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Do uncertainties affect clean energy markets? Comparisons from a multi-frequency and multi-quantile framework

Yiying Li [a], Cheng Yan [b,*], Xiaohang Ren [c,*]

[a] School of Finance, Renmin University of China, Beijing, China
[b] Essex Business School, University of Essex, Colchester CO4 3SQ, UK
[c] School of Business, Central South University, Changsha 410083, China

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ABSTRACT

Clean energy market has great potential to promote the balance between economic development and environmental protection, and has gradually become one of the vital energy markets. This paper investigates the real effects of external uncertainties from oil price shocks (supply, demand, and risk shocks) and political factors on the clean energy market based on a multi-frequency and multi-quantile framework. The empirical results show that both oil price shocks significantly impact the clean energy market, especially the oil demand shock. Two political factors, economic policy uncertainty and geopolitical risk, also have a one-way influence on the clean energy market. Additionally, the impact of most external uncertainties on the clean energy market is more prominent in the long term than in the short and medium term. Finally, the clean energy market with different market conditions also has different abilities to resist external uncertainties. Our research analyses all the joint distributions between each external uncertainty and the clean energy index in identical time frames. It is helpful for investors to construct more rational investment strategies and for policymakers to make appropriate policy arrangements.

1. Introduction

Clean energy is a category of energy that has been found to be environmentally friendly in its development and utilization process (Chen et al., 2022). As global climate risks intensify and traditional energy reserves become increasingly depleted, clean energy has become an important source of energy for daily consumption (de Abreu et al., 2021; Ren et al., 2021). Therefore, to a certain extent, clean energy can be a competitive or alternative energy source to traditional fossil energy. Additionally, the clean energy market is emerging as one of the major financial markets, on the horizon of investors and policymakers worldwide (Elie et al., 2019). The development of clean energy markets is closely linked to political factors such as policy support and inter-sovereign relations (Barrett et al., 2002; Ćetković et al., 2016; Breetz et al., 2018; Sohail et al., 2022). This shows that the importance of clean energy cannot be underestimated, but at the same time, the clean energy market is inevitably likely to be hit by a number of external uncertainties. In order to better help market participants grasp the characteristics of the clean energy market and to bring out the actual performance of the clean energy market, this paper examines the impact of two types of external uncertainty, crude oil price shocks and political factor shocks, on the clean energy market. Additionally, we treat all uncertainties equally to compare which external shock has a more violent or far-reaching impact on the clean energy market in the same time dimensions.

Clean energy has the advantage of not producing carbon emissions in the process of use, catering to the current global trend of low carbon economic development (Lin and Li, 2022). At the same time, many clean energy sources are renewable, so the use of clean energy is not limited by the total amount of energy available. These advantages have contributed to the gradual emergence of clean energy as an alternative to traditional fossil energy sources (Tenaw, 2022). As one of the most representative traditional energy sources, crude oil has a significant influence on numerous macro and micro factors (Liang et al., 2020; Wang et al., 2021). Therefore, there is a high probability that crude oil will also have an impact on the clean energy market (Ghabri et al., 2021). Many studies have linked clean energy and crude oil and examined the relationship between the two. These studies have confirmed that the volatility of crude oil prices significantly impacts the performance of clean energy stocks (Henriques and Sadorsky, 2008; Managi and Okimoto,

* Corresponding authors.
E-mail addresses: cheng.yan@essex.ac.uk (C. Yan), domrxh@outlook.com (X. Ren).

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2013; Naeem et al., 2020; Ren et al., 2022b). Furthermore, Geng et al. (2021) also find that changes in crude oil prices and clean energy stock returns move in the same direction, with a high degree of information interdependence between them.

