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An empirical study of the time-varying spillover effects between China's crude oil futures market and new energy markets

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ABSTRACT
The time-varying spillover effect of China's crude oil futures market and new energy market has an important impact on promoting the green development of China's economy. This study uses the dynamic connectedness method based on DCC-GARCH model to analyze the time-varying spillover effects between Shanghai crude oil futures and various industries in new energy markets. The results show that there was a stable volatility correlation and high degree of connectedness between Shanghai crude oil futures and the new energy stock market. The new energy vehicle and energy storage industries were driving the market, while Shanghai crude oil futures and both wind power and photovoltaic industries were driven by the market.With the analysis results, the study provides scientific policy recommendations for the development of China's crude oil futures market and new energy market, which are expected to contribute to the sustainable development of the energy market.

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1. Introduction

Green economy concept is an important idea of sustainable economic development. It has become a global consensus to deal with the challenges of ecological environment, economic and social developments. Based on this concept, considering the exhaustible characteristics of traditional fossil energy resources and environmental pollution, governments and research institutions have realized the importance of developing renewable and clean new energy sources. In China for instance, the country is not only facing energy crisis but also environmental pollution problems (Wang et al., 2020). In September 2020, at the 75th session of the United Nations General Assembly, China's president, Xi Jinping has announced that China would strive to achieve 'peak carbon' by 2030 and 'carbon neutrality' by 2060 which is also known as 'Double-Carbon' policy. In the context of the policy, the State Council proposed that

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the proportion of non-fossil energy consumption should reach about 20% by 2025 and more than 80% by 2060. China's strive to achieve its emission reduction targets, has escalated the new energy industry growth (Zhang & Du, 2017). It has drawn attention from capital market investors toward investing in the stocks of the new energy industry sector where venture capital investment plays an important role in promoting the new energy development (Kortum & Lerner, 2000). Therefore, it is important to study the financial mechanism of the new energy market and its influence in stabilizing the new energy market development (Lin & Chen, 2019).

As an alternative to traditional energy sources, investments in new energy sources are largely influenced by the level of traditional energy prices. It has been pointed out that price changes in crude oil are considered one of the main systematic risks for new energy companies (Reboredo, 2015) and there is relationship between returns of the new energy companies with the oil prices changes (Narayan & Sharma, 2014; Phan et al., 2015), and the existence of different companies in new energy changes the price elasticity of demand for oil (Gupta, 2017), which suggests the need to study the dynamic changing of relationships between new energy markets and oil based industries (Zhu et al., 2019).

Along with the development of the financial industry, crude oil futures prices have gradually become an important basis for trading among crude oil market participants and for financial institutions to predict the crude oil spots prices. Since the listing of Shanghai crude oil futures in March 2018, many scholars have started to focus on research that are related to China's crude oil futures market. Xue and Guo (2020) have found that there is a strong spillover effect of Shanghai crude oil futures on the crude oil spots of Shengli, Daqing, and Oman, and further suggested the way to determine the oil spot prices. Another study by Niu and Xu (2020) has empirically demonstrated that the listing of Shanghai crude oil futures has enhanced the volatility and volatility asymmetry of the crude oil spot prices to some extent. Also, other scholars have found that Chinese crude oil futures prices have attracted large number of traders in the Chinese domestic market (Palao et al., 2020; Wang et al., 2022; Zhang et al., 2021). However, studies on the crude oil futures market and the new energy market as represented by the Chinese crude oil futures price are relatively rare.

Therefore, to fill the gap, this study considers Shanghai crude oil futures market as the representative of crude oil prices of China, to analyze the connectivity and the dynamic spillover effects of stock prices between several energy industries such as photovoltaic, energy storage, wind power, and new energy vehicles industries in the new energy market. Shanghai crude oil futures and new energy stock markets are relatively had strong linkage and stable volatility correlation. Among the new energy stock market, the wind power and the photovoltaic industries are the net receivers of the spillover effect, and the spillover effect between each market is asymmetric.

The paper is organized as follows: In Section 2, the existing literatures were reviewed. Section 3 is dedicated to theoretical and model construction including the dynamic conditional correlational autoregressive conditional heteroscedasticity (DCC-GARCH) model, volatility impulse response function (VIRF), and dynamic connectivity theory. Meanwhile, Section 4 presents the process and results of the empirical analyses. Conclusions and countermeasure suggestions are presented in Section 5 and finally, the innovations and limitations of the study are mentioned in Section 6.

2. Literature reviews

To promote high-quality development of the new energy market, many scholars have conducted studies on the contagion mechanism between the crude oil futures market and new energy markets in China (Qu et al., 2021). Generally, researchers have found that there is a strong mutual influence between them. For example, Wen et al. (2012) examined the asymmetry and volatility spillover effects between the stock market of Chinese new energy companies and the WTI crude oil futures market. The findings have shown that there was a mutual influence between crude oil prices and new energy stocks. Also, Hu and Ding (2016) find evidence on spillover effect between international crude oil price volatility and the stock price volatility among China's new energy industries. Some scholars argue that fossil energy prices have a positive impact on new energy stock prices, however the impact is not as high as one would expect (Reboredo, 2015; Sun et al., 2019). Meanwhile, Shah et al. (2018) suggest that higher oil prices contribute to the increment investments in new energy, and therefore by studying the oil price changes will help to understand the outlook for new energy consumption. It is worth noting that there is an isotropic impact of the crude oil price on the new energy stock market changes (Brini et al., 2017; Padhan et al., 2020), and the rise of the new energy stock market not only accelerates the development of new energy market itself but also benefits the development of green low-carbon economy (Zeqiraj et al., 2020). Although various studies have been done in this new energy area, it is not difficult to see that they mostly analyzed the mutual influence between new energy stocks and crude oil prices, by choosing the prices of WTI and Brent crude oil futures as the representatives of the international oil prices. Less have been done on evaluating the dynamic relationships between new energy market and crude oil futures market.

Some studies on crude oil prices and the new energy market in China tend to look at all new energy industries, but less on different industries in the new energy market (Ahmad & Rais, 2018; Dutta, 2017). Also, it is common to use only one new energy index to represent the new energy market (Hsiao et al., 2019; Lin & Chen, 2019; Wen et al., 2014; Zhang & Du, 2017) while this will ignore the internal heterogeneity among new energy indices. In studying the heterogeneity and nonlinear relationship between oil and stock prices among China's new energy subsectors, Lv et al. (2021) find that there are strong impacts from oil prices towards the new energy vehicle stock prices, while there is indirect impact between wind and solar industries. Zhu and Su (2022) find the inconsistency in causal relationship between new energy industry index which are hydropower, wind and solar with crude oil prices. Therefore, refining the new energy industry sectors and studying the spillover effects between each new energy industry and crude oil prices can better provide more targeted advice to governments and investors.

Spillover effects are results from economic activity or different types of processes, which affect other markets, participants, or processes that are not directly connected.

In recent years, spillovers between financial markets have been a concerned among scholars. Most studies on the spillover effects of different financial markets, have used vector autoregressive models (VAR) (Cross & Nguyen, 2018; Hoque et al., 2019; Sun et al., 2019), Granger causality (Bekiros et al., 2016; Odhiambo, 2021; Peng et al., 2018, 2020; Su et al., 2022), cointegration theory (Lin & Li, 2015; Marques et al., 2019), and GARCH models (Ahmed & Huo, 2021; Chen et al., 2020; Kumar & Anandarao, 2019; Lv et al., 2021; Zhang & Mani, 2021). Diebold and Yilmaz (2012, 2014) proposed a dynamic connectedness approach based on the forecast variance decomposition of a VAR model. The model is commonly called DY(Diebold and Yilmaz) model, has been widely used to evaluate the spillover effects between different financial markets in several regions (Gomez-Gonzalez et al., 2021; Su et al., 2022; Sugimoto & Matsuki, 2019; Tiwari et al., 2018; Yoon et al., 2019). Then, Gabauer (2020) proposed a dynamic connectedness measure based on the combination of the volatility impulse response (VIR) function of the DCC-GARCH model and the DY spillover index model, in which can overcome the limitations of the traditional dynamic connectedness estimation method. It also can avoid arbitrary window selection and the loss of observed data in rolling window analysis (Bouri et al., 2021), providing a new idea in volatility spillover theory, as empirically applied by Bouri et al. (2021) and Zhang et al. (2022).

