al. (2007) to adjust the jump test statistics. The Z-ratio test is defined as:

\[ Z_{t+1}(\Delta) = \Delta^{-1} \left[ \frac{RV_{t+1}(\Delta) - BPV_{t+1}(\Delta)}{RV_{t+1}(\Delta)} \right] \]

For a given significance level \( \alpha \), the Z-ratio test statistic is compared with a critical value \( \Phi_{\alpha} \) to define the significant jump component; that is:

\[ J_{t+1}(\Delta) = I(Z_{t+1}(\Delta) > \Phi_{\alpha}) \left[ RV_{t+1}(\Delta) - BPV_{t+1}(\Delta) \right] \]

where \( \Phi_{\alpha} \) is the standard normal cumulative distribution function of \( \alpha \). In our empirical study, the nonnegativity truncation corresponds to adjusted BPV and realized tri-power quantility are defined as:

\[ BPV_{t+1}(\Delta) = \mu_1^2 \left( 1 - 2\Delta^2 \right) \sum_{j=2}^{n} \left| r_{t,j-1} \Delta \right| \]

\[ TJ_{t+1}(\Delta) = \Delta^{-1} \mu_1^2 \left( 1 - 4\Delta^2 \right) \sum_{j=2}^{n} \left| r_{t,j-1} \Delta \right| \left| r_{t,j-2} \Delta \right| \left| r_{t,j-3} \Delta \right| \left| r_{t,j-4} \Delta \right| \]

3.2. Jump and co-jump intensity

This study uses the intraday returns of energy stocks to construct the daily realized variance (RV), which represents the total variation (Andersen et al., 2007), as follows:
directly to $a = 0.01$.

Co-jump detection rules are also defined here. Assuming that whenever a certain proportion of the leading stocks in the selected market jumps, that market jumps. When two or more markets jump simultaneously, this represents a co-jump. Based on the jumps detected using the Z-ratio test described above, and referring to the method introduced by Ma et al. (2019), this study defines the co-jump detection for different China’s energy stock markets as:

$$\sum_{i=1}^{K} \left\{ \begin{array}{ll} I(Jump_{i} > 0) & \geq K - \text{co-jump} \\ \leq K - 1 & \text{Noco-jump} \end{array} \right.,$$

where $Jump_{i}$ is the jump at time $t$ of the $i^{th}$ stock, and $I(Jump_{i} > 0)$ is an indicator function that takes the value of 1 when a jump is detected in asset $i$ for day $t$, and 0 otherwise. According to the definition, we discuss only frequency and not intensity in the following empirical process.

3.2. Wavelet coherence analysis

To capture the short- and long-term interaction relationships between the COVID-19 pandemic and the market jumps in different time and frequency domains, and then to deeply analyze the impact of the COVID-19 pandemic on jumps, as well as the jump characteristics, this study adopts the wavelet coherence method first proposed by Goupillaud et al. (1984).

The wavelet coherence is estimated by using the cross-wavelet transform and cross-wavelet. According to Torrence and Compo (1998), the cross wavelet transforms of two time-series $Jump(t)$ and Case (t) with the continuous wavelet transforms $W_{Jump}(u,s)$ and $W_{Case}(u,s)$ can be defined as:

$$W_{Jump,Case}(u,s) = W_{Jump}(u,s)W_{Case}^{*}(u,s),$$

where $u$ refers to the location, and $s$ is the scale. The * denotes the complex conjugate. The cross-wavelet power can easily be computed using the XWT as $|W_{Jump, case}(u,s)|$, and this reveals areas in the time-frequency space where the time series show a high common power.

Wavelet coherence can capture covariance contributions in the time-frequency space but may not have high power. Following Torrence and Webster (1999), the wavelet coherence is the squared absolute value of the smoothed cross wavelet power spectra of each selected time series. Therefore, the squared wavelet coherence coefficient is estimated as:

$$R^{2}(u,s) = \frac{|S(s^{-1}W_{Jump,Case}(u,s))|^{2}}{S(s^{-1}|W_{Jump}(u,s)|^{2})S(s^{-1}|W_{Case}(u,s)|^{2})},$$

where $S$ denotes a smoothing operator of both time and scale, with values ranging from $0 \leq R^{2}(u,s) \leq 1$. Specifically, the value close to 1 indicates a strong correlation, surrounded by a black line and represented by the color red. Meanwhile, the value close to 0 means a scenario of no correlation exists, which is displayed by blue. Hence, the squared wavelet coherence measures the local linear correlation between two stationary time series at each scale and is analogous to the squared correlation coefficient in linear regression.

