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Research article

Identifying the volatility spillover risks between crude oil prices and China's clean energy market

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Abstract: Since the COVID-19 outbreak, the global economy has been hit hard, and the development of renewable energy and energy transitions has become a common choice for all countries. The development of clean energy firms has become a hot topic of discussion among scholars, and the relationship between the stock prices of clean energy firms and the international crude oil market has attracted more attention. In this paper, we analyze the volatility connectedness between crude oil and Chinese clean energy firms from 2016 to 2022 by building time-varying vector autoregressive models with stochastic volatility components and time-varying spillover index and dynamic conditional correlation GARCH models. The results of the shock effects analysis show that international crude oil volatility had a significant short-term positive impact on Chinese clean energy firms during the COVID-19 outbreak period. Regarding spillover analysis, firms with large total market capitalization tended to be the senders of volatility spillovers, while smaller firms were likely to be the recipients. In terms of dynamic correlation analysis, the correlation between international crude oil and each clean energy firm was found to be volatile, and the dynamic correlation coefficient tended to reach its highest point during the COVID-19 outbreak. Meanwhile, from the optimal portfolio weighting analysis, it is clear that all optimal weights of international crude oil and medium clean energy firms will increase during an epidemic outbreak, and that more assets should be invested in clean energy firms.

Keywords: clean energy; oil prices; time-varying impulse responses; volatility spillover risks; portfolios

1. Introduction

To date, since the COVID-19 outbreak, the global economy has been hit hard and countries have generally chosen large-scale investments to boost their economies. The development of renewable energy and energy transitions has become a common choice for all countries. Energy transitions have become one of the most prominent megatrends in the world. In this context, the impact of the COVID-19 pandemic on crude oil and clean energy markets has become the focus of scholars' attention. In the study by De Blasis and Petroni [1], we learn that the COVID-19 pandemic has had a two-fold impact on crude oil and clean energy markets: on the one hand, the predictability of volatility has strongly decreased; on the other hand, the linkages of the price time series have been modified. For this reason, it is of great importance to re-analyze the volatility relationship between crude oil and clean energy markets. As the world's largest producer and consumer of renewable energy and the world's largest importer of crude oil and natural gas, China has become one of the most important segments of the global energy landscape. An analysis of the Chinese case can provide an important basis for existing research findings. However, in terms of the amount of available literature, relatively few articles have been analyzed with China in mind, which clearly does not satisfy the need for scholars to study crude oil and clean energy markets. In this paper, we analyze the volatility connectedness between international crude oil and Chinese clean energy firms, which will provide an important reference for the development of clean energy firms in all regions of the world.

At present, although China's GDP still maintains high-speed growth, the problems of energy consumption and environmental degradation are becoming increasingly serious (e.g., high pressure on internal energy supply, high external dependence on energy consumption and high vulnerability to fluctuations in international crude oil prices). To solve the conflict between energy consumption and nature, China has put forth a lot of discussions on energy structure innovation. In recent years, government reports, development outlines, and other documents have pointed out that it is the general trend that new types of clean energy will replace traditional energy. The development and utilization of renewable and clean energy resources such as hydropower, wind energy, and nuclear power are more in line with the trajectory of energy development, and they play an important role in establishing a sustainable energy system and promoting economic development and environmental protection. Considering that the composition of China's coal-dominated energy resources will not change in the short term, the transition of power-generation firms from traditional energy to clean, low-carbon and renewable energy is a gradual and long-term process, not a one-time sudden change. Long-term observation of volatility in crude oil energy markets is important for China's economic growth and business development.

In the field of international research, the analysis of the relationship between the international crude oil market and the clean energy industry has been the focus of research in energy economics. Many conclusions with important implications have been obtained in the literature. Although these studies did not draw conclusions for China, they provide an important basis for our analysis. For example, Managi and Okimoto [2] concluded that oil prices and clean energy stock prices are positively correlated after structural disruptions. Özdurak [3] had similar findings. The results of their study indicated that, when oil prices fall, the volatility index typically rises while investments in renewable energy tend to fall. Henriques and Sadorsky [4] indicated that there is a linear Granger causality from the prices of crude oil and clean energy stocks. Reboredo [5] argued that oil prices have a significant impact on the clean energy index; in particular, oil prices contribute about 30% to the downside and upside risk of renewable energy stocks. Bondia and Ghosh [6] found that oil prices have a unilateral effect on the stock prices of alternative energy firms. In the causal relationship, global crude oil prices will show a downturn in the short term, which may lead to a decline in the share prices of alternative energy firms. Similarly, Zhang et al. [7] found that short-term oil supply shocks have a major impact on clean energy. Su et al. [8] used the USA EPU (Economic Policy Uncertainty) monthly index and WTI (West Texas Intermediate) spot price data from 1996 to 2019; they revealed that there is a one-way Granger causality link between the USA EPU and spot price of WTI crude oil. The above findings represent previous scholars' analysis of the relationship between the international crude oil market and clean energy firms. Based on their studies, we can understand that there is indeed a significant and complex relationship between the international crude oil market and clean energy firms in the international context. However, in China, we are unable to draw sufficient conclusions echoing this because the relevant studies are not systematic. With this paper, we aim to complement this aspect of research.

In addition, through a recent research literature search, we found that the impact of crude oil price shocks on various markets changed after the COVID-19 outbreak (Jiang et al. [9] and Ouyang et al. [10]). In this regard, if we can analyze the relationship between the international crude oil market and clean energy in the current COVID-19 era, this will be of great significance for the development of Chinese clean energy companies. Meanwhile, we believe that constructing spillover indexes using time-varying parametric models and considering the volatility correlation analysis between clean energy firms and other markets is an important method to study clean energy firms in the COVID-19 era. Several international scholars have already obtained some meaningful conclusions by using this method. Liu and Hamori [11] showed that the return and volatility spillovers may be enhanced due to specific events or sudden price changes. Using a time-varying VAR (Vector Auto Regressive) model with stochastic volatility, Ghabri et al. [12] found that clean energy stocks tend to see a marked increase in returns following a sharp collapse in crude oil prices. Tiwari et al. [13] showed that the dynamic total connectedness between clean energy markets and green bonds and carbon prices is heterogeneous over time and related to economic events. Clean energy dominates all other markets, and it is considered a major net spreader of shocks across the network. Using a TVP-VAR (Time Varying -Vector Auto Regression) model, Liu and Hamori [14] indicated that the dynamic aggregate connectedness between clean energy stocks, technology stocks and crude oil varies over time and increases significantly during financial turbulence. Dynamic aggregate volatility connectedness is very sensitive to financial turmoil. In the study by Yahya et al. [15], they observed the dynamic effects of the financial crisis and the COVID-19 epidemic on the clean energy index and crude oil prices by dividing the data sample into several phases. Their research confirmed that the price transmission path between the two asset classes is nonlinear. And, in the post-crisis subsample, the clean energy index became the main factor affecting crude oil prices.

The above research results show that, due to the frequent occurrence of financial market volatility events in recent years, which were affected by uncertain factors such as the COVID-19 epidemic, the volatility transfer between the international crude oil and clean energy markets is more significant, and the dynamic correlation between the two is enhanced. However, whether the above findings hold true in China and whether there are differences across different types of clean energy firms, which is the focus of our study. We know from the studies of Hsiao et al., Lv et al. and Zhu et al. [16–18] that fluctuations in international oil prices tended to affect the share prices of listed Chinese renewable energy firms before the COVID-19 outbreak, and that there are significant bidirectional risk spillovers between oil and several clean energy sectors in China. Nowadays, the change in the spillover effect between international oil prices and Chinese clean energy firms due to the COVID-19 outbreak deserves to be analyzed again. It has also become more important to consider the spillover effects of oil on clean energy markets from a time-varying perspective. Therefore, combining the empirical summary of the above literature and the new impact brought by the COVID-19 epidemic now, we also considered the TVP-VAR model for data analysis. The time-varying impulse response analysis of TVP-VAR can obtain the response of each firm after receiving the crude oil shock and preliminarily obtain the impact form of the crude oil. Next, we can construct a spillover index by using variance decomposition to further analyze the volatility shocks received or sent by each firm.