In summary, the analysis of the dynamic spillover effect between China's crude oil futures and its new energy stock markets is significant to study to ensure a stable policy and better development of China's new energy market. The study proposed the using of a dynamic connectedness approach based on DCC-GARCH (Gabauer, 2020) to empirically analyze the dynamic spillover effects between Shanghai crude oil futures and the new energy stock markets. The main innovations and contributions of this study are as follows: (1) The study used the Shanghai crude oil futures main-linked contract price as a proxy for domestic crude oil prices, laying the foundation for more accurate in revealing and explaining the interactions between China's crude oil market and its new energy industries. (2) The study presented the dynamic inter-market linkages based on the DCC-GARCH model as proposed in Gabauer (2020). Compared with Diebold and Yilmaz (2012, 2014), this can avoid the loss of the observation data due to the selection of rolling window and can measure relationships between the relevant impacts of different markets under the changing situations more scientifically. It is hope that the study will enrich the theoretical foundation of the field. (3) The study further subdivided the new energy market according to different sectoral indices to examine in detail the development of different industries of the new energy market. This will provide new scientific evident and reference to other researchers and eventually to the policies maker.

3. Model construction

This study adopts the connectivity approach of DCC-GARCH model (Gabauer, 2020) by constructing a combination of volatility impulse response (VIR) function of the DCC-GARCH model and dynamic connectivity approach of Diebold and Yilmaz

(2014). In contrast to the existing studies, the approach ignored the window size (Mishra & Ghate, 2022) in estimating the volatility transmission.

First, a DCC-GARCH model (Engle, 2002) was constructed using daily log returns of China's crude oil futures and its new energy stock markets which includes the photovoltaic, wind power, energy storage and new energy vehicles industries. Mathematically, the equation was written as

$$y_t = \mu_t + \theta_1 y_{t-1} + \phi_1 \varepsilon_{t-1} + \varepsilon_t, \quad \varepsilon_t | F_{t-1} \sim N(0, H_t), \tag{1}$$

$$\varepsilon = H_t^{1/2} u_t \quad u_t \sim N(0, 1), \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

where F_{t-1} denotes all the information available before $t-1$, y_t represents the daily log return series of the five markets (crude oil futures plus stock markets from four new energy industries), $\mu_t, \varepsilon_t, u_t$ are 5×1 matrices, each representing conditional mean, error term, and the standardized error term respectively. θ_1 and ϕ_1 represent the first-order autocorrelation coefficients of the variables and the first-order moving average coefficients of the disturbance terms respectively. Meanwhile, R_t, H_t, D_t are 5×5 matrices representing the dynamic conditional correlation matrix, time-varying conditional variance-covariance matrix, and the time-varying conditional variance matrix respectively.

In the first stage, the components were estimated by the GARCH model for each series. The shock and persistence parameters were assumed according to Hansen and Lunde (2005) as:

$$h_{ii,t} = \omega + a_1 \varepsilon_{i,t-1}^2 + b_1 h_{ii,t-1} \tag{4}$$

Then, in the second stage, the dynamic conditional correlation was calculated as follows:

$$R_t = diag(q_{iit}^{-1/2}, \ldots, q_{NNt}^{-1/2}) Q_t diag(q_{iit}^{-1/2}, \ldots, q_{NNt}^{-1/2}), \tag{5}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{6}$$

where $Q_t, \bar{Q}$ are 5×5 positive definite matrices representing the variance-covariance matrices of the conditional and unconditional normalized residuals respectively. α and β are non-negative shocks and persistent parameters that satisfying $\alpha + \beta \leq 1$. The residuals of the mean equation were assumed to follow a normal distribution with zero means, and the dynamic correlation coefficient can be written as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}} \sqrt{q_{jj,t}}}. \tag{7}$$

Next, the estimation of the volatility impulse response function (VIRF). The VIRF represents the effect of a shock in variable i on the conditional volatility of variable j, denoted as:

$$\Psi^{g} = VIRF(J, \delta_{j,t}, F_{t-1}) = E(\mathrm{H}_{t+J}|\varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(\mathrm{H}_{t+J}|\varepsilon_{j,t} = 0, F_{t-1}) \tag{8}$$

$$\delta_{j,t} = \begin{cases} 1, \ t = j \\ 0, \ \text{else} \end{cases}.$$

The estimation involved three steps where in the first step, a univariate GARCH(1,1) model was used to predict a conditional volatility $D_{t+h}|F_t$ as follows:

$$E(h_{ii,t+1}|F_t) = \omega + \alpha\delta^2_{1,t} + \beta h_{ii,t} h = 1 \tag{9}$$

$$E(h_{ii,t+1}|F_t) = \sum_{i=0}^{h-1} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1} E(h_{ii,t+h-1}|F_t) h > 1 \tag{10}$$

Secondly, $E(Q_{t+h}|F_t)$ was calculated as:

$$E(Q_{t+h}|F_t) = (1-a-b)\bar{Q} + a u_t u'_t + b Q_t h = 1 \tag{11}$$

$$E(Q_{t+h}|F_t) = (1-a-b)\bar{Q} + aE(u_{t+h-1}u'_{t+h-1}|F_t) + bE(Q_{t+h-1}|F_t) h > 1 \tag{12}$$

where $E(u_{t+h-1}u'_{t+h-1}|F_t) \approx E(Q_{t+h-1}|F_t)$, contributed to the prediction of the conditional correlation of the dynamics.

In the final step, the conditional variance-covariance was predicted as:

$$E(R_{t+h}|F_t) \approx diag[E(q^{-1/2}_{iit+h}|F_t), \ldots, E(q^{-1/2}_{NNt+h}|F_t)] \, E(Q_{t+h}) diag[E(q^{-1/2}_{iit+h}|F_t), \ldots, E(q^{-1/2}_{NNt+h}|F_t)]$$

$$E(H_{t+h}|F_t) \approx E(D_{t+h}|F_t) E(R_{t+h}|F_t) E(D_{t+h}|F_t) \tag{13}$$

Meanwhile, the generalized forecast error variance decomposition (GFEVD) was calculated based on the VIRF where the variance shared the explanation of one variable over the other variables. The variance was normalized so that it summed to 1 in each row, indicated that all variables explained a 100% of the prediction error variance of variable i. Based on the method in Gabauer (2020), this process was presented as the following.

Calculate the pairwise directional connectedness as:

$$\tilde{\varphi}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \psi^{2,g}_{ij,t}} \tag{14}$$

where $\sum_{j=1}^{N} \tilde{\varphi}^{g}_{ij,t}(J) = 1$. Here the numerator denotes the cumulative effect of the i-th shock and the denominator denotes the total cumulative effect of all shocks. Next, the total connectivity index (TCI), directional connectivity index (DCI), and net directional connectivity index (NCI) were calculated.

The TCI represents the average degree of impact of a shock to one variable on all other variables and was computed as:

$$C_t^g(J) = \frac{\sum_{i,j=1,\, i\neq j}^{N} \tilde{\varphi}_{ij,t}^{g}(J)}{N} \tag{15}$$

The DSI represented the spillover effect that passed from spillover variable i to another variable j or received from other variable j, and was calculated as:

$$C_{i\to j,t}^g(J) = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{\varphi}_{ji,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\varphi}_{ji,t}^{g}(J)} \tag{16}$$

$$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{\varphi}_{ij,t}^{g}(J)}{\sum_{i=1}^{N} \tilde{\varphi}_{ij,t}^{g}(J)} \tag{17}$$

The difference value between the two equations (16) and (17) yields the NCI, which represented the net risk spillover from variable i to the remaining variables as written in the following eq (18),

$$C_{i,t}^g = C_{i\to j,t}^g(J) - C_{i\leftarrow j,t}^g(J). \tag{18}$$

If the NCI of variable i is a positive (negative) value, it means that variable i is a net transmitter (receiver) of volatility shocks or variable i is driving (being driven by) the network.