However, we can see that the wavelet squared coherence takes only positive values, so in this case, no distinction can be made between the positive and negative correlations. However, the phase difference proposed by Torrence and Compo (1998) provides information about the positive and negative co-movement, as well as the causal relationship between the COVID-19 pandemic and jumps, which can be defined as:

$$\Psi_{Jump,Case} = \tan^{-1} \left( \frac{3\{S(s^{-1}W_{Jump,Case}(u,s))\}}{8\{S(s^{-1}|W_{Jump,Case}(u,s)|^{2})\}} \right), \quad \Psi_{Jump,Case} \in [-\pi, \pi]$$

where $3$ and $8$ are the imaginary and real parts of the smooth power spectrum, respectively.

Additionally, phase relationships between the COVID-19 pandemic and market jumps are indicated by black arrows on the wavelet coherence plots. A zero-phase difference implies that the two-time series move together, while a $\pi(-\pi)$ phase difference means that they move in opposite directions. The arrows point to the right (left) when $Jump_{i}$ and $Case_{i}$ are in phase (anti-phase) or when the correlation is positive (negative). The arrows point down (up) when the second (first) series leads the first (second) series by $\pi/2$. Specifically, arrows pointing left imply that $Case_{i}$ leads $Jump_{i}$ and arrows pointing right indicate that $Jump_{i}$ leads $Case_{i}$.

4. Data description

4.1. COVID-19 cases

This paper selected the new confirmed cases as the proxy of the impact of the COVID-19 pandemic. Most of the references to the pandemic in existing literature include confirmed infections and death cases, which can be further divided into new and cumulative cases (Hou et al., 2021; Dawoud, 2020; Wong et al., 2020). In this study, due to the long sampling time, death cases will not be prominent in the late stages of the Chinese pandemic and thus cannot accurately reflect the impact. Also, since the COVID-19 pandemic led to millions of cumulative confirmed cases, it was difficult for investors to perceive fluctuations, due to the pandemic’s large base (Ashraf, 2020). Meanwhile, considering that the COVID-19 pandemic that occurred in China differed from the whole world in timing, duration, and severity, this study distinguished the Chinese and global new confirmed cases, to explore the comprehensive impact of the pandemic.

Wind database provides thematic data on the COVID-19 pandemic. This study collected Chinese and global new confirmed cases from the start date to the present date in the thematic database. Specifically, January 20, 2020, to February 26, 2021, is the sample period.

As can be clearly seen from Fig. 2, the Chinese pandemic peaked during the period from January to February 2020, and then declined rapidly. However, spikes in infection numbers occurred in April, June, July, and November 2020, and in January 2021. The pandemic in the whole world, on the other hand, showed a continuous increase in new confirmed cases, with a marked acceleration in June and October 2020, but a significant decline around January 2021. Considering the development characteristics of the Chinese and global pandemic (peak and improvement points), the study distinguishes the sample time into pre-, mid-, and post- phases, namely January–March 2020, April–September 2020, and October 2020–February 2021.

4.2. China’s energy stocks

High-frequency data contain more transaction information and can accurately capture the subtle jump processes of financial assets (Martens and Zein, 2004; Koopman et al., 2005; Wei, 2012). However, the higher the frequency is, the noisier the microstructure will be. To reduce the noise of the microstructure, this study chose 5-min high-frequency data, an approach that is effective (Andersen and Bollerslev, 1998; Liu et al., 2015).

Also, to better reflect the jumps and capture the interaction between jumps (co-jumps) and the COVID-19 pandemic, this study chose individual stocks rather than indices to complete the empirical process. The method of selection can be elaborated as follows: all stocks in the oil, coal and renewable energy stock markets were collected during the sample period, ranked in descending order of trading volume, and the three leading stocks with the highest trading volume were selected as the corresponding typical representatives of the market. The market jumps or co-jumps described in the following sections are based on this, just as the definition in Section 3.1. The reasons for this selection are, first, for investors, extreme fluctuations in individual stock prices can give them a more intuitive impact, since the rise and fall of individual
stocks could affect their returns which is what they care more about when investing. In this way, the extreme fluctuations of individual stock prices can better reflect the change in investors’ psychological expectations under the pandemic, and thus, jumps and the corresponding interactions will be more pronounced. Second, the leading stocks with the highest trading volume can absorb unexpected news more quickly (Caporin et al., 2017), and the top three are enough to fully reflect the trend of investors’ confidence in a certain type of market, thus representing the overall market change (Sadorsky, 2001, 2012; Wen et al., 2014; Xie et al., 2021). Therefore, the 5-min high-frequency price data of the top three leading stocks (in terms of trading volume) during the sample period is this study’s selection target.