Combining the current state of the COVID-19 epidemic with the findings of Liow et al. [19], we can get an idea of the current situation in the Chinese financial markets. As China is currently accelerating the relaxation of various capital controls and promoting the further opening of its domestic market, its financial markets are attracting increasing interest from both domestic and foreign investors. To deal with the risks associated with financial market volatility events, the direction of venture capital research is also worthy of our consideration. From an international perspective, there are already some reports analyzing the international situation from which we can gain some experience. For example, Dutta [20] found that a reduction in the oil price implied volatility index implies a reduction in the volatility of clean energy realizations. If there are risk seekers who wish to obtain higher returns from risk, their asset allocation must be optimized or reset. At the same time, considering the impact of substitution effects, we also believe that it is worthwhile to analyze portfolios of international crude oil and clean energy firms under different scenarios. On the one hand, higher oil prices can promote the use of new energy sources, thus reducing the production costs of firms. On the other hand, falling oil prices can reduce the use of clean energy sources (Song et al. [21]). In addition, the effect of the stock market cannot be ignored, and the tail dependence of clean energy and oil prices is more moderate in the case of a bull market for clean energy and high oil prices coexisting (Tiwari et al. [22]). If we want to grasp the situation mentioned above, we should analyze the portfolio from a dynamic perspective; and, investors need to determine a reasonable energy investment policy based on the way volatility is transmitted in different periods (Foglia and Angelini [23] and Li et al. [24]). Regarding methods to develop portfolios, both Sadorsky [25] and Ahmad et al. [26] used MGARCH (Multivariate Generalized Autoregressive Conditional Heteroskedasticity) models to construct optimal diversification strategies for clean energy stocks. Maghyereh et al. [27] combined wavelet analysis and MGARCH to confirm a strong volatility transfer between clean energy and technology stock indices. They both obtained meaningful conclusions and demonstrated that the GARCH family of models has some advantages for this application. However, to better consider the portfolio from a dynamic perspective, we consider the analysis through a time-varying spillover index and dynamic conditional correlation GARCH (DCC-GARCH) model. Moreover, to diversify clean energy stock portfolios more effectively, we should consider the unique characteristics of each clean energy subsector and analyze portfolio management at a disaggregated level, which is an important idea proposed by Pham [28]. In conclusion, oil price volatility plays a crucial role in portfolio strategies. Different portfolio strategies should exist in different periods. Studying the link between different types of clean energy firms and the international crude oil market is extremely important to establish optimal investment strategies for the firms concerned.

Based on the above analysis, a large number of scholars have carried out fruitful research on the connection between oil and clean energy firms from the perspective of qualitative and quantitative analysis by using theoretical and quantitative methods, but the following aspects are still worthy of further consideration. First, most of the studies on the relationship between international crude oil and clean energy firms have been analyzed from a global perspective, and the analysis on China is less comprehensive and less frequent. China, as a major clean energy development country, has clean energy market development opportunities that are worth exploring. Second, the existing literature does not consider changes in the form of impact in sufficient detail when analyzing the impact of the international crude oil market on clean energy firms. Often, only positive or negative correlations between the two are simply described. An analysis like the time-varying impulse response could better illustrate how the international crude oil market affects clean energy firms over time. This is important to consider the relationship between international crude oil markets and clean energy firms in the COVID-19 era. Third, when considering portfolio issues, most articles consider the use of MGARCH models for analysis, which are not good at giving dynamic portfolio recommendations; this may also return to the problem of lack of adaptability in the COVID-19 era. Finally, the existing literature tends to describe the use of various clean energy indices to represent the operations of the clean energy industry. However, such data may not be intuitive. In China, clean energy indexes are not disaggregated in terms of energy type, and they do not take into account the effect of firm size. We cannot consider well the relationship between each type of firm and international crude oil by using the index. Therefore, a direct analysis of each firm's stock price can provide more realistic results. Moreover, the firms we selected are all firms that play a leading role in various types of clean energy industries and have the top firm size in the industry, so their returns are representative.

In this regard, to better explore the connectedness between the clean energy market and the crude oil market, we selected the stock price of clean energy firms as a proxy indicator of the clean energy industry and conducted analysis and research in the following three aspects using this indicator. First, we analyzed the impact of different clean energy firms from international crude oil shocks based on the impulse response function of the time-varying vector autoregressive model with stochastic volatility components (TVP-SV-VAR) to analyze the shock effects. Second, we calculated the spillover index and used it to analyze the volatility connectedness between international crude oil and clean energy firms, as well as to empirically demonstrate the spillover connectivity within the clean energy market. Third, we used the DCC-GARCH model to analyze the relationship between international crude oil and clean energy firm stock prices from the perspective of portfolio diversification and risk management, and give related investment strategies.

The main contributions of this paper are as follows. i). We have established the TVP-SV-VAR model from a dynamic perspective to analyze the impact of international crude oil on different Chinese clean energy firms at different times based on their impulse response; this solves the defects of traditional econometric models with constant parameters and static analysis. ii). We calculated the time-varying spillover index by referencing the study of Antonakakis [28] to more effectively analyze the international crude oil and clean energy industry between spillover effects. The advantage of the time-varying spillover index is that it can more accurately accommodate potential changes in parameter values, does not require consideration of the size of the rolling window, and does not lose observations in the calculation. iii). The DCC-GARCH model enables us to calculate the dynamic conditional correlation coefficient and construct the optimal portfolio diversification strategy. This allows us to analyze the relationship between oil prices and Chinese clean energy stock prices from a portfolio diversification and risk management perspective, thereby reducing investment risk during major macroeconomic events. iv). This paper describes the use of a representative selection of Chinese clean energy firms for the empirical analysis, which allowed us to analyze the volatility connectedness between international crude oil prices and the Chinese clean energy market in a more intuitive way than has been done in previous studies on the Chinese clean energy market. The analysis also gives each firm a clearer understanding of its own situation, which is important for each firm's own planning, as well as for the experience of other firms. The above-mentioned contributions largely complete the study of the development of clean energy firms in China.

Based on the above analysis, the sections of this paper were organized. In Section 1, we point out the significance and contribution of this paper by presenting the background and existing research. In Section 2, the model used in this study will be described as a way to provide the theoretical basis. In Section 3, the rationale for data selection will be described, along with a preliminary data analysis. In Section 4, we analyze the impact of the international crude oil market on clean energy firms by constructing impulse response functions using the TVP-VAR model. In Section 5, we examine the volatility linkage between the international crude oil market and clean energy firms by calculating the spillover index using the TVP-VAR model. In Section 6, we give portfolio recommendations for different periods as a basis for investors to consider investment risk. Finally, in Section 7, the conclusions of this paper are presented.

2. Materials and methods

In this section, the TVP-SV-VAR model and the DCC-GARCH model are presented, which are used for the analysis of shock effects and dynamic correlation and portfolio management, respectively. For the analysis of spillover effects, we calculated the time-varying volatility spillover index based on the work of Antonakakis et al. [29].

2.1. TVP-SV-VAR

The assumption that the coefficients of the traditional VAR model are constant limits the attention to the problem of the existence of nonlinear relationships between the effects of variables in the event of sudden changes in the system. In response to the shortcomings of VAR models in practical use, Primiceri [30] introduced a nonlinear time-varying analysis tool, i.e., the time-varying parameter vector autoregressive (TVP-SV-VAR) model, for explaining the time-varying and nonlinear characteristics among economic phenomena. To study the dynamic shock effects of international crude oil prices on the clean energy market, we constructed a TVP-SV-VAR model for analysis. The coefficients and covariance matrix of this model can change continuously over time, so it can flexibly capture the time-varying and asymptotic characteristics of the relationship between variables and accurately observe the interaction mechanisms among economic variables at different times. Compared with the previous models, the TVP-SV-VAR model can not only effectively improve the estimation accuracy, but also better fit the economic data at different time points.

The TVP-SV-VAR model evolved from the structural vector autoregressive (SVAR) model. The form of the SVAR model with s-lags is as follows:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_S y_{t-S} + \mu_t, t = s+1, \ldots, n \tag{1}$$

where y_t is a vector of endogenous variables, A is a $k \times k$ matrix, $F_1, \ldots, F_s$ are $k \times 1$ coefficient matrices, $t-1, \ldots, t-s$ are different lags, μ_t is a $k \times 1$ vector of errors, $\mu_t \sim N(0, \Sigma\Sigma)$ and can be written as follows:

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{k1} & \cdots & \alpha_{k,k-1} & 1 \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix},$$

Now, we can write (1) as

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_S y_{t-S} + A^{-1}\Sigma\varepsilon_t \tag{2}$$

where $B_i = A^{-1}F_i$ and $\varepsilon_t \sim N(0, I_k)$, and we stack the coefficient matrix B_i by row elements and define $X_t = I_k \otimes (y'_{t-1}, y'_{t-2}, \ldots, y'_{t-s})$; (2) can be written as

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t, t = s+1, ..., n \tag{3}$$

$\otimes$ denotes the Kronecker product. The SVAR model usually assumes that the parameters are constant. Here, we assume that all parameters of this class are time-varying. Ultimately, the TVP-SV-VAR model is as follows:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \tag{4}$$

A_t and are time-varying, α_t is the lower triangular element of A_t and $h_t = (h_{1t}, \cdots, h_{kt})'$. The log variances are $h_{jt} = \ln\sigma_{jt}^2$, $j = 1, \cdots, k$, $t = s+1, \cdots, n$. $\beta_{t+1} = \beta_t + \mu_{\beta t}$, $\alpha_{t+1} = \alpha_t + \mu_{\alpha t}$ and $h_{t+1} = h_t + \mu_{ht}$.