4. Empirical analysis

4.1. Data selection and processing

Generally, new energy refers to a new energy source such as solar energy, wind energy and geothermal energy. It can be further divided into new energy vehicles, photovoltaic(PV), wind power, energy storage and other segments. This study focused on the interaction between the Shanghai crude oil futures market and the development of the new energy industries. The daily crude oil futures main contract prices and the new energy stock indexes of four different sectors were considered as the five variables for the analyses. The variables are listed in Table 1 with its code in which representing the stock symbol for each stock index. The WPII is the CSI Wind Power Industry Index (code is 931672), consists of up to 50 listed companies in the Shanghai and Shenzhen markets whose businesses are related to the wind power industry. It reflects the overall performance of the listed securities in the photovoltaic (PV) industry in the Shanghai and Shenzhen markets. The ESII represents the CSI Energy Storage Industry Index (931746) and consisted of 50 listed companies in the energy storage industry selected from the Shanghai and Shenzhen markets to reflect the overall performance of the listed securities in the energy storage industry. Meanwhile, NEVII (coded as 930997) represents by 59 listed companies in the

Table 1. List of the index and its code.

Code	Name of index	Frequency
931151.CSI	CSI Photovoltaic Industry Index (PII)	Daily
931672.CSI	CSI Wind Power Industry Index (WPII)	Daily
931746.CSI	CSI Energy Storage Industry Index (ESII)	Daily
930997.CSI	CSI New Energy Vehicle Industry Index (NEVII)	Daily
SC.INE	Shanghai Crude Oil Futures Main Contract (SC)	Daily

Source: own work.

Shanghai and Shenzhen markets whose business is related to the new energy auto industry. It reflects the overall performance of the listed companies in new energy auto sector. All the data were extracted from the Wind Financial Database.

Since the Shanghai crude oil futures market was first listed on March 26, 2018, the sample was considered from March 26, 2018, to June 23, 2022. The dates with inconsistent trading days were excluded to obtain a total of 1024 sets of observations. The daily log returns were computed as $R_t = 100 \times \ln(P_t/P_{t-1})$, where P_t is the closing price on day t and P_{t-1} the closing price on the previous day. The time series of the daily log return of each stock index was shown in Figure 1, and the descriptive statistical analysis was presented in Table 2.

As can be seen from Table 2, the mean of each series was greater than zero during the study period, and the standard deviation of the Shanghai crude oil futures was the largest, indicating that the volatility was more intense, which was consistent with the complexity of crude oil prices. The sample data were left skewed and kurtosis was greater than 3, which indicated that both the Shanghai crude oil futures and the new energy stock price return series were characterized by sharp peaks and thick tails and did not follow a normal distribution. Meanwhile, from the augmented dickey-fuller (ADF) test, each series was smooth and the ARCH test was significant at lag 20, with a significant volatility heteroskedasticity. Also, from the correlation coefficients between the variables, there was a strong positive correlation between the return series of the new energy stocks, while the correlation between Shanghai crude oil futures price returns and new energy stocks was relatively weak and positive. The correlation chord diagram was presented in Figure 2. Clearly, from the chord diagram, it showed that SC has the smallest share on the arc, implying that there was smallest correlation between SC and the other four markets. The width of the lines suggested the strongest correlation between ESII and NEVII, and the weakest correlation was between SC and NEVII.

4.2. Analysis of dynamic linkages between shanghai crude oil futures and the new energy stocks

To evaluate the dynamic correlation between Shanghai crude oil futures and new energy stocks, a DCC-GARCH (1,1) model was constructed first. The estimation of the model was done under the assumption that the residuals of the univariate GARCH model followed a normal distribution. Results from the analysis were presented in Table 3 with $\alpha > 0, \beta > 0,$ and $\alpha + \beta < 1$. Notice that a smaller α as compared to β indicated that the correlation process has rejected the shock and quickly recovered to the average level, indicating that the established model was significant.

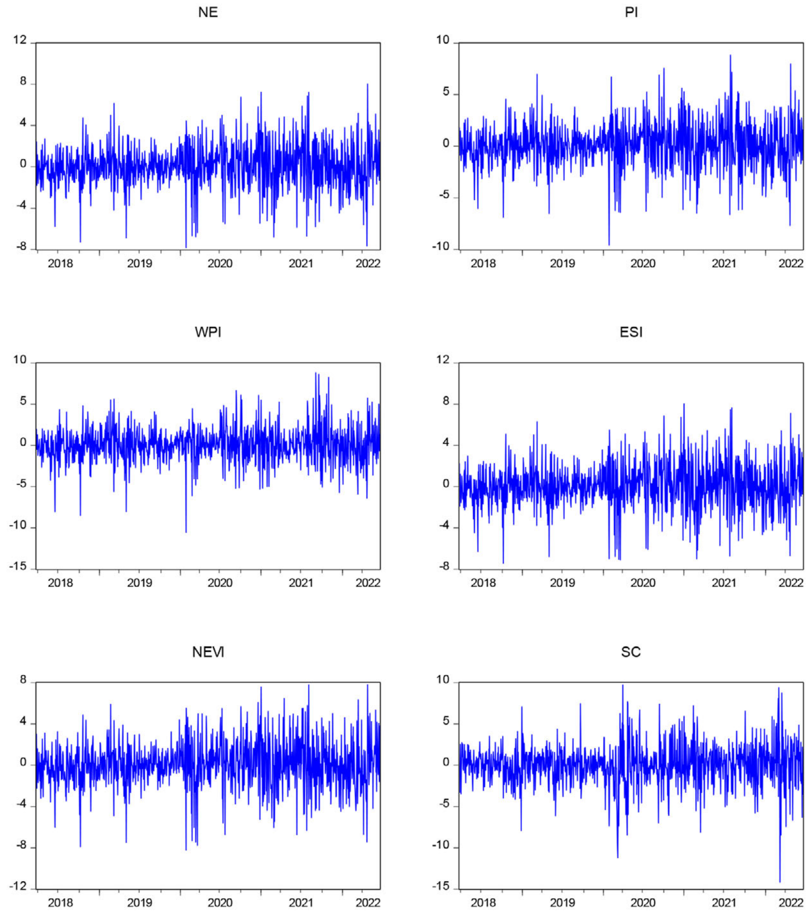

Figure 1. Time series of return series for each stock index.
Source: own work.

Table 2. Descriptive statistics of the log return series.

	PI	WPI	ESI	NEVI	SC
Mean	0.096	0.072	0.117	0.088	0.049
Max	8.832	8.822	8.045	7.830	9.732
Min	−9.578	−10.550	−7.430	−8.222	−14.132
S.D	2.125	2.096	2.146	2.212	2.444
Skewness	−0.093	−0.002	−0.079	−0.080	−0.276
Kurtosis	4.606	5.090	4.249	4.269	5.853
J-B	111.364***	186.170***	67.5322***	69.732***	359.952***
ADF	−22.867***	−22.3847***	−22.7855***	−22.4937***	−21.2387***
ARCH	54.64***	44.039***	62.971***	69.47***	176.95***
Unconditional Correlation Coefficient					
PII	1	0.772	0.916	0.800	0.115
WPII	0.772	1	0.750	0.675	0.118
ESII	0.916	0.750	1	0.940	0.104
NEVII	0.800	0.675	0.940	1	0.121
SC	0.115	0.118	0.104	0.121	1

Note: Asterisks ***, **, * denote significance at 1%, 5%, and 10% significance levels, respectively; J-B test represents normality test (Jarque and Bera 1980); ADF test represents series smoothness test; ARCH-LM denotes lagged ARCH effect test statistic of order 20.
Source: own work.

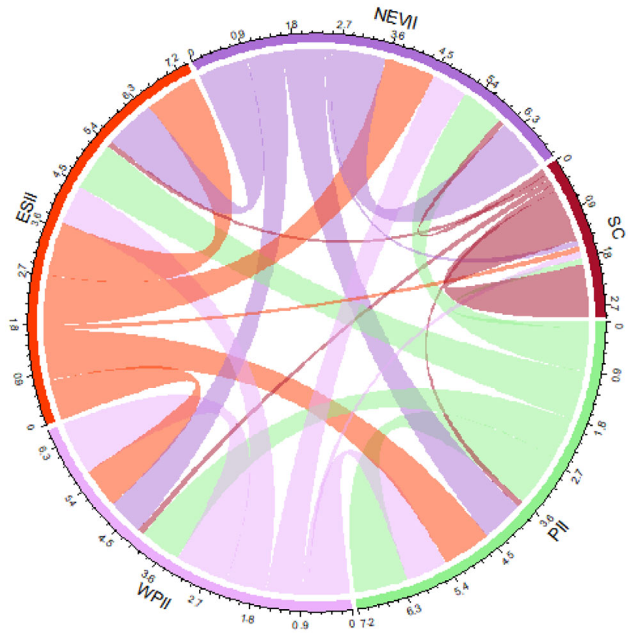

Figure 2. Correlation chord diagram.
Source: own work.