Wind database provides information on China’s stock market quotes. As mentioned above, three leading stocks with the highest trading volume of each of the three main energy sub-sectors were selected as follows, which sample from January 20, 2020, to February 26, 2021, for a total of 266 trading days, consisting of 5-min returns from 9:30 to 11:30, and from 13:00 to 15:00, or 12,768 high-frequency data for each of the nine energy stocks. The results are shown in Table 1.

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Table 1
Selected leading stocks with the highest trading volume in each of the three energy stock markets.

| Types          | Ticker code | Financial institution                  |
|----------------|-------------|---------------------------------------|
| Oil            | 600,346.SH  | Hengli Petrochemical Co., Ltd.        |
|                | 600,028.SH  | Sinopec Group                         |
|                | 601,857.SH  | PetroChina Co., Ltd.                  |
|                | 000723.SZ   | Shanshi Meijin Energy Co., Ltd.       |
| Coal           | 600,546.SH  | Shanshi Coal International Energy Co., Ltd. |
|                | 601,088.SH  | China Shenhua Energy Co., Ltd.        |
|                | 601,012.SH  | Xi’an LONGI Silicon Materials Corp.   |
| Renewable energy| 300,750.SZ  | Contemporary Amperex Technology Co., Ltd. |
|                | 600,438.SH  | Tongwei Co., Ltd.                     |

Note: The classification based on the CITIC Securities Industry Classification of CS Petroleum & Petrochemicals, CS Coal, and CS Electrical Equipment & renewable energy on Wind database.

Table 2
Percentage of days with jumps in the oil, coal, and renewable energy stock markets (typical sample stocks), before and after the COVID-19 pandemic.

|                      | Days with jumps / Total days | Days with jump values above the median / Total days |
|----------------------|-------------------------------|---------------------------------------------------|
|                      | Before                        | After                                             |
| Oil                  | 48.47%                        | 49.81%                                            |
| Coal                 | 47.51%                        | 47.89%                                            |
| Renewable energy     | 43.30%                        | 39.08%                                            |

Note: (1) The total days are from January 1, 2019, to February 26, 2021, with January 20, 2020, as the cut-off point, before and after the pandemic. (2) The market jumps follow the previous definition of Section 3.1; the median market jump is calculated as the average value of the jumps.

5. Empirical analysis

5.1. Jumps of China’s energy stocks during the COVID-19 pandemic

Generally, energy stock markets would undeniably generate price jumps due to various macro and micro factors shocks (Chen et al., 2021; Liu et al., 2020a, 2020b; Mensi et al., 2021b; Pan et al., 2020). Therefore, the pre-pandemic jumps cannot be ignored. Here, they are set as a control group, which is from January 1, 2019, to January 20, 2020. This is done to better explore the impact of the COVID-19 pandemic. We report empirical results for the 1% significance level considering that a smaller critical level can filter out more noise for large-scale data (Bjursell et al., 2015; Liu et al., 2018; Gkillas et al., 2021). The comparison result can be seen in Table 2.

Table 2 presents very interesting results, showing significant jumps both before and after the pandemic. However, in contrast, only the oil stock market jumps increase significantly in frequency and intensity after the pandemic. This is especially true of the intensity, which increases by 10.28%, much more than the other two. Meanwhile, coal stock market jumps increase in frequency but decrease slightly in intensity; conversely, renewable energy stock market jumps greatly decrease in frequency but increase in intensity.

It can be concluded that all the three energy stock market jumps showed significant differences before and after the COVID-19 pandemic.
Just as documented by Sakurai and Kuroasaki (2020), the COVID-19 pandemic could enhance the shock intensity for the stock market more than an equivalent shock could before the pandemic. However, what is certain is that the pandemic shock triggered more frequent, intense, and extreme volatility in the oil stock market. This finding is in line with those of Devpura and Narayan (2020), lyke (2020), and others, while the coal and new energy stock markets suffered less. Similarly, the high frequency of co-jumps both before and after the pandemic was confirmed. This finding validates the evidence found by Manejuk et al. (2022) of a correlation between COVID-19 shocks and all energy markets, while further suggesting that the correlation will be in the form of co-jumps. However, the results in Table 3 are still surprising. It seems that the co-jumps between different energy stock markets were not affected by the pandemic. Except for co-jumps in the oil and coal stock markets, co-jump frequencies of all other three pairs show an unusual weakening under the pandemic.