2.2. DCC-GARCH

To calculate the dynamic conditional correlation coefficients, we will use the DCC-GARCH model:

$$r_t = \mu_t(\theta) + \varepsilon_t \tag{5}$$

$$\varepsilon_t = H_t^{1/2} u_t, u_t \sim iid\left(0, I_n\right) \tag{6}$$

where r_t is a vector of volatilities, μ_t denotes a vector of conditional means, ε_t is residual, and H_t is a conditional covariance matrix of μ_t and r_t. H_t can be decomposed as $H_t = D_t R_t D_t$, where $D_t = diag(h_{iit}^{1/2}, \cdots, h_{NNt}^{1/2})$ is the diagonal square root conditional variance that stands for the time-varying conditional correlations matrix, which is defined as $R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$, where Q_t is a symmetric positive definite matrix, i.e.,

$$Q_t = (1-\lambda-\nu)\overline{Q} + \lambda u_{t-1}u'_{t-1} + \nu Q_{t-1} \tag{7}$$

where $\overline{Q}$ is a correlation matrix of the standardized residuals u_{t-1}, while λ and ν are non-negative parameters satisfying $\lambda + \nu < 1$. Finally, the time-varying correlations are calculated as follows:

$$\rho_{ij,t} = \rho_{ji,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{8}$$

2.3. Time-varying volatility spillover index

The TVP-VAR method proposed by Antonakakis et al. [29] extends the originally proposed connectedness approach of Diebold and Yılmaz [31] by allowing the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factors, in the spirit of Koop and Korobiliz [32]. To calculate the GIRF (Generalized Impulse Response Function) and GFEVD (Generalized Forecast Error Variance Decomposition), we transform the TVP-VAR to its vector moving average representation:

$$y_t = J'(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}), \tag{9}$$

where

$$M_t = \begin{pmatrix} A_t & 0_{p\times m} \\ I_{m(p-1)} & 0_{m(p-1)\times m} \end{pmatrix}, \eta_t = \begin{pmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}, J = \begin{pmatrix} I \\ 0 \\ \vdots \\ 0 \end{pmatrix}, z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix}, A_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{pt} \end{pmatrix}.$$

Taking the limit as k approaches ∞ yields

$$y_t = \lim_{k\to\infty} J'(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}) = \sum_{j=0}^{\infty} J' M_t^j \eta_{t-j} \tag{10}$$

where it directly follows:

$$y_t = \sum_{j=0}^{\infty} J' M_t^{k-1} J \varepsilon_{t-j} = \sum_{j=0}^{\infty} B_{jt} \varepsilon_{t-j} \ . \tag{11}$$

The $GIRFs(\Psi_{ij,t}(H))$ represent the responses of all variables j, following a shock in the variable i. We computed the differences between an H-step-ahead forecast, which can be calculated by

$$GIRF_t(H, \delta_{j,t}, \Omega_{t-1}) = E(y_{t+H} \mid e_j = \delta_{j,t}, \Omega_{t-1}) - E(y_{t+J} \mid \Omega_{t-1}) \tag{12}$$

$$\begin{aligned} \Psi_{j,t}(H) &= \frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}}, \quad \delta_{j,t} = \sqrt{\Sigma_{jj,t}} \\ \Psi_{j,t}(H) &= \frac{B_{H,t}}{\sqrt{\Sigma_{jj,t}}} \Sigma_t e_j \end{aligned} \tag{13}$$

where Ω_{t-1} represents all information available until $t-1$ and e_j is a selection vector with unity in the j-th position, and zero otherwise. In turn, we compute the $GFEVD(\phi_{ij,t}(H))$, which represents the pairwise directional connectedness from j to i and illustrates the influence that the variable j has on the variable i in terms of its forecast error variance share. These variance shares are then normalized so that each row sums up to one, meaning that all variables together explain 100% of the variable i forecast error variance. This is calculated as follows:

$$\phi_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\Sigma_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{14}$$

$\sum_{j=1}^{m} \phi_{ij,t}(H) = 1, \quad \sum_{i,j=1}^{m} \phi_{ij,t}(H) = m$, where the denominator represents the cumulative effect of all of the shocks, while the numerator illustrates the cumulative effect of a shock on the variable i. Now, we can calculate the various types of spillover indexes:

(I) Total connectedness index

$$C_t(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \phi_{ij,t}(H)}{\sum_{i,j=1}^{m} \phi_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{m} \phi_{ij,t}(H)}{m} \times 100 \tag{15}$$

(II) The directional volatility spillover index

Total directional connectedness to others:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \phi_{ji,t}(H)}{\sum_{j=1}^{m} \phi_{ji,t}(H)} \times 100 \tag{16}$$

Total directional connectedness from others:

$$C_{i\leftarrow j,t}(H)=\frac{\sum_{j=1,i\neq j}^{m}\phi_{ij,t}(H)}{\sum_{i=1}^{m}\phi_{ij,t}(H)}\times 100 \tag{17}$$

(III) Net total directional connectedness

$$C_{i,t}=C_{i\rightarrow j,t}(H)-C_{i\leftarrow j,t}(H) \tag{18}$$

3. Data presentation and variable interpretation

Our data set comes from the wind database of eight Chinese clean energy firms and WTI daily closing prices, among which the clean energy firms are wind power, nuclear power, hydropower, photovoltaic (PV) power, and other types, specifically, Xinjiang Goldwind Science and Technology Co., Apparatus Stock Co., Ltd., China National Nuclear Power Co., Ltd., China General Nuclear Power Group and China Yangtze Power Co. The WTI crude oil price index was derived from the USA Energy Information Administration. Specifically, we used these firms' stock data (daily closing prices). To ensure that the selected firms are representative, we selected firms based on the following three constraints: 1) the selected firms should play a leading role within a certain type of clean energy industry and have a large size (with high total assets); 2) the firm's stock data should be available and should have been listed before 2016 to ensure an adequate sample size; 3) the main business is clean energy. Also, considering the estimated cost of the model, the eight firms mentioned above are the ones that best met our requirements. In terms of international crude oil data selection, based on the results of the study of Foglia and Angelini [23], we chose to use the WTI as a representative data source for international crude oil to study its impact on clean energy firms. The sampling period was from January 4, 2016, to March 7, 2022, excluding the time when all firms did not open at the same time, leaving 1447 samples. At the same time, considering the existence of dividends and allotment of shares in individual stocks, the closing price on the dividend date is treated as ex-rights and ex-dividends in this paper, and the treated closing price can reflect a more realistic stock price. In this work, the log returns were set as follows:

$$r_{i,t}=(\ln P_{i,t}-\ln P_{i,t-1})\times 100 \tag{19}$$

where $P_{i,j}$ is the closing price of the firm i on the day t.

Table 2 provides a descriptive analysis of the returns of each firm and shows that the mean of the returns of all eight clean energy firms and the WTI were close to 0. The returns of XGST, GGEP, LGET, and TW had a left-skewed distribution, while TEAS, CNNP, CGNP, and CYP were right-skewed. The kurtosis of all Clean Energy and WTI returns are all above 3 for High Kurtosis.

Table 1. Symbol descriptions.

Firm Name	Xinjiang Goldwind Science And Technology Co., Ltd.	Tebian Electric Apparatus Stock Co., Ltd.	China National Nuclear Power Co., Ltd.	China General Nuclear Power Group
Self-name abbreviation	XGST	TEAS	CNNP	CGNP
Main business type	Wind Power	Wind Power	Nuclear Power	Nuclear Power
Firm Name	China Yangtze Power Co., Ltd.	Guangxi Guiguan Electric Power Co., Ltd.	LONGi Green Energy Technology Co., Ltd.	Tongwei Co., Ltd.
Self-name abbreviation	CYP	GGEP	LGET	TW
Main business type	Hydropower	Hydropower	Photovoltaic (PV)	Photovoltaic (PV)

Table 2. Description statistics**.**

Firm	Mean	Median	Maximum	Minimum	S.D.	Skewness	Kurtosis
XGST	−0.02	−0.07	11.00	−28.09	2.82	−0.55	11.64
TEAS	0.04	0.00	9.95	−10.61	2.30	0.28	7.20
CNNP	−0.01	0.00	13.15	−9.06	1.63	0.24	10.64
CGNP	−0.02	0.00	13.04	−10.58	1.70	0.15	8.58
CYP	0.04	0.00	6.59	−6.07	1.12	0.08	5.86
GGEP	−0.01	0.00	12.07	−30.20	1.92	−2.68	50.19
LGET	0.13	0.08	9.56	−36.75	3.26	−1.70	21.28
TW	0.08	0.00	10.74	−67.84	3.71	−4.15	80.34
WTI	0.12	0.25	46.56	−28.22	3.37	1.52	47.25

4. Impact effect analysis

Since non-stationary time series cannot be directly used to build TVP-SV-VAR models, the results obtained were biased and suffered from spurious regression problems. Therefore, the selected variables needed to be tested for smoothness, i.e., via the unit root test. In this study, the ADF (Augmented Dickey-Fuller) test, which is most commonly used in empirical studies, was used to test the smoothness of each variable. The test results show that, after calculating the log returns, all variable series were smooth at the 5% level, and that a TVP-SV-VAR model can be constructed for the returns.