Table 3. Estimations of the DCC-GARCH model.

Panel A: Estimations of Univariate GARCH Models

	PII	WPII	ESII	NEVII	SC
μ_t	0.087	0.063	0.105***	0.082	0.101***
θ_1	−0.749	−0.848***	−0.865***	−0.500	0.969***
ϕ_1	0.778	0.872***	0.884***	0.552	−0.978***
ω	0.170**	0.185**	0.100**	0.082*	0.221**
a_1	0.109***	0.127***	0.079***	0.0767***	0.129***
b_1	0.859***	0.841***	0.902***	0.910***	0.838***

Panel B: Estimation of the Multivariate DCC-GARCH Model

	coefficients	S.D.	T-statistic	p-value
α	0.0224	0.004	6.130	0
β	0.971	0.006	164.873	0

Note: Asterisks ***, **, * denotes significance at 1%, 5% and 10% significance levels, respectively.
Source: own work.

This suggested that there was a strong linkages, and a stable volatility correlation among the markets during the study periods.

The dynamic time-varying coefficient diagram is a portrayal of the dynamic relationship between markets as they change over time. Figure 3 showed the obvious time-varying properties of the correlation coefficients. Meanwhile, results presented in Table 4 suggested the overall strong linkages with a positive correlation and there were volatility spillover effects between the markets. Findings further indicated the largest correlation coefficients were between ESII and NEVII and ESII and PII with the smallest standard deviation. This suggested that the energy storage industry was closely related to the returns of the new energy vehicles and photovoltaic industry, and also they were relatively stable. While the correlation between Shanghai crude oil futures and the four new

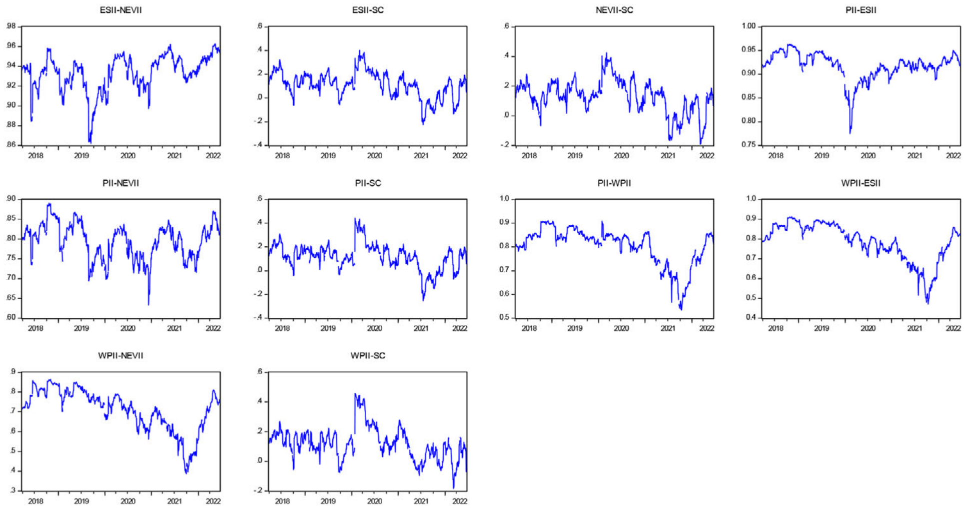

Figure 3. Plots of dynamic correlation coefficient among the markets.
Source: own work.

Table 4. Descriptive statistics of dynamic correlation coefficients.

	Mean	Median	Maximum	Minimum	Std. Dev.
PII vs WPII	0.803	0.831	0.911	0.534	0.079
PII vs ESII	0.918	0.921	0.963	0.775	0.029
PII vs NEVII	0.795	0.802	0.891	0.633	0.044
PII vs SC	0.119	0.126	0.441	−0.254	0.110
WPII vs ESII	0.785	0.806	0.912	0.472	0.096
WPII vs NEVII	0.709	0.728	0.865	0.387	0.106
WPII vs SC	0.120	0.116	0.458	−0.182	0.109
ESII vs NEVII	0.933	0.936	0.963	0.862	0.018
ESII vs SC	0.111	0.119	0.402	−0.225	0.109
NEVII vs SC	0.130	0.139	0.425	−0.193	0.112

Source: own work.

energy industries was small, the correlation between Shanghai crude oil futures and new energy vehicles was slightly stronger in comparison.

4.3. The network connectivity between shanghai crude oil futures and new energy markets

For better estimation of the conditional volatility transmission between Shanghai crude oil futures and the new energy market stocks, this study applied a multivariate DCC-GARCH (1,1) model with a 100-step ahead generalized forecast error variance decomposition. A DY index (Diebold & Yilmaz, 2014) was also used to evaluate the volatility connectivity based on the DCC-GARCH model. The results of the connectivity analyses were presented in Table 4.

Table 5 showed the dynamic connectedness between the Shanghai crude oil futures market and the other four new energy stock markets; the photovoltaic, wind power, energy storage and new energy vehicles. Each row represented the spillover effect of the variable from the other variables, indicating the contribution magnitude of the

Table 5. Average dynamic connectedness metric between Shanghai crude oil futures and the new energy markets.

	PII	WPII	ESII	NEVII	SC	FROM
PII	29.35	17.75	28.41	23.47	1.02	70.65
WPII	21.15	32.71	23.63	21.23	1.28	67.29
ESII	21.4	15.2	32.34	30.16	0.9	67.66
NEVII	17.2	13.37	29.49	38.74	1.19	61.26
SC	2.2	1.87	2.2	2.75	90.98	9.02
TO	61.96	48.19	83.73	77.61	4.38	TCI
NET	−8.69	−19.1	16.07	16.36	−4.64	55.18

Source: own work.

shocks from other variables to the predicted variance of a variable. Meanwhile, each column represented the magnitude of the spillover effect of a variable on the other variables, indicating the magnitude of the shock contribution to the predicted variance of the other variables. The net directional connectivity represented the net spillover effect of a variable on the whole system, where a positive (negative) value indicating that the variable was a net shock transmitter (recipient).

As can be seen in Table 5, the total connectivity index was 55.18%, represents a highly interconnected market and indicated that an average of 55.18% shocks in one market overflowed to the rest of the whole system, and that an average of 44.82% of the shocks will affect itself in future periods. The main shock's transmitters were ESII and NEVII, which transmitted on average 83.73% and 77.61% of shocks, respectively. The least transmitter was SC, which transmitted an average of 4.38% of shocks. Overall, the main recipients of the spillover effects were PII, ESII and WPII. They received the spillover effects at 70.65%, 67.66% and 67.29%, respectively. Among the new energy industries, energy storage industry has a high level of spillover effect transmission and reception, and played the intermediate role as a bridge in the whole system. Also, the analysis suggested that the directional spillover across markets was asymmetric, and the net directional connectedness index showed that NEVII (16.36%) and ESII (16.07%) are the main net shocks transmitters and they affect other markets more compared the effects of others to them. The WPII (-19.1%), PII (-8.69%), and SC (-4.64%) were found to be the main shock receivers. This implied that the new energy vehicle industry and energy storage industry were the market driven, while the wind power industry, PV industry and Shanghai crude oil futures were driven by the market. These findings are significant to a portfolio manager and risk management as it revealed relative shock spillovers between the new energy markets. For example, a portfolio manager will be more interested in the new energy industry stocks that drive the market rather than those that are driven by the market. Also, the new energy industry stocks that are primarily affected by their past shocks will expose to fewer sources of risk, while the one that are affected by many other influences are exposed to more sources of risk.