Table 3

Percentage of days with systemic co-jumps between the combination of oil, coal, and renewable energy stock markets (typical sample stocks), before and after the COVID-19 pandemic.

| Days of co-jumps / Total days | Before | After |
|-------------------------------|--------|-------|
| Oil and coal                  | 46.74% | 46.74% |
| Oil and renewable energy      | 42.72% | 38.12% |
| Coal and renewable energy     | 41.76% | 36.78% |
| Oil, coal, and renewable energy | 41.19% | 35.82% |

Note: (1) The total days are from January 1, 2019, to February 26, 2021, with January 20, 2020, as the cut-off point, before and after the pandemic. (2) The market co-jumps follow the previous definition of Section 3.1, without considering intensity.

In the short term (1–4 days length period), small red islands appear frequently in the first panel, with arrows pointing mostly to the up-right in the pre- (January–March 2020) and mid-sample period (April–September 2020). More arrows are pointing to the up-left in the post-period (October 2020–February 2021). This finding suggests that oil stock market jumps are constantly led by the Chinese pandemic, especially in the during the peak and re-deterioration phases; the pre- and mid-sample phases mainly show a positive correlation, while the post-sample period is mainly negative. For the pandemic from the perspective of the whole world, jumps are subject to a stronger leading role of the pandemic in the mid- and post-sample period, but the negative correlation is significant.

Frequent jumps in the short term are closely related to the shift in investor psychological expectations caused by the COVID-19 pandemic. The initial shock from the increase in new confirmed COVID-19 cases has the most direct and profound impact on investors. Security scares, triggered by media reports of new confirmed cases and combined with the heavy blow of negative oil prices news, continue to fuel the psychological expectations of energy investors (Narayan, 2020) and therefore influence oil market volatility (Xiao and Wang, 2021). However, the shift in the positive and negative correlation between jumps and the pandemic on different time-frequency domains (especially under the influence of the Chinese pandemic, which has recurved several times) suggests that investors can adapt to changes in new confirmed cases over time. Thus, the shock to their psychological expectations is mitigated. However, when the pandemic gradually spreads and worsens, fears of a second peak will continue to disrupt investors’ psychological expectations (Jefferson, 2020). The second peak would imply stricter quarantine measures, lower energy demand, and bleaker economic development prospects, and may therefore account for the greater impact on investors in the post-sample period. When fears became reality and the pandemic resumed in China and worsened globally (after October 2020), any significant change in the pandemic strongly stimulated investors’ nerves and profoundly affected their trading behavior.

In the medium term (4–32 days length period), the red area increases significantly. This indicates an increased correlation in the time domain, but the pointing arrows show that jumps are mainly negatively correlated with both the Chinese and global pandemics, and both of the pandemics also do not lead jumps. In the long term (over 32 days length period), however, jumps are more severely impacted by the Chinese pandemic than in the medium term, especially showing a positive leading effect in the pre- and post-sample period. Meanwhile, the long-term impact of the global pandemic is not significantly larger than in China, but the leading effect is also reflected in the post-sample period.

It is worth noting that the positive leading effect of the COVID-19 pandemic persisted from the short term into the medium- to long-term. This finding is consistent with those of Gil-Alana and Monge (2020). However, supply and demand, as well as the state of the world economy, are all more critical factors in terms of influencing investors’ long-term psychological expectations (Reboredo et al., 2017). For example, in the case of the oil stock market, China (as a major oil importer), the restrictions on people’s movement under the pandemic, the sharp decline in oil demand, and the unstable energy geopolitics have all led to an imbalance in supply and demand for oil in the medium to long term. This situation has caused a plunge in international oil prices and has shocked the psychological expectations of related investors. Also, after October 2020, the worsening of the pandemic internationally further dominated oil price movements and continued to hit investors’ psychological expectations hard, making the positive leading effect of the pandemic on the oil stock market jumps even more pronounced in the long term.