4.1. Parameter estimation results

In this study, the lag order of the VAR model was selected according to the AIC (Akaike Information Criterion), HQ (Hannan-Quinn criterion), SC (Schwarz Criterion), and FPE (Final Prediction Error) criteria. The results all show that the lag order was optimal when set to 1, so the model lag order was set to 1. In this study, MATLAB software was used for simulation testing, and the number of Markov Monte Carlo algorithm sampling runs was set to 10,000 considering the computational volume and other issues. Meanwhile, to ensure that the obtained samples did not depend on the selection of the initial values, the burn-in samples of the first 1,000 draws were discarded in the simulation process. The posterior means, standard deviations, Geweke values, and inefficiency factors (Inef.) of the parameters to be estimated are shown in Table 4. As can be seen in Table 3, the posterior means of each parameter were within the 95% confidence interval, and the Geweke values were all below 1.96, which indicates that the parameters converged to the posterior distribution; so, the parameters estimated by the model are more stable. Burn-in sampling in the iteration cycle can effectively make the Markov chain converge.

Table 3. TVP-SV-VAR model parameter estimation.

Parameter	Mean	S.D.	Upper 95% confidence interval	Lower 95% confidence interval	Geweke	Inef.
sb1	0.0023	0.0002	0.0018	0.0028	0.663	53.05
sb2	0.0023	0.0003	0.0018	0.0029	0.365	66.75
sa1	0.0153	0.0043	0.0097	0.0246	0.019	203.05
sa2	0.0059	0.0016	0.0038	0.0095	0.055	185.96
sh1	0.3593	0.0353	0.2940	0.4306	0.760	73.39
sh2	0.2904	0.0276	0.2395	0.3492	0.000	77.67

4.2. Impulse response analysis

First, this paper will describe the effect of unit shocks of the independent variable on the dependent variable at fixed time intervals based on the equal-interval impulse responses. Here, the lags of the equal-interval impulse responses were set to 0, 1, and 2 periods, respectively. Accordingly, we were able to analyze the impact of short-term international crude oil volatility shocks on the volatility of clean energy firms (the long-term impact is smaller, so we did not analyze it specifically in this study). The impulse response results are shown in Figure 1. The impulse response results show that shocks from international crude oil volatility have a mostly positive impact on the volatility of every clean energy firm. Using February 4, 2020, as the opening date of the COVID-19 outbreak, we found a few things. After the outbreak of COVID-19, the impact of international crude oil on most clean energy firms tended to be positive. Wind-type firms performed more significantly, while PV-type firms performed more moderately. Also, since the equal-interval impulse response has been varying with time, we can understand that the impact of international crude oil on the clean energy industry is susceptible to changes due to various macroeconomic events. By comparing the effects of international crude oil shocks on clean energy firms at different time intervals, it can be seen that the effects of international crude oil shocks on clean energy firms are stronger at 1-period ahead than at 2-periods ahead, indicating that the effects of international crude oil on clean energy firms are very short-term, and that clean energy firms need to be wary of sudden shocks from international crude oil in the event of macroeconomic turbulence like the COVID-19 epidemic. This is consistent with the findings of Ferrer et al. [33]. Moreover, the shock from international crude oil to itself comes mainly from its current period, and its impact has remained almost unchanged up to 2022.

Next, we used the time-sharing impulse responses to analyze the impact of international energy prices on each clean energy firm at a specific time. Specifically, we selected May 6, 2019 (USA tariff hike), February 3, 2020 (China COVID-19 outbreak), and February 24, 2022 (China stock market turmoil) as specific time points. After giving a one-unit shock to international crude oil, we analyzed the response of each firm to it. As shown in Figure 2, it can be seen that, when international crude oil was hit by a major macroeconomic event, all firms responded in the short term, but almost all firms returned to flatness within five periods. This indicates that international crude oil volatility will only have a short-term impact on individual clean energy firms in the event of a major event. It is also easy to see that the response of the same firm to international crude oil prices tended to take the same form in all three events. This situation suggests that the three major events in recent years have had a relatively similar impact. Comparing the situation of each firm, only the hydropower type of firm had a more obvious negative response, while all other firms had a positive response; and, the event that produced a negative response was the USA tariff hike on May 6, 2019. Therefore, when major events occur, clean energy firms need to be aware of the stronger short-term impact of international crude oil. Hydropower-type firms need to develop better countermeasures because the form of response is not easily determined.

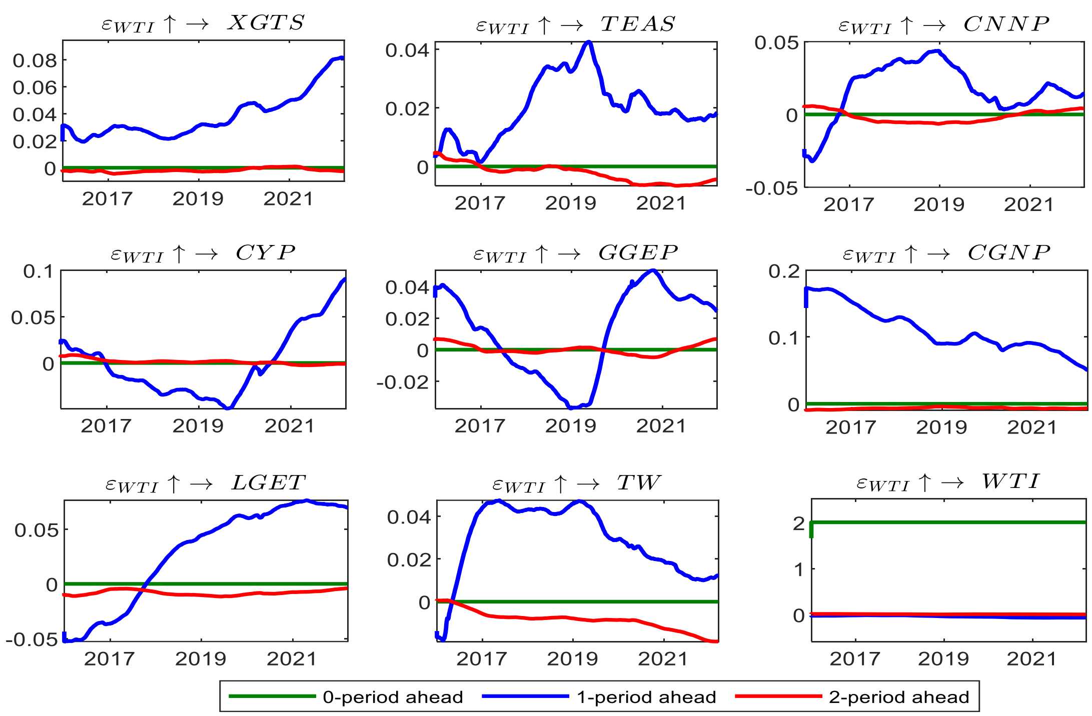

Figure 1. Equal-interval impulse response plots of international crude oil for eight clean energy firms.

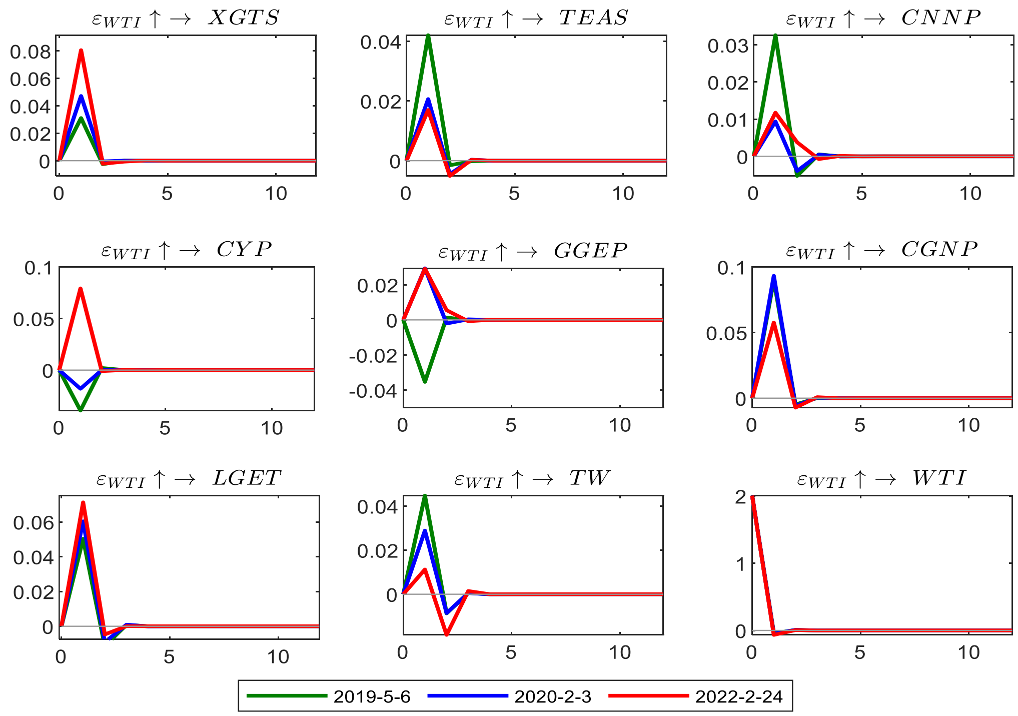

Figure 2. Time-sharing impulse response plots for international crude oil to clean energy firms.