Figure 4 showed the evolution of the dynamic total connectedness, exhibiting the risk mobility of the Shanghai crude oil futures and four sectors of the new energy market. The total connectedness of the whole system was mainly maintained between 60% and 80% throughout the sample period, and the changes were not significant without drastic changes in the risk of the whole system. However, this total connectedness showed a significant drop in July 2021 and reached the lowest value at the end of September, indicating a significant decreased in correlation across the system

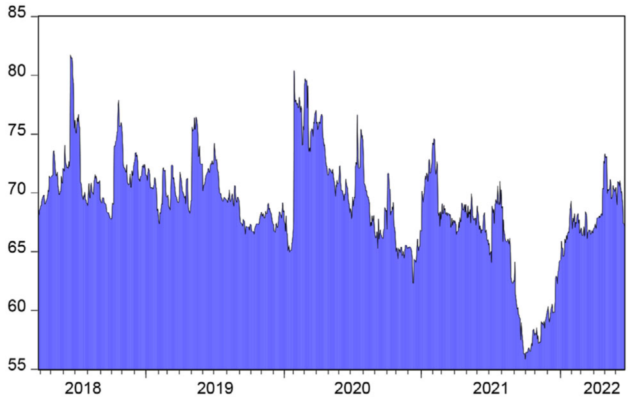

Figure 4. Dynamic connectedness between Shanghai crude oil futures and the new energy markets.
Source: own work.

and a decreased in market risk during this period. This was followed by a continued rise of the overall market correlation towards to the end of January 2022 and it remained at around 70% until the end of the sample period.

The dynamics of the net total directional connectedness index, provided the idea in identifying the net transmitters and receivers of shocks. From a portfolio perspective, markets that are net transmitters of shocks throughout the sample period have fewer potential sources of risk and are therefore of greater interest to investors. Figure 5 showed that ESII was almost a constant net shock transmitter and its net transmission was improved with time. The findings suggested that the energy storage industry could be an attractive asset to portfolio managers. Meanwhile WPII almost always a net recipient of shocks and was driven by the market, implied that it could be less attraction to the investors. However, Shanghai crude oil futures, was found to be a net recipient of shocks, with a short-term net spread only in the second quarter of 2020. This indicated that the Shanghai crude oil futures market cannot be a safe harbor for equity risk in the new energy market.

4.4. The network connectedness among new energy stock markets

Table 6 presented the dynamic connectedness of daily log returns of stock index among PV, wind, energy storage and new energy vehicles industries in the new energy market. The total connectedness index of the system was recorded as 66.19%, indicated that the new energy market was highly interconnected. The change of 66.19% in the system was due to the interaction between the four sectoral indices, with a high degree of connectedness among the industries. There was relatively large spillover effect from other markets to the PV industry and it reached to 70.2%, followed by the energy storage industry (67.21%). The total spillover effect transmitted by the energy storage industry to other markets was the largest (recorded as 29.72%), while the total spillover effect transmitted by the wind power industry to other markets was the lowest (46.8%). Both the energy storage industry and new energy vehicles were the main transmitters of spillover shocks to other new energy markets in the whole system, while the wind and photovoltaic industries were the net recipients of the spillover effects. This indicated that among the new

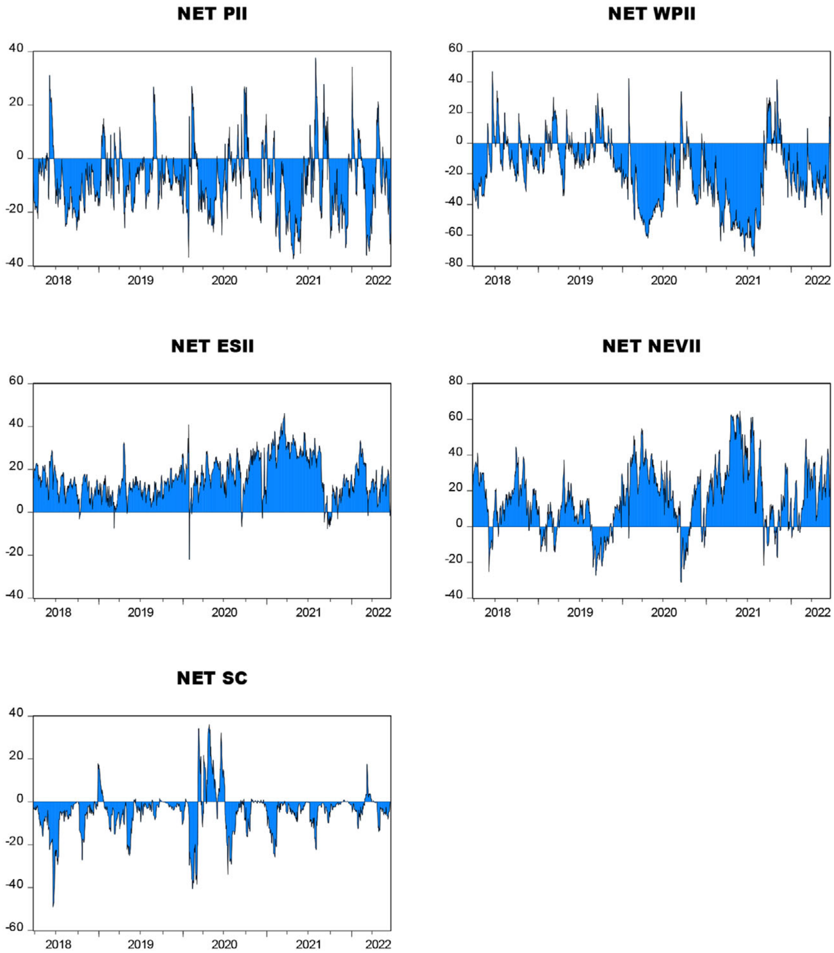

Figure 5. Dynamic net total directional connectivity among the new energy markets.
Source: own work.

Table 6. Connectivity measures among the new energy stock markets.

	PII	WPII	ESII	NEVII	FROM
PII	29.8	17.92	28.62	23.66	70.2
WPII	21.39	33.25	23.88	21.48	66.75
ESII	21.53	15.34	32.79	30.33	67.21
NEVII	17.33	13.54	29.72	39.41	60.59
TO	60.25	46.8	82.22	75.48	TCI
NET	−9.95	−19.95	15.01	14.89	66.19

Source: own work.

energy industries, the changes in the prices of the energy storage industry were the most significant influencing factor, with a total contribution to the system was 15.1%. The largest spillover effect transmitted to other markets is from ESII, followed by NEVII, and the smallest was WPII. This gave evident that among new energy equity market, ESII contributed the most to market connectivity, while WPII contributed less. Each the energy storage industry and the new energy vehicle industry was the one that driven the market risk and therefore contributed important role in the new energy market.

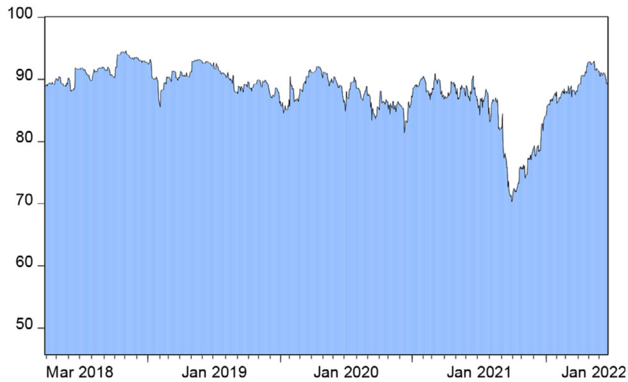

Figure 6. Dynamic total connectivity among the new energy markets.
Source: own work.

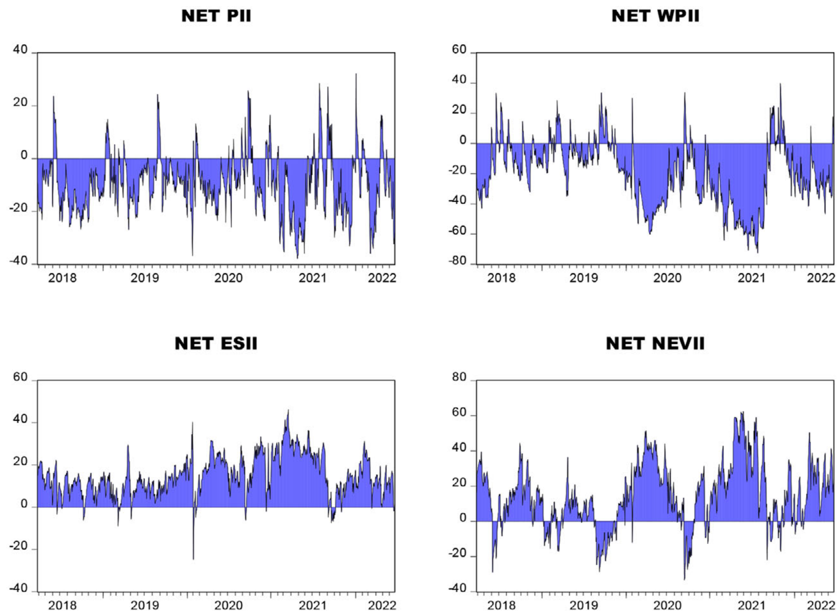

Figure 7. Net total directional connectivity among the new energy markets.
Source: own work.