Coal stock market jumps have some similar characteristics to those of oil stock market jumps. In the same way, comparing Fig. 4 with Fig. 5, jumps are also more affected by the Chinese pandemic, with constant but small shocks in the short term and significantly stronger shocks in the medium to long term. However, judging from the size of the red areas, in the short term, coal stock price jumps are significantly weakened by the intensity of the shock, compared to the oil stock market. Jumps were also mainly led by the Chinese pandemic in the short and long term of the mid- to post-sample time (after April 2020). The positive and negative correlations were irregular, but the negative correlations were...
more prominent. The global pandemic also played a leading role, mainly in the mid- to post-sample period, with stronger long-term effects than in the medium term, and again with negative correlations.

The significant negative correlation between coal market jumps and the pandemic is very interesting. It suggests that most of China’s coal stock market jumps showed a weakening effect under the pandemic, implying that investors’ psychological expectations can be eased more quickly in coal markets than in the case of oil markets. In other words, investors’ confidence in the coal sector (and coal prices) was less dominated by the pandemic. This extends the findings that no significant causal link in the coal market has been discovered by capturing the dynamic causal relationship (Wang and Su, 2021). As for the reason, this phenomenon would happen, in addition to similar factors mentioned above, the relatively small coal supply affected by imports and the support of the Chinese government during the COVID-19 pandemic could be the potential factors why investors’ psychological expectations with coal are better than with oil.

More unusual is the renewable energy stock market. There are significantly fewer red areas and more blue areas in Fig. 5, suggesting that renewable energy stock jumps have been the least affected by the pandemic. Also, the jumps are not significantly different from the intensity of the shock of the pandemic in China and the whole world. This may be related to the fact that during the pandemic all countries discovered the great potential of renewable energy sources (Khanna, 2021).

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**Table 3. Wavelet coherence between oil stock market jumps and new confirmed cases of the COVID-19 pandemic.**

| Oil stock market | Chinese pandemic | Global pandemic |
|------------------|------------------|----------------|
|                  | 1-4 days         | 4-32 days      | Over 32 days  | 1-4 days         | 4-32 days      | Over 32 days  |
| Jan., 2020-Mar., 2020 | Positive lead | Negative not lead | Positive lead | Not significant | Not significant | Positive not lead |
| Apr., 2020-Sept., 2020 | Positive lead | Positive not lead | Not significant | Positive lead | Negative not lead | Not significant |
| Oct., 2020-Feb., 2021 | Negative lead | Negative not lead | Positive lead | Negative lead | Negative not lead | Positive lead |

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3 Chinese local governments issued 19.7GW of new coal capacity permits from January 1 to June 30, 2020, to boost coal investment activity.
In the short term, jumps are also subject to frequent shocks from the pandemic, but at a much lower intensity. The Chinese pandemic played a leading role, mainly in the pre- and post-sample period, with a positive correlation in the pre-sample period and a negative correlation later. It is worth noting, however, that renewable energy stock jumps were more significantly led by the global pandemic (excluding China), in the short, medium, and long term, with a short-term negative correlation and a medium- to long-term positive correlation. This indicates that investors in the renewable energy stock market are more concerned about the development of the pandemic in the whole world than the one in China, probably because global renewable energy development is more advanced in many parts of the world than in China, which has long relied on traditional energy sources.

As an alternative to traditional energy sources such as oil and coal, renewable energy is the current direction of the development of energy products. Related products are strongly supported by government policies around the world, especially by leading companies, such as automobile, photovoltaic, and wind power companies. Corbet et al. (2020) pointed out that renewables can be viewed as a more reliable mechanism to generate long-term, stable and low-cost supply; the analysis here shows the same result. Even under the impact of the COVID-19 pandemic, the demand for renewables grew month-by-month after a short-term decline; corporate performance was not significantly affected, and the overall share price maintained an upward trend. This means that the increasing number of new confirmed cases was not enough to significantly change investors’ optimistic psychological expectations about renewable energy.

5.3. Systemic co-jumps in China’s energy stock markets under the COVID-19 pandemic

The findings in Table 3 seem to suggest that the COVID-19 pandemic did not significantly affect the frequency of co-jumps between different energy stock markets, which are contradictory with the conclusions of Yang et al. (2017), who found that the co-movement of related asset prices during the crisis would increase. However, the findings described previously only show a preliminary static result, which cannot reveal the dynamic interactions between the COVID-19 pandemic and the co-jumps of different Chinese energy stock markets at every moment. Therefore, a wavelet coherence analysis is further applied here to investigate their interactions in different time and frequency domains.