4.3. Robustness test

In this section, to illustrate the robustness of the model and the representativeness of the selected firms, we added four other large clean energy firms to the TVP-SV-VAR model and constructed the impulse response functions again. These four firms are Shanghai Huitong Energy Co., Ltd. (HT, wind power), Sufa Technology Industry Co., Ltd. (STI, nuclear power), SDIC Power Holdings Co., Ltd. (SDIC, hydropower), and Shenzhen Topray Solar Co., Ltd. (TS, photovoltaic). From the equal-interval impulse response and time-sharing impulse response results, we found that the original eight clean energy firms' impulse results did not change, which indicates the robustness of our results. As for the four new firms added to our model, we found that the previous findings also apply here. After the outbreak of COVID-19, the impact of international crude oil on most clean energy companies tended to be positive. The wind energy types reacted more strongly, while the PV types reacted more moderately. When international crude oil is hit by a major macroeconomic event, all firms will respond in the short term, but almost all firms return to flatness within five periods. All firms of the hydropower type responded significantly negatively. Thus, our conclusions based on the impulse responses of the eight firms are representative. And, since these eight firms have higher market capitalization, larger sizes, and better earnings, which are difficult for other firms to surpass, it will be more convincing to continue the analysis using the eight firms in this paper. Therefore, for the next analysis, we did not replace the data but still used these eight firms to represent the operation of different types of clean energy industries for analysis.

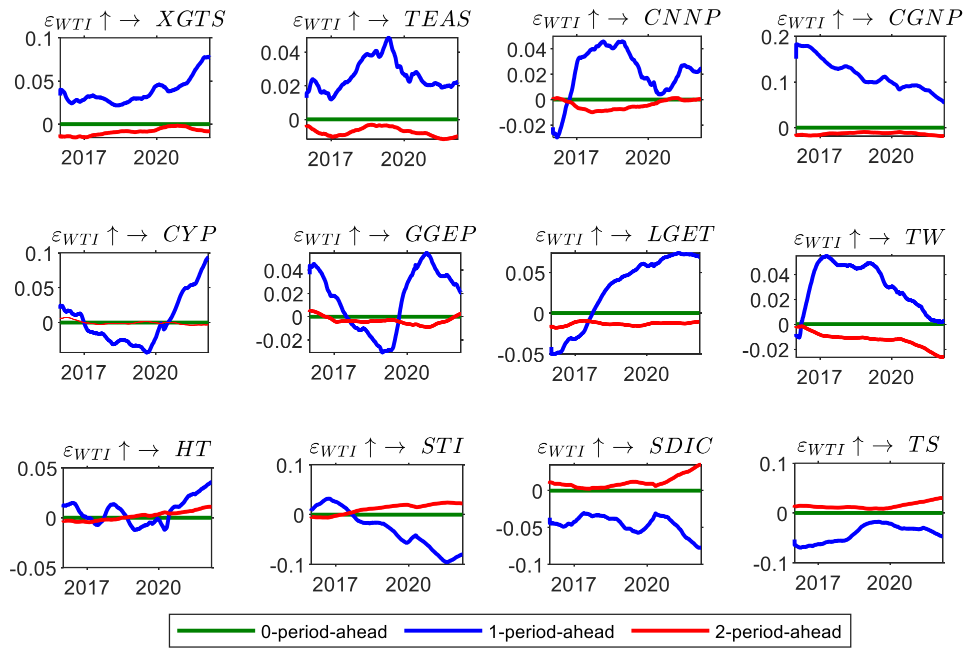

Figure 3. Equal-interval impulse response plots of international crude oil for 12 clean energy firms.

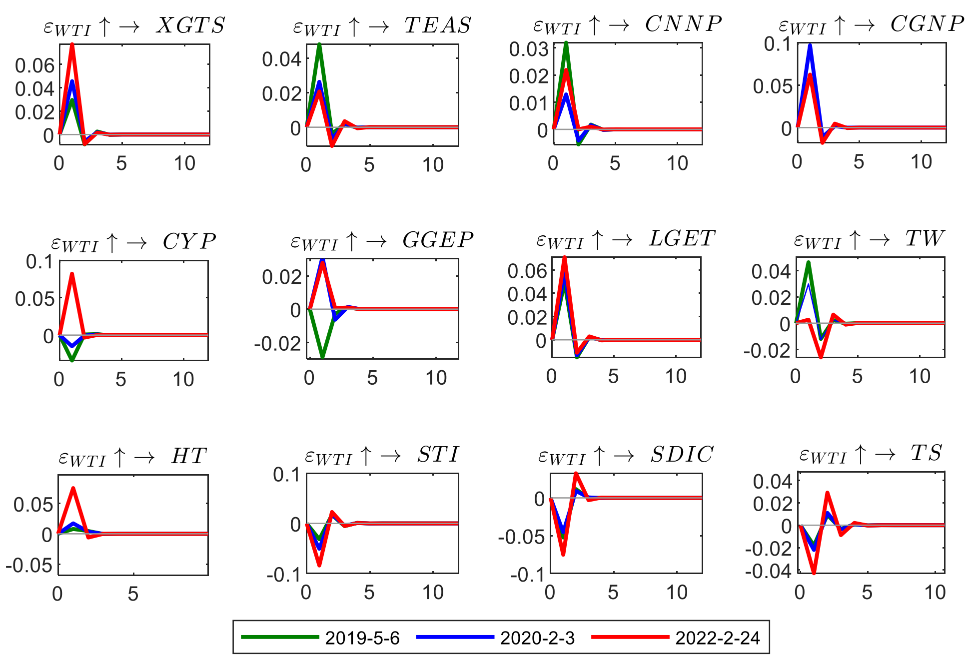

Figure 4. Time-sharing impulse response plots of international crude oil for 12 clean energy firms.

5. Analysis of time-varying spillover effects

In this section, we will describe a further study of volatility connectedness by calculating a spillover index. The spillover index was used to compare volatility spillovers between international crude oil firms and clean energy firms, and likewise to demonstrate spillover connectivity within the clean energy market. To identify periods of high inter-market spillover, we first plotted the TOTAL index to identify periods of high inter-market spillover, and then plotted the related images based on the TO spillover index, FROM spillover index, and NET spillover index for each firm to visualize the related spillover.

The TOTAL spillover index has been volatile with significant fluctuations since the beginning of 2016. At the end of 2017, the spillover index dropped to its lowest point, and then the TOTAL spillover effect for international crude oil and clean energy firms increased to its first extreme point of about 35% when the USA began imposing foreign tariffs. In late 2018, USA stock prices fell sharply, causing the spillover index for crude oil and clean energy firms to increase once again to more than 40%. As the USA continued to impose tariffs, the TOTAL spillover index continued to increase, continuing to reach a new extreme point. In early 2020, following the COVID-19 outbreak, the TOTAL spillover index rose again, reaching over 50% and peaking at nearly 55% throughout the COVID-19 outbreak. Notably, the decline in crude oil prices that occurred in 2019 also contributed to the increase in the total volatility spillover. A possible explanation is that low oil prices stimulated investors to sell "clean energy products" and buy oil. According to the substitution effect theory mentioned by Uddin et al. [34], low oil prices reduce the efficiency of the use of clean energy products due to the high cost of building these clean energy facilities, which means less revenue for clean energy firms. By early 2021, the TOTAL spillover index began to decline because all aspects of the market stabilized and the TOTAL spillover index gradually returned to its pre-COVID-19 epidemic level.

In Figure 5, we can see very clearly that there were two high spillover periods after 2019 and 2020, where the highest spillover index was close to 55%. In the rest of the time, the TOTAL premium index tended to be no higher than 40%. These two periods just covered the two major events mentioned in the previous subsection (the USA foreign tariff increase on May 6, 2019, and the COVID-19 outbreak on February 3, 2020). Accordingly, we highlight the TO spillover index, the FROM spillover index, and the NET spillover index for each firm for both periods in Figure 6.

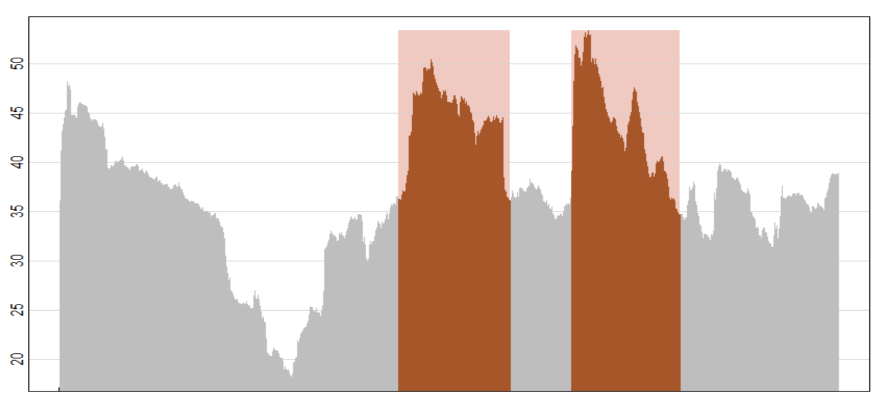

Figure 5. Dynamic total connectedness.