New energy as one of the emerging industry is still very volatile in terms of its development and subjects to some perturbations at different stages. The dynamic TCI in Figure 6 stayed roughly between 70% and 90%, indicating a strong and overall time-varying connectedness. There was a sharp dropped in total connectedness to about 70% from September 2021, and then it slowly picked up until it reached about 85% in January 2022, which a similar trend to Figure 4.

In the net total directional connectivity metric for the four segments of the new energy market, the results shown in Figure 7 were consistent with the analyses in the previous section. The energy storage industry was also a net shock transmitter in the overall system, and over time, it also has improved its net transmission capacity. The energy storage industry and new energy vehicles were the main transmitters of spillover shocks to other new energy markets in the whole system, while the wind and PV industries were the net recipients of the spillover effects.

4.5. Robustness analysis

4.5.1. Robustness test on the DCC-GARCH model

In the construction of the DCC-GARCH model, the distribution of the random error term affects the model estimations. So this study assumed that the residuals of the univariate GARCH model followed student's t-distribution assumption and the estimation results were shown in Table 7. Comparing the results in Tables 3 and 7, the estimates and significance levels did not differ significantly. The established models were significant and there were strong linkages and more stable volatility correlation among the markets during the study period. Besides, results showed that the estimation were robust according to DCC-GARCH model based on normal distribution.

4.5.2 The robustness test of the DCC-GARCH-DY index model

To further illustrate the robustness of the DCC-GARCH-DY index mode, this section established the construction of the DY index based on the VAR model to analyze the dynamic spillover effect between Shanghai crude oil futures and new energy stock market. As shown in Figures 8 and 9, the trend of dynamic total connectedness was robust under the spillover effect index based on the DCC-GARCH and the VAR models. Besides, the analysis of the net directional spillover effect based on the VAR model was consistent with the previous section, where the energy storage industry was determined as the largest net transmitter of the spillover effect, while Shanghai crude oil futures was the net recipient of the spillover effect.

5. Conclusion

The study used the Shanghai crude oil futures market price as a representative of the domestic crude oil price, and constructed a DCC-GARCH network connectedness model to realize dynamic connectivity analysis and more scientific measure on the time-varying spillover effect of China's crude oil futures market and the new energy market. Based on the results, the research innovations, research limitations and outlook were presented.

5.1. Analysis of the time-varying spillover effects between China's crude oil futures market and the new energy market

This study analyzed the dynamic linkages among the markets using the DCC-GARCH model, and used the DCC-GARCH-based dynamic connectivity approach to

Table 7. Estimation of Multivariate DCC-GARCH Model based on student t-distribution.

	coefficients	S.D.	T-statistic	p-value
α	0.0216***	0.0036	6.0219	0.000
β	0.9721***	0.0055	175.8811	0.000

Source: own work.

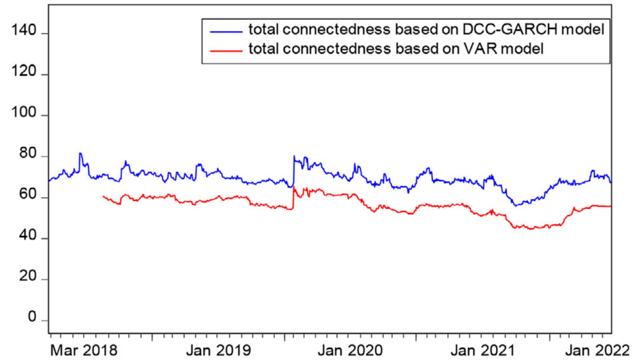

Figure 8. Variation of dynamic total connectivity under two models.
Source: own work.

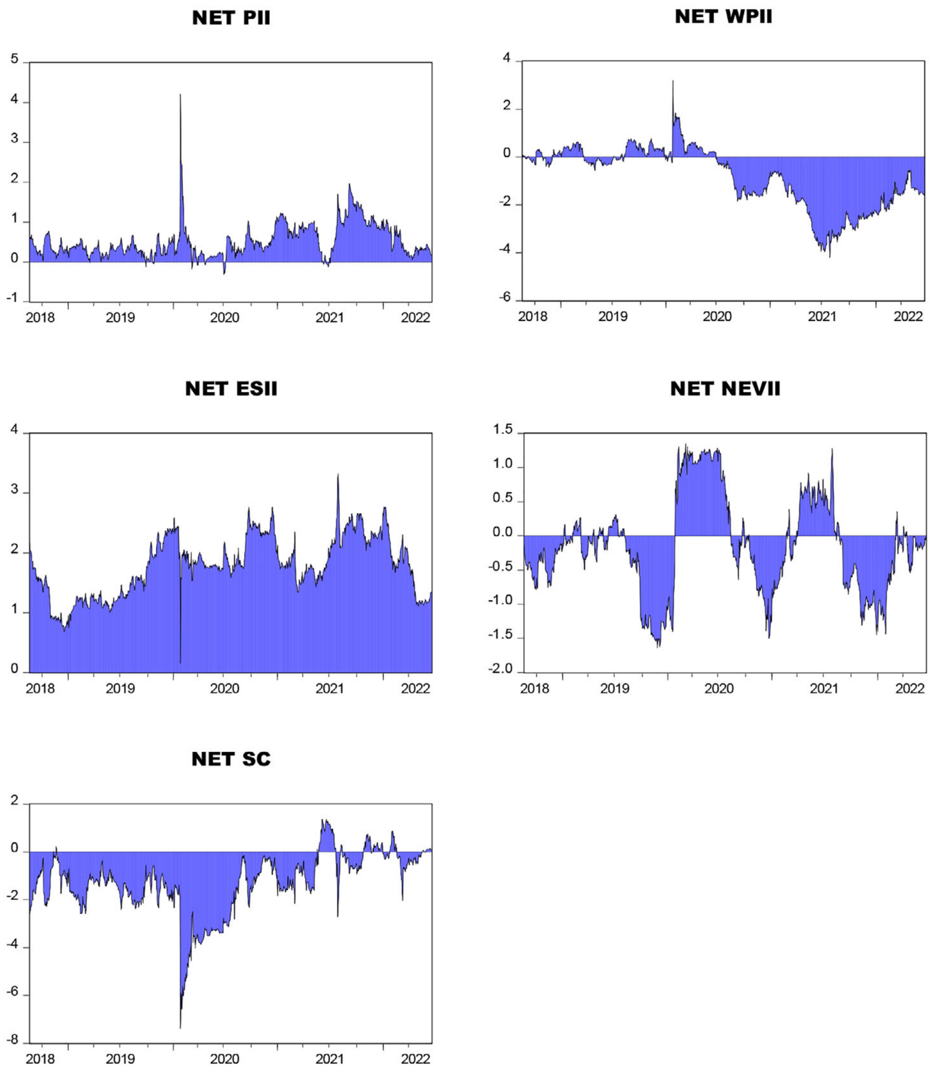

Figure 9. Net directional connectivity based on VAR-DY index.
Source: own work.

investigate the time-varying spillover effects among industries in the Shanghai crude oil futures and new energy markets for the first time. Among the findings are: (1) The price return series of Shanghai crude oil futures and new energy stocks both were featured with spikes and thick tails and have a significant volatility heteroskedasticity. Also, there was a strong positive correlation among the new energy stocks, while there was a weak positive correlation between Shanghai crude oil futures and new energy stocks. During the study period, there was a strong linkage and stable volatility correlation between Shanghai crude oil futures and the new energy stock market. (2) Shanghai crude oil futures and new energy stock markets showed a high degree of interconnectedness, with an average dynamic connectedness of 55.18%. In the whole system, energy storage industry and new energy vehicles were found as the main transmitters of shocks, while Shanghai crude oil futures were the lowest transmitters. The new energy vehicle and energy storage industries were driving the market, while Shanghai crude oil futures and both wind power and photovoltaic industries were driven by the market. (3) There was high degree of connectedness among the four new energy markets. The energy storage industry was the main transmitter of spillover shocks in the whole new energy stock market, with 29.72% spillover effect on the transmission of the new energy vehicles. The energy storage industry and new energy vehicles were the main transmitters of spillover shocks to other new energy markets' yields, while the wind power and photovoltaic industries were the net recipients of the spillover effect yield. (4) The promotion of the double carbon policy was a strong impact to new energy stock market therefore more attention received by this new energy market. For investors, they can diversify their investment by paying more attention to the energy storage industry and new energy vehicles as they both were the driving force for the development of the new energy industry market. Also, findings suggested that Shanghai crude oil futures did not imposed any market risk towards the new energy market stock.