As can be seen in Fig. 6, from a dynamic perspective, the pandemic did have a significant impact on the co-jumps of different Chinese energy stock markets. Specifically, the co-jumps in the oil and coal stock markets were the most severely affected by the pandemic. In the short term,
there was a frequent but relatively small impact of the pandemic on them, while the impact of the global pandemic was even milder than the Chinese pandemic, which is consistent with the analyses of the jumps in Section 5.2. Meanwhile, the short-term impact of the Chinese pandemic was able to persist into the long term, mainly showing a negative relationship, especially during the peak and re-deterioration phases of the pandemic. In contrast, the impact of the global pandemic could only last until the medium term, with a long-term negative correlation after January 2021 when the pandemic was recurred. However, the leading effect was significant regardless of China/global pandemic tolls.

Interestingly, the wavelet coherence results for the other three combinations show interactions that are not as strong as the pandemic impact on co-jumps in the oil and coal stock markets. Although the short-term frequent but small impact still existed, but mainly showed negative correlations, and the leading role of the pandemic was not significant enough, as in the case of the interactions between the pandemic and co-jumps in the oil and renewable energy stock markets. Even more, co-jumps in the coal and renewable energy stock markets, as well as those in the oil, coal and renewable energy stock markets are more slightly affected by the pandemic, and the characteristics of the two combinations do not differ much.

Different China/global pandemic tolls and occurring phases have heterogeneous effects on co-jumps. It is worth noting in Fig. 6 that, in addition to the initial (peak) phases of the pandemic, impact during the re-deterioration phases of the pandemic cannot be ignored, and even the risk of systemic co-jumps will be higher than when it first occurred, such as the period after January 2021. This further extends the findings of Yu et al. (2022), who, by showing that a second peak would cause a more serious correlation across markets, found that the correlations between stock markets and pandemic anxiety indexes varied with time. Further, this also indicates that the systemic co-jumps between traditional energy stock markets are more impacted, while co-jumps in the presence of renewable energy stock market jumps all show some degree of a weakening effect. Considering the findings of single market jumps, the renewable energy stock market jumps were the least impacted by the pandemic, and the jumps were more heterogeneous. This made it difficult to generate systemic co-jumps with traditional energy sources such as oil and coal, and even weakened the jumps, due to the good psychological expectations of investors for the renewable market, compared to other energy types, during the pandemic. This finding once again proves the good resilience of the renewable energy stock market.

5.4. Discussion

Wavelet coherence between new confirmed Chinese and global cases of COVID-19 and three energy stock markets jumps or co-jumps reveals
their short-, medium-, and long-term co-movements in different time-frequency domains. As summarized in Fig. 7, the impact of COVID-19 on different China's energy stock market jumps varied with market specifications, investment horizons, and China/global pandemic tolls.

Highly volatile levels of new confirmed cases can cause a greater shock to the psychological expectations of energy stock investors, independent of the base size of the pandemic itself. This shock will also diminish as the pandemic gradually plateaus until a second peak of the pandemic will again deepen the process. While the shock from the pandemic frequently shows a significant leading effect in the short term, the positive and negative correlations change in line with the turn of the pandemic. This finding is consistent with the conclusions of Arif et al. (2021). In the medium to long term, the impact of the pandemic on energy stock price jumps is more severe, but the pandemic’s dominant effect has diminished, and jumps are influenced by a combination of more exogenous factors. As found by Zhang and Hamori (2021), the impact of the COVID-19 pandemic on financial markets is uncertain in both the short and long terms. Indeed, market specifications also influence this process. Apparently, the renewable energy stock market has shown good resilience in the face of the pandemic, while the oil stock market is the most impacted one. The oil market also shares a consistent trend with the coal stock market and is thus subject to greater systemic risks. This result is in line with the findings of Hemrit and Benlagha (2021), who found that external factors (such as suitable policies) could turn the threat of pandemic uncertainty into a great opportunity for the renewable energy market, thus hedging various risks. Further, the result confirms the decoupling of the renewable energy industry from the traditional energy market, as proposed by Ferrer et al. (2018). Even under the impact of the COVID-19 pandemic, the correlation did not change greatly.