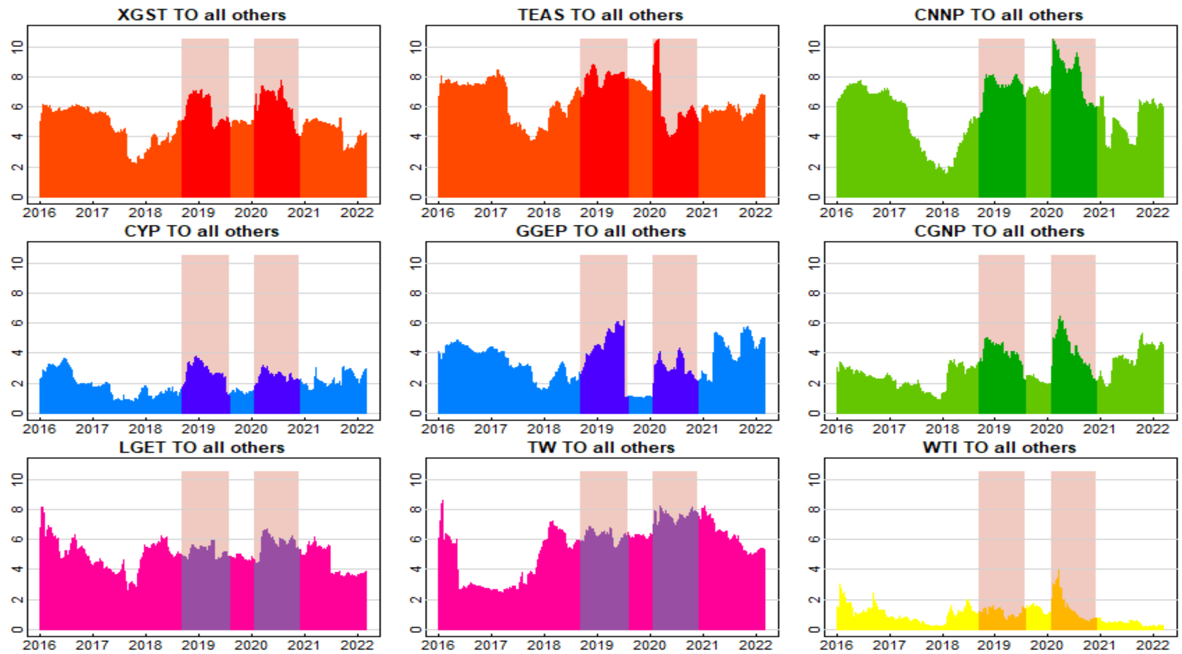

Figure 6. TO spillover index.

Here, we can analyze the main recipients by using Figure 7. After some macroeconomic events, the value of the FROM spillover index for the hydropower-type firms increased significantly. However, it did not have a high FROM spillover index compared to other firms. Such a situation shows that, in some major macro events, the hydropower industry is more vulnerable than other firms and has a heightened risk of being impacted. Among the other firms, PV and wind power firms had higher FROM spillover indexes over time, indicating that they are the main recipients of volatility shocks. Again, we obtained relevant conclusions by comparing the FROM spillover indexes between the firms. Here, we found a similar situation to the TO spillover index. Firms of the same type had similar levels of the FROM spillover index, and even their trends were very similar. The firms of nuclear power type had similar trends of change, although they also had differences in the level of the spillover index. The level of the FROM spillover index was also significantly higher in the shaded regions of each firm than in the other regions. This also indicates that clean energy firms will experience more volatility than other firms due to major macroeconomic events. The FROM spillover index for the hydropower-type firms did not rise too much during major macroeconomic events, again showing that the volatility connectedness between the hydropower-type firms and other firms is more stable. As can be seen in Figure 7, the level of WTI's FROM spillover index was also not high, but its FROM spillover index increased very significantly during major macroeconomic events as well. Combined with the trend of WTI's TO spillover index, we show that the volatility connectedness between the clean energy market and the international crude oil market is enhanced by major macroeconomic events. This has also been echoed by the findings of Peng et al. [35]. The influence mechanism of crude oil price fluctuation is asymmetric when the crude oil price is at different positions and under different trends.

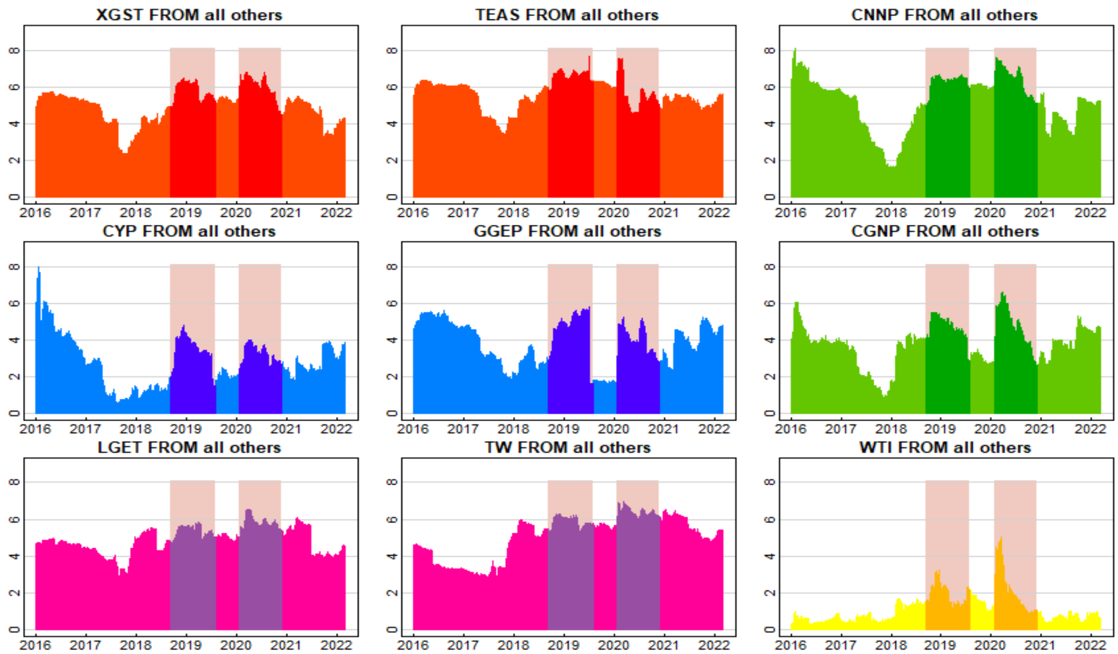

Figure 7. FROM spillover index.

Next, we can get the actual impacted situation of each firm from the NET spillover index. The Net volatility spillover shows information about the direction of volatility, i.e., from one firm to all other firms. A negative (positive) value means that a market receives (sends) more volatility than it sends (receives). By subtracting the FROM spillover index from the TO spillover index, we can obtain the NET spillover index and analyze each firm's situation. Wind power firms were mainly in the positive spillover situation, while hydropower firms were mainly in the negative spillover situation. This situation indicates that the fluctuations in market spillover may end up being absorbed by hydropower firms. Combined with the assets of each firm, the larger the total market capitalization, the more likely the firm is to be the sender of volatility spillover, while the smaller market capitalization is likely to be the receiver.

In each figure, we can find that the WTI spillover index was also affected by major macro events. Its TO spillover index did not change much during the USA foreign tariff increase on May 6, 2019, but it has fluctuated more significantly since the COVID-19 outbreak, reaching 4%, which was an extreme value throughout the period; and, it took a year to fall back to its usual value. It's FROM spillover index had a more similar situation, also reaching an extreme value after the COVID-19 outbreak. This shows that the impact of the COVID-19 outbreak was much larger than the impact of the USA foreign tariff increases on May 6, 2019. Regarding the WTI's NET spillover index, its value was mainly positive until 2018, while its value was negative for a long time after 2018; and, the WTI became a recipient of volatility spillover, with the price of international energy sources having a diminishing impact on China with the development of clean energy in China.

Now, we present Table 4, which gives the average volatility spillover indices for the full-time period to summarize the situation for the full-time period, and "FROM" shows the total share of volatility shocks received by other firms, which can be obtained by summing the spillover indices of other firms in the peer group. This value shows that TEAS was the main recipient of volatility shocks, while the WTI received less volatility, which indicates that shocks in the Chinese clean energy market have less impact on international energy prices. “TO” is the sum of the firm’s share of volatility shocks to other clean energy firms and international crude oil, and its maximum value remained at 59.2% of TEAS, indicating that it was also the main sender of volatility; “NET” shows the net spillover of a firm to other clean energy firms and international crude oil, with a maximum value of 8.4% for TEAS and a minimum value of −8.2% for CGNP. The “TCI” shows the total spillover index for a market, which is 38.2% in the table; this indicates that the average spillover index over the full time period was 38.2%, and that, on average, each firm received 38.2% of its volatility shocks from other firms.