5.2. Suggestions

In response to the findings of this study, we propose the following policy recommendations:

(1) The new energy industry has developed in recent years and were actively traded in capital market. Investors should fully understand the current development among different industries in new energy sector. Findings suggest that investors should pay more attention to the energy storage industry and new energy vehicles, if to diversify their investment portfolio with new energy stocks market. (2) For the government, to better promote the development of the new energy market, they should pay attention to develop the energy storage industry and new energy vehicles. This should include a further improved incentive mechanism for the new energy development. (3) Study found evidence of the weak total spillover effect of Shanghai crude oil futures on the new energy market. This indicates the potential future growth of the Shanghai crude oil futures market. Therefore, the launching of crude oil options and refined oil futures could be good strategies to improve China's oil derivatives market system. This will further strengthen the cooperation among other

major exchange platforms, improve the cooperation mechanism, smooth the communication channels, and attract more foreign institutional investors to participate in Shanghai crude oil futures trading.

5.3. Limitations of the study and further work

Due to the timing of the listing of Shanghai crude oil futures, the selected sample data of the study have a short period and did not consider the changes in spillover effects under the occurrence of extreme risk scenarios. Future research can further explore the propagation paths and influencing factors of spillover effects under extreme risk scenarios to better understand the relationship between China's crude oil futures market and new energy markets.

Disclosure statement

No conflict of interest has been reported by the authors.

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Data Availability statements

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

References

Ahmad, W., & Rais, S. (2018). Time-varying spillover and the portfolio diversification implications of clean energy equity with commodities and financial assets. *Emerging Markets Finance and Trade*, *54*(8), 1837–1855. https://doi.org/10.1080/1540496X.2018.1467314

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. https://doi.org/10.1016/j.eneco.2020.104741

Bekiros, S., Gupta, R., & Kyei, C. (2016). On economic uncertainty, stock market predictability and nonlinear spillover effects. *The North American Journal of Economics and Finance*, *36*, 184–191. https://doi.org/10.1016/j.najef.2016.01.003

Bouri, E., Gabauer, D., Gupta, R., & Tiwari, A. K. (2021). Volatility connectedness of major cryptocurrencies: The role of investor happiness. *Journal of Behavioral and Experimental Finance*, *30*, 100463. https://doi.org/10.1016/j.jbef.2021.100463

Brini, R., Amara, M., & Jemmali, H. (2017). Renewable energy consumption, International trade, oil price and economic growth inter-linkages: The case of Tunisia. *Renewable and Sustainable Energy Reviews*, *76*, 620–627. https://doi.org/10.1016/j.rser.2017.03.067

Chen, Y., Zheng, B., & Qu, F. (2020). Modeling the nexus of crude oil, new energy and rare earth in China: An asymmetric VAR-BEKK (DCC)-GARCH approach. *Resources Policy*, *65*, 101545. https://doi.org/10.1016/j.resourpol.2019.101545

Cross, J., & Nguyen, B. H. (2018). Time varying macroeconomic effects of energy price shocks: A new measure for China. *Energy Economics*, *73*, 146–160. https://doi.org/10.1016/j.eneco.2018.05.014

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. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dutta, A. (2017). Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. *Journal of Cleaner Production*, *164*, 1157–1166. https://doi.org/10.1016/j.jclepro.2017.07.050

Engle, R. (2002). Dynamic conditional correlation. *Journal of Business & Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Gabauer, D. (2020). Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. *Journal of Forecasting*, *39*(5), 788–796. https://doi.org/10.1002/for.2648

Gomez-Gonzalez, J. E., Hirs-Garzón, J., & Sanín-Restrepo, S. (2021). Dynamic relations between oil and stock markets: Volatility spillovers, networks and causality. *International Economics*, *165*, 37–50. https://doi.org/10.1016/j.inteco.2020.11.004

Gupta, K. (2017). Do economic and societal factors influence the financial performance of alternative energy firms? *Energy Economics*, *65*, 172–182. https://doi.org/10.1016/j.eneco.2017.05.004

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, *20*(7), 873–889. https://doi.org/10.1002/jae.800

Hoque, M. E., Soo Wah, L., & Zaidi, M. A. S. (2019). Oil price shocks, global economic policy uncertainty, geopolitical risk, and stock price in Malaysia: Factor augmented VAR approach. *Economic Research-Ekonomska Istraživanja*, *32*(1), 3700–3732. https://doi.org/10.1080/1331677X.2019.1675078

Hsiao, C. Y. L., Lin, W., Wei, X., Yan, G., Li, S., & Sheng, N. (2019). The impact of international oil prices on the stock price fluctuations of China's renewable energy enterprises. *Energies*, *12*(24), 4630. https://doi.org/10.3390/en12244630

Hu, Q., & Ding, M. (2016). Research on the volatility spillover effect of international crude oil price to China's new energy industry stock price. *Accounting and Finance*, *3*, 78–84. https://doi.org/CNKI:SUN:SYCH.0.2016-016. [in Chinese]

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, *31*(4), 674–692. https://doi.org/10.2307/2696354

Kumar, A. S., & Anandarao, S. (2019). Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. *Physica A: Statistical Mechanics and Its Applications*, *524*, 448–458. https://doi.org/10.1016/j.physa.2019.04.154

Lin, B., & Chen, Y. (2019). Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: A case of Beijing CET market in China. *Energy*, *172*, 1198–1210. https://doi.org/10.1016/j.energy.2019.02.029

Lin, B., & Li, J. (2015). The spillover effects across natural gas and oil markets: Based on the VEC–MGARCH framework. *Applied Energy*, *155*, 229–241. https://doi.org/10.1016/j.apenergy.2015.05.123

Lv, X., Dong, X., & Dong, W. (2021). Oil prices and stock prices of clean energy: New evidence from Chinese subsectoral data. *Emerging Markets Finance and Trade*, *57*(4), 1088–1102. https://doi.org/10.1080/1540496X.2019.1689810

Marques, L. M., Fuinhas, J. A., & Marques, A. C. (2019). Are there spillovers from China on the global energy-growth nexus? Evidence from four world regions. *Economies*, *7*(2), 59. https://doi.org/10.3390/economies7020059

Mishra, A. K., & Ghate, K. (2022). Dynamic connectedness in non-ferrous commodity markets: Evidence from India using TVP-VAR and DCC-GARCH approaches. *Resources Policy*, *76*, 102572. https://doi.org/10.1016/j.resourpol.2022.102572

Narayan, P. K., & Sharma, S. S. (2014). Firm return volatility and economic gains: The role of oil prices. *Economic Modelling*, *38*, 142–151. https://doi.org/10.1016/j.econmod.2013.12.004

Niu, H. W., & Xu, Z. (2020). Research on the impact of Shanghai crude oil futures on the volatility of domestic crude oil spot prices. *Price:Theory & Practice*, (02), 107–110. https://doi.org/10.19851/j.cnki.CN11-1010/F.2020.02.296.[in Chinese]

Odhiambo, N. M. (2021). Trade openness and energy consumption in sub-Saharan African countries: A multivariate panel Granger causality test. *Energy Reports*, *7*, 7082–7089. https://doi.org/10.1016/j.egyr.2021.09.103