In this case, investors with short investment horizons will find it difficult to realize spread gains during the pandemic, as any large fluctuations in the change of new confirmed cases will shake investors' psychological expectations. The damage could even be exacerbated by “herding effects” in the market (Zheng et al., 2015; Chang et al., 2020), making stock price fluctuations difficult to predict using traditional methods. Pricing methods may also become dysfunctional, which is the very thing portfolio managers should consider in portfolio management. Thus, investors with short investment horizons need to be wary of the abnormal short-term jumps in energy stock prices caused by any reoccurrence of the pandemic, as short-term shocks remain significant, even in the post-sample period. Also, in the medium to long term, energy

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4 Quitzow et al. (2021) pointed out that, with the transformation of the world’s energy structure, green, low-carbon, renewable energy sources are being promoted internationally, and high-carbon fossil energy sources are being phased out.

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![Fig. 6. Wavelet coherence between co-jumps among different energy stock market pairs and new confirmed cases of COVID-19. Note: Summarized interaction between two specific series on different frequency domains is shown to the right of the figure, manifested in the pre- (January–March 2020), mid- (April–September 2020) and post- (October 2020–February 2021) phases of the sample time, as well as the short- (1–4 days length period), middle- (4–32 days length period) and long-term (more than 32 days length period) frequency bands.](image-url)
stock market investors still seem to have the potential to make a profit. A valid conclusion is that the best long-term investment option is to strengthen the weight of renewable energy stocks in the portfolio, especially considering the performance of the renewable energy stock market and the irreversible transformation trend of the overall energy structure. Besides, the superior performance of renewable energy stock markets during the pandemic could also inspire relevant regulatory authorities to promote the development of renewable energy to some extent and to take timely measures to reduce the impact on investors' psychological expectations.

6. Conclusions

Price jumps in different China’s energy stock markets during the COVID-19 pandemic have highlighted the severe impact of the extreme events of the COVID-19 pandemic on investors’ psychological expectations. These jumps invalidate traditional asset pricing, making risk management difficult, and exposing a wide range of market participants to more severe potential losses, the characteristics of which have not been studied. Thus, this paper is one of the seminal studies on the impact of the COVID-19 pandemic on the energy industry and also provides a new perspective for subsequent research.

The study’s findings suggest that, first, oil stock market jumps were most severely correlated with the COVID-19 pandemic, and the shock brought about by the Chinese pandemic was larger than the shock caused by the pandemic in the whole world. Jumps were particularly pronounced during the peak and re-deterioration phases of the pandemic and were positively led by the pandemic, mainly in the short term (1–4 days length period) and long term (more than 32 days length period). Second, coal stock market jumps have similar characteristics to those in the oil stock market, but were less correlated with the pandemic in the short term than oil; the jumps also mainly show a negative relationship with the pandemic. Third, renewable energy stock market jumps are the least correlated ones, but they are also more significantly led by the global pandemic and show an overall positive short-term and negative long-term correlation. Finally, systemic co-jumps and jumps exhibit the same characteristics with respect to the China/global pandemic tolls and the occurring phases, but co-jumps in the oil and coal stock markets are the most severely affected, while the combinations of other energy stock market are less correlated with the pandemic.

The empirical evidence in this study may have important implications for various market participants. For example, investors with short investment horizons need to be alert to phenomena such as pandemic re-deterioration and abnormal oil price volatility, and they must be prepared in advance for co-jumps and systemic risks. Meanwhile, investors with long investment horizons might as well shift their portfolio holdings of energy assets to diversify investment risk. This could be done by, for example, appropriately increasing the proportion of renewable energy assets. As for portfolio managers, asset valuation and portfolio construction need to take into account the presence of jumps and systemic risk in the event of a “black swan-like” event; otherwise, biases will occur. Meanwhile, policymakers ought to establish a crisis early warning mechanism, in order to mitigate the impact of unexpected events on investors’ psychological expectations. Timely measures should also be taken to promote the development of renewable energy markets, thereby improving the risk resistance of energy stock markets under crisis and reducing the systemic risk of traditional energy sources, such as fossil fuels.

CRediT authorship contribution statement

Yuan Tong: Writing – original draft, Software, Data curation, Formal analysis. Ning Wan: Writing – original draft, Software. Xingyu Dai: Writing – review & editing, Methodology, Software, Conceptualization. Xiaoyi Bi: Writing – original draft, Software. Qunwei Wang: Supervision, Writing – review & editing, Funding acquisition, Project administration.

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Appendix A. Supplementary data

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