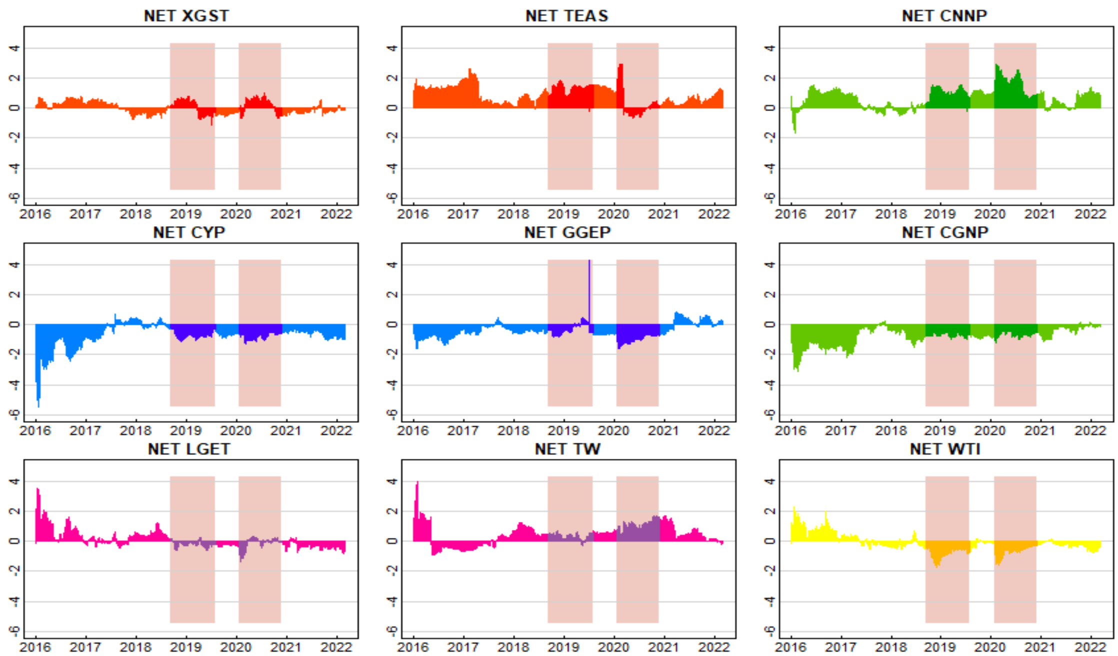

Figure 8. NET spillover index.

Table 4. Average volatility spillover index over the full time period (%).

	XGST	TEAS	CNNP	CYP	GGEP	CGNP	LGET	TW	WTI	FROM
XGST	54.9	13.1	7.7	1.4	3.1	3.3	6.7	8.9	0.9	45.1
TEAS	11.4	49.2	11	1.1	5.3	3.6	7.4	9.9	1	50.8
CNNP	7.4	11.3	53	4.4	8.6	6.4	3.9	3.9	1	47
CYP	2.2	2	6.3	73.6	5.7	4.3	2.6	1.9	1.4	26.4
GGEP	3.7	6.6	10.5	4.9	64.6	4.7	2.5	1.3	1.2	35.4
CGNP	4.2	5.2	8.2	4	4.6	63.2	3.5	4	3.2	36.8
LGET	7	8.1	4.1	1.2	2.3	2.1	55.7	18.9	0.6	44.3
TW	8.3	10.3	3.8	0.9	1.2	2.7	17.8	54	1	46
WTI	1.4	2.6	1.8	1.1	0.9	1.4	1.2	2.2	87.5	12.5
TO	45.6	59.2	53.5	19	31.7	28.5	45.6	50.9	10.3	TCI
NET	0.5	8.4	6.5	−7.4	−3.8	−8.2	1.3	4.9	−2.2	38.2

6. Dynamic correlation and portfolio management analysis

In this section, we analyze the relationship between international crude oil and clean energy firm stock prices from the perspective of portfolio diversification and risk management. First, we calculated the dynamic conditional correlation; second, we used the results of the DCC-GARCH model to construct the optimal portfolio diversification strategy.

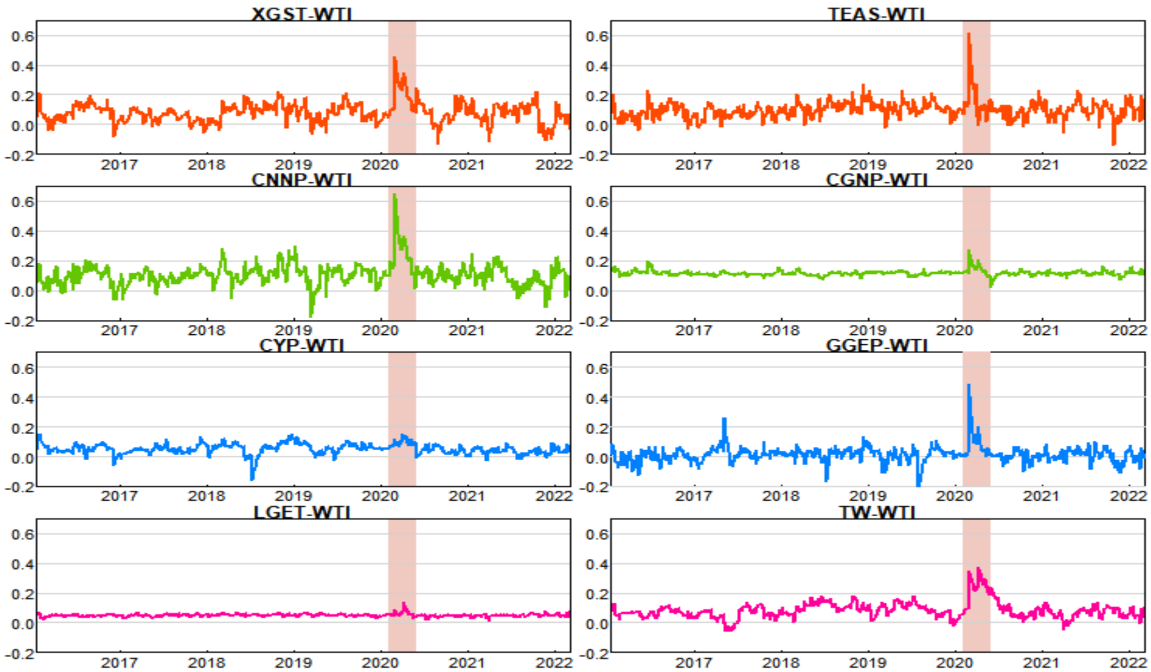

Figure 9. Dynamic conditional correlation coefficient.

6.1. Dynamic conditional correlation analysis

Figure 9 shows the conditional correlation between international crude oil and clean energy firms. February to April 2020 was the higher correlation time period. We can see that the correlation between international crude oil and the various clean energy firms was not constant, and even had some fluctuations. After the COVID-19 outbreak, the correlation coefficient between each firm and international crude oil reached an extreme value, while the minimum value in the extreme value was 0.134 (WTI-LGET) and the maximum value was 0.648 (CNNP-WTI). Regardless of the size of the values, it can be observed in Figure 9 that, at the time of the COVID-19 outbreak (February 3, 2020), there was a significant increase in the dynamic conditional correlation coefficient for each firm and international crude oil. This finding is consistent with the findings of Naeem et al. [36].

Combined with the results of the previous part of the study, the volatility connectedness, as well as the correlation between clean energy firms and international crude oil, can change significantly over time due to extreme events; therefore, it was important to investigate whether there was an optimal diversification strategy during the epidemic. Here, we calculate the optimal portfolio weights as a diversification strategy.

6.2. Optimal weighting analysis

In this section, we calculate the optimal portfolio weights for international crude oil prices and clean energy firm stock prices. According to Kroner and Ng [37], we define

$$\omega_{of,t} = \frac{g_{ff,t} - g_{of,t}}{g_{oo,t} - 2g_{of,t} + g_{ff,t}} \tag{20}$$

$$\omega_{of,t} = \begin{cases} 0 & ,\text{if } \omega_{of,t} < 0 \\ \omega_{of,t} & ,\text{if } 0 \le \omega_{of,t} \le 1 \\ 1 & ,\text{if } \omega_{of,t} > 1 \end{cases} \tag{21}$$

where $g_{of,t}$ is the conditional covariance of WTI volatility and clean energy firm volatility, $g_{ff,t}$ is the conditional variance of clean energy firm volatility, $\omega_{of,t}$ is the weight of WTI volatility in a USD 1 portfolio of WTI volatility and one clean energy firm stock price volatility at time t. The weight of the one clean energy firm volatility is equal to $1-\omega_{of,t}$.