Padhan, H., Padhang, P. C., Tiwari, A. K., Ahmed, R., & Hammoudeh, S. (2020). Renewable energy consumption and robust globalization(s) in OECD countries: Do oil, carbon emissions and economic activity matter? *Energy Strategy Reviews*, *32*, 100535. https://doi.org/10.1016/j.esr.2020.100535

Palao, F., Pardo, Á., & Roig, M. (2020). Is the leadership of the Brent-WTI threatened by China's new crude oil futures market? *Journal of Asian Economics*, *70*, 101237. https://doi.org/10.1016/j.asieco.2020.101237

Peng, Y., Chen, W., Wei, P., & Yu, G. (2020). Spillover effect and Granger causality investigation between China's stock market and international oil market: A dynamic multiscale approach. *Journal of Computational and Applied Mathematics*, *367*, 112460. https://doi.org/10.1016/j.cam.2019.112460

Peng, C., Zhu, H., Guo, Y., & Chen, X. (2018). Risk spillover of international crude oil to China's firms: Evidence from granger causality across quantile. *Energy Economics*, *72*, 188–199. https://doi.org/10.1016/j.eneco.2018.04.007

Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Oil price and stock returns of consumers and producers of crude oil. *Journal of International Financial Markets, Institutions and Money*, *34*, 245–262. https://doi.org/10.1016/j.intfin.2014.11.010

Qu, F., Chen, Y., & Zheng, B. (2021). Is new energy driven by crude oil, high-tech sector or low-carbon notion? New evidence from high-frequency data. *Energy*, *230*, 120770. https://doi.org/10.1016/j.energy.2021.120770

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics*, *48*, 32–45. https://doi.org/10.1016/j.eneco.2014.12.009

Shah, I. H., Hiles, C., & Morley, B. (2018). How do oil prices, macroeconomic factors and policies affect the market for renewable energy? *Applied Energy*, *215*, 87–97. https://doi.org/10.1016/j.apenergy.2018.01.084

Sugimoto, K., & Matsuki, T. (2019). International spillovers into Asian stock markets under the unconventional monetary policies of advanced countries. *Journal of the Japanese and International Economies*, *52*, 171–188. https://doi.org/10.1016/j.jjie.2018.10.001

Su, C. W., Meng, X.-L., Tao, R., & Umar, M. (2022). Policy turmoil in China: A barrier for FDI flows? *International Journal of Emerging Markets*, *17*(7), 1617–1634. https://doi.org/10.1108/IJOEM-03-2021-0314

Sun, C., Ding, D., Fang, X., Zhang, H., & Li, J. (2019). How do fossil energy prices affect the stock prices of new energy companies? Evidence from Divisia energy price index in China's market. *Energy*, *169*, 637–645. https://doi.org/10.1016/j.energy.2018.12.032

Su, C.-W., Yuan, X., Tao, R., & Shao, X. (2022). Time and frequency domain connectedness analysis of the energy transformation under climate policy. *Technological Forecasting and Social Change*, *184*, 121978. https://doi.org/10.1016/j.techfore.2022.121978

Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, *70*, 194–202. https://doi.org/10.1016/j.qref.2018.05.001

Wang, J., Qiu, S., & Yick, H. Y. (2022). The influence of the Shanghai crude oil futures on the global and domestic oil markets. *Energy*, *245*, 123271. https://doi.org/10.1016/j.energy.2022.123271

Wang, K.-H., Su, C.-W., Lobonţ, O.-R., & Moldovan, N.-C. (2020). Chinese renewable energy industries' boom and recession: Evidence from bubble detection procedure. *Energy Policy*, *138*, 111200. https://doi.org/10.1016/j.enpol.2019.111200

Wen, X., Guo, Y., Wei, Y., & Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics*, *41*, 63–75. https://doi.org/10.1016/j.eneco.2013.10.018

Wen, X., Wei, Y., & Huang, D. (2012). Volatility spillover and correlations between stock prices of Chinese new energy companies and crude oil prices. *Management Review*, (12), 20–30. https://doi.org/10.14120/j.cnki.cn11-5057/f.2012.12.001.[in Chinese]

Xue, J., & Guo, W. S. (2020). Research on the international pricing ability of Shanghai crude oil futures-analysis of the dynamic dependence of futures and spot based on the time-varying T-copula model. *Shanghai Journal of Economics*, (07), 81–90. https://doi.org/10.19626/j.cnki.cn31-1163/f.2020.07.010.[in Chinese]

Yoon, S.-M., Al Mamun, M., Uddin, G. S., & Kang, S. H. (2019). Network connectedness and net spillover between financial and commodity markets. *The North American Journal of Economics and Finance*, *48*, 801–818. https://doi.org/10.1016/j.najef.2018.08.012

Zeqiraj, V., Sohag, K., & Soytas, U. (2020). Stock market development and low-carbon economy: The role of innovation and renewable energy. *Energy Economics*, *91*, 104908. https://doi.org/10.1016/j.eneco.2020.104908

Zhang, Q., Di, P., & Farnoosh, A. (2021). Study on the impacts of Shanghai crude oil futures on global oil market and oil industry based on VECM and DAG models. *Energy*, *223*, 120050. https://doi.org/10.1016/j.energy.2021.120050

Zhang, G., & Du, Z. (2017). Co-movements among the stock prices of new energy, high-technology and fossil fuel companies in China. *Energy*, *135*, 249–256. https://doi.org/10.1016/j.energy.2017.06.103

Zhang, W., He, X., & Hamori, S. (2022). Volatility spillover and investment strategies among sustainability-related financial indexes: Evidence from the DCC-GARCH-based dynamic connectedness and DCC-GARCH t-copula approach. *International Review of Financial Analysis*, *83*, 102223. https://doi.org/10.1016/j.irfa.2022.102223

Zhang, S., & Mani, G. (2021). Popular cryptoassets (Bitcoin, Ethereum, and Dogecoin), Gold, and their relationships: Volatility and correlation modeling. *Data Science and Management*, *4*, 30–39. https://doi.org/10.1016/j.dsm.2021.11.001

Zhu, F., Jin, F., Wu, H., & Wen, F. (2019). The impact of oil price changes on stock returns of new energy industry in China: A firm-level analysis. *Physica A: Statistical Mechanics and Its Applications*, *532*, 121878. https://doi.org/10.1016/j.physa.2019.121878

Zhu, M. Y., & Su, Z. W. (2022). Time series analysis of international crude oil prices and China new energy sector stock market. *Journal of Qingdao University (Natural Science Edition)*, (03), 148–155. https://doi.org/CNKI:SUN:QDDD.0.2022-023. [in Chinese]

Appendix

Table A1. Nomenclature of variables in this study.

Nomenclature
y_t is the daily logarithmic return series for the t-th market.
F_{t-1} denotes all the information available before $t-1$
μ_t represents the error term
ε_t represents the error term
u_t is the standardized error term
θ_1 represents the first-order autocorrelation coefficients of the variables themselves
ϕ_1 represents the first-order moving average coefficients of the disturbance terms
R_t is the dynamic conditional correlation matrix
H_t is the time-varying conditional variance-covariance matrix
D_t is the time-varying conditional variance matrix
$\rho_{ij,t}$ is the dynamic correlation coefficient
Ψ^g is the volatility impulse response function
$D_{t+h}\|F_t$ is the predicting conditional volatility of the model
$\tilde{\varphi}^g_{ij,t}(J)$ is the pairwise directional connectedness
$C^g_t(J)$ is the total connectivity index
$C^g_{i\to j,t}(J)$ is the directional connectivity index passed from spillover variable i to other variable j
$C^g_{i\leftarrow j,t}(J)$ is the directional connectivity index received from other variable j
$C^g_{i,t}$ is the net total directional connectivity index
a_1, b_1 are the estimated parameter in the volatility series of the GARCH model
α, β are the non-negative shock and persistence parameters

Source: own work.

Table A2. The description of all abbreviation.

Abbreviation	Description
DCC	dynamic conditional corelational
GARCH	generalized autoregressive conditional heteroskedasticity
VAR	vector autoregressive models
DY	Diebold and Yilmaz
VIRF	volatility impulse response function
GFEVD	generalized forecast error variance decomposition
TCI	total connectivity index
DSI	directional connectivity index
NSI	net total directional connectivity index
PII	photovoltaic industry index
WPII	wind power industry index
ESII	energy storage industry index
NEVII	new energy vehicle industry index

Source: own work.