According to Timonina-Farkas [38], in the financial sector, the ongoing COVID-19 pandemic has demonstrated the lack of robust multi-stage investment strategies in terms of non-stationary returns. Here, we consider the different stages of the portfolio. In order to give portfolio recommendations for different periods, we have combined the results of the analysis in the previous section and the calculation of the optimal weights, and we have deliberately given the results of the average of the weights for the COVID-19 outbreak period (February 2020 to June 2020) for reference.

As can be seen in Table 5, the mean values of the optimal weights of international crude oil prices for the full time period ranged from a minimum of 0.355 for TW to a maximum of 0.831 for CYP. These values can be interpreted as meaning that, for a portfolio of USD 1, 0.645 (0.169) should be invested in TW (CYP) and 0.355 (0.831) in WTI. Once again, we can see the significant impact of the COVID-19 outbreak. The optimal weights of all portfolios calculated in this study increased. The average for the COVID-19 outbreak period was significantly higher than the full time period average. This situation suggests that clean energy firms have become important in a diversified investment strategy. Finally, we can observe that the optimal portfolio weights for all sectors of clean energy changed significantly again over time as the COVID-19 outbreak has eased, all dropping to a lower level, or even to a zero weight, i.e., a zero-dollar investment in WTI, which means that the portfolio was obtained by using one asset (i.e., one clean energy firm).

In summary, short-term investors can create profits from the high volatility spillover of international crude oil shocks to clean energy firms based on the findings in this paper. The results of the full sample and subsamples provide important evidence of the role of different clean energy firms as diversification switching and safety preserving assets for oil shocks. For policy-makers, the findings in this paper suggest that policy formulation should distinguish between short-term and long-term policies. For example, in the short term, they need to consider the relationship between oil shocks and nuclear-type clean energy firms. In the long run, they should focus on the relationship between oil shocks and hydropower-type clean energy firms. Time-varying spillover effects or connectivity would be helpful in developing regulations related to clean energy investments. This finding was also confirmed by the research results of Yahya et al. [15].

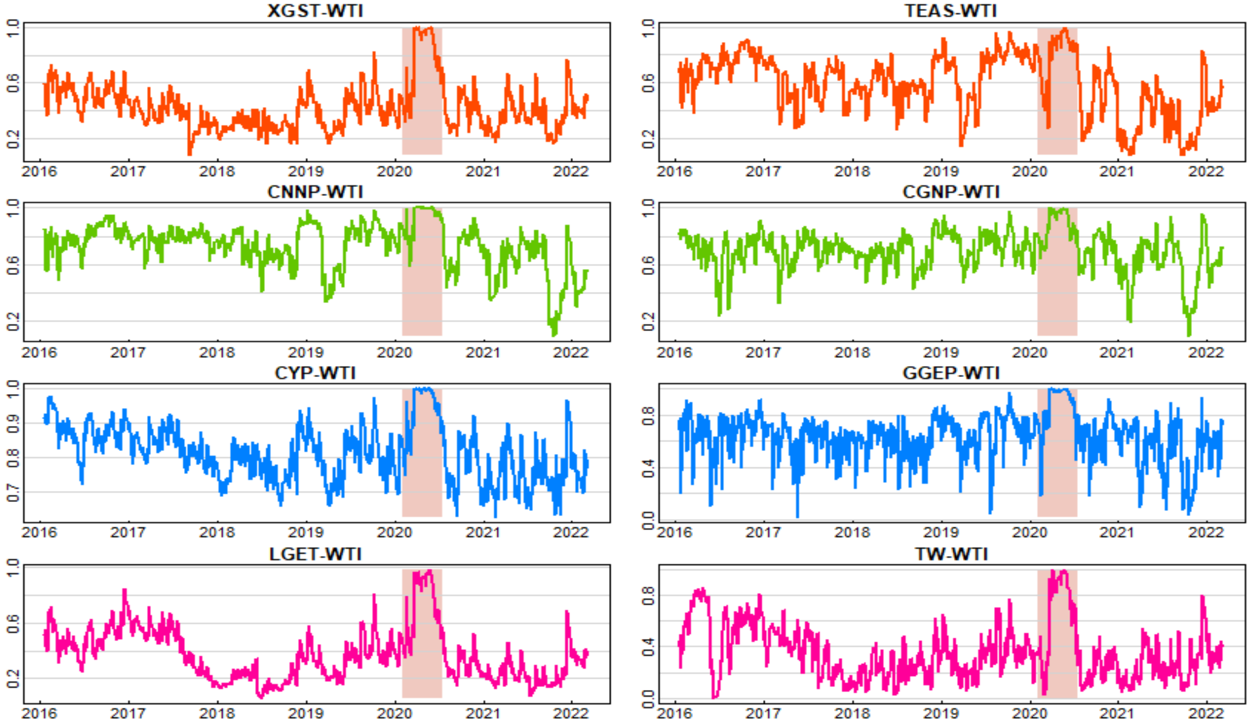

Figure 10. Optimal portfolio weighting line charts.

Table 5. Time-varying portfolio weight mean values by time period.

Portfolio	Full time period	COVID-19 era
WTI/XGST	0.420	0.766
WTI/TEAS	0.585	0.787
WTI/CNNP	0.731	0.918
WTI/CGNP	0.696	0.877
WTI/CYP	0.813	0.940
WTI/GGEP	0.633	0.865
WTI/LGET	0.369	0.736
WTI/TW	0.355	0.647

7. Conclusions

This study empirically analyzed the volatility connectedness between international crude oil and Chinese clean energy firms and included a portfolio analysis based on daily closing price data from January 4, 2016 to March 7, 2022.

In terms of shock effects, we analyzed the responses of eight clean energy firms to international crude oil volatility from a dynamic perspective through the use of a TVP-SV-VAR model. In general, the impact of WTI volatility shocks on different clean energy firms had a strong time-varying effect. The equal-interval impulse response results show that the impact of international crude oil shocks is stronger at Lag 1 than at Lag 2, indicating that the impact of international crude oil on clean energy firms is extremely short-term. The time-phased impulse response results show that most clean energy firms need to be aware of strong positive shocks from international crude oil when a major macroeconomic event occurs. This impact is mainly short-term, and most firms will return to a steady state within five periods. Only the hydropower firms will experience a significant negative response. Therefore, when major events occur, clean energy firms need to be aware of the stronger short-term impact from international crude oil. And, hydropower firms need to develop a better strategy for their response because the way that they respond is not easy to determine.

In terms of the time-varying spillover analysis, the TOTAL spillover index showed two distinct periods of high spillover after 2019 and 2020, with the highest spillover values approaching 55% during this period, while the market spillover index tended to be no higher than 40% in the other periods. These two periods covered two major events (i.e., the USA foreign tariff increase on May 6, 2019 and the COVID-19 outbreak on Feb. 3, 2020). Based on the TO spillover index for each firm, it can be seen that wind power firms are generally the main senders of volatility shocks, but nuclear power firms may also be the main senders after major macroeconomic events. The FROM spillover index shows that hydropower firms are at higher risk of being hit during major macroeconomic events (i.e., the increase in the FROM spillover index is higher for hydropower firms). PV and wind power firms had chronically higher levels of the FROM spillover index, indicating that they were the main recipients of volatility shocks. Considering the assets of each firm, firms with large total assets are prone to be senders of volatility spillovers, while firms with small total assets are prone to be receivers. In the previous analysis, we found that the WTI's spillover index is also influenced by major macroeconomic events. Regarding the NET spillover index for WTI, its value was mainly positive before 2018, while its value was negative for a long time after 2018; and, WTI became a receiver of volatility spillover; such a situation can indicate that the impact of international crude oil prices on China gradually decreases.

Regarding dynamic correlation and portfolio management analysis, we focused on asset management through the use of a DCC-GARCH model. The following conclusions can be drawn from the correlation analysis. First, the correlations between international crude oil and individual clean energy firms are volatile. Taking the COVID-19 epidemic as an example, the dynamic conditional correlation coefficient between each firm and international crude oil always increased after such a major macroeconomic event. Second, the analysis of the optimal portfolio weights shows that the optimal weights of all international crude oil and clean energy firms increased at the time of the COVID-19 outbreak. Over time, the optimal portfolio of all clean energy firms decreased to a lower level.

In this study, we selected different types of clean energy firms to study the volatility linkage between international crude oil and Chinese clean energy firms. Through the use of impulse response functions and spillover indexes, policy-makers can have a clearer understanding of the forms of shocks and spillover effects between international crude oil and clean energy firms, which allows for more targeted policy formulation for clean energy development. Meanwhile, the heterogeneity within the clean energy market is emphasized in this paper. Different clean energy industries will have different levels of portfolio stability. This will have important implications for investor decision-making and clean energy investment policy formulation. Investors should give more consideration to portfolios based on the relationship between the type of clean energy firm and international crude oil. The policies to promote clean energy investments should take into account the characteristics of each clean energy industry and ensure stock price stability in the event of major macroeconomic events.

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Conflict of interest

The authors declare that there is no conflict of interest.

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