On the other hand, the impact of political factors on the clean energy market also cannot be ignored (Ćetković and Buzogány, 2019; Aleluia et al., 2022; Wang et al., 2023a). We chose the economic policy uncertainty as one of the proxies of political factors to conduct our analysis since the economic policies could directly determine the future direction of economic development (Wang et al., 2022a). Firstly, economic policy uncertainty has been proven to have numerous direct or indirect effects on the clean energy market infrastructure and investment (Ji et al., 2018; Wang et al., 2023b). Moreover, a high level of economic policy uncertainty may greatly influence whether the clean energy market can develop smoothly or rapidly, and so on (Al-Thaqeb and Algharabali, 2019; Nilavongse et al., 2020; Wang et al., 2022b; Ren et al., 2023). From another political perspective, the study by Su et al. (2021) also found that geopolitical risks arising from competition and cooperation between different sovereign actors can significantly affect the performance of renewable energy. Therefore, we also consider the impact of geopolitical risk in our analysis since the disruption of geopolitical factors brings many opportunities or challenges to the survival environment of the clean energy market.

While scholars have studied related topics to a greater or lesser extent, very little has been written on the exposure of clean energy to crude oil price shocks and political factors. To fill the gap, this paper simultaneously examines the real impact of three decomposed oil price shocks (supply, demand, and risk shocks) and two political factors (economic policy uncertainty and geopolitical risk) on clean energy market performance. Three levels of time dimensions and multiple quantile dimensions are distinguished for specific analysis to uncover a more comprehensive picture of the characteristics and resilience of clean energy market performance.

We refer to the methodology of Ready (2018), which decomposes oil price volatility into three perspectives, the demand side, the supply side, and the overall volatility aspect of market volatility. This helps to better verify which crude oil shocks can have a more significant impact on the clean energy market. We used a maximum overlap wavelet decomposition approach to minimise the noise in the time series, decomposing the individual uncertainty variables and the clean energy market index into waves of six frequencies (Patnaik et al., 2021). And based on this, the time dimension of the study was divided into three scenarios: short-, medium- and long terms. Once these preparations were made, using the quantile Granger approach, we initially determined that each of these uncertainties had significant unidirectional Granger causal effects on the clean energy market. These effects essentially hold across the frequency and quantile distributions. The quantile-on-quantile approach further confirmed the powerful impacts of all uncertainty series on the clean energy market and could clearly observe their effects' differences.

The main contributions of our study are as follows. Firstly, by taking into account uncertainties arising from both crude oil shocks and shocks from political factors, with the clean energy market as the core of the study, this study is able to visualise the extent to which the clean energy market is affected by these uncertainties and facilitate comparative analysis between individual uncertainties. We consider more factors and scenarios, extending previous relevant works, such as the studies of Naeem et al. (2020) and Zhang et al. (2020). Even if three kinds of oil price shocks are refined from oil price fluctuations, the decomposition allows for a more direct tracing of the causes of these oil shocks. This helps multiple stakeholders to more accurately understand the characteristics of the clean energy market and to anticipate the outcomes of shocks from different events.

Secondly, we have used a combination of wavelet decomposition and quantile methods to embed the complete analysis into a multi-dimensional framework, allowing the core issues of the study to be analysed from a broader range of perspectives. Because of this analytical approach and framework, we do find that uncertainty has a greater impact over a longer time horizon and that clean energy markets are more prone to extreme market movements in response to uncertainty shocks when they are in extreme market conditions. This also makes the comparative analysis of the influence of different external uncertainties in more dimensions. It helps to help investors build a more cautious or rational investment strategy.

Finally, the clean energy market acts as an essential player in balancing economic development and environmental protection. Our study of the performance of clean energy in an uncertain environment will help policymakers consider more factors related to clean energy in their economic policy making and think more cooperation with other players to promote clean energy development.

The remainder of the paper is organised as follows: Section 2 is a review of the relevant literature, which is used to understand the research developments on the topic. The third section deals with oil price decomposition methods, the quantile Granger test, and the quantile-on-quantile methodology. The fourth section deals with data sources and basic descriptive statistics. Section 5 is devoted to the empirical results and discussion. Finally, Section 6 concludes with a summary.

2. Literature review

Clean energy is currently being developed in many countries and regions worldwide, especially the regions which are focusing on environmentally friendly economic development (Dincer and Acar, 2015). He et al. (2018) point out that, at present, the combined development index for clean energy is relatively high in developed countries. In emerging nations, the opportunity for clean energy development with additional potential is even more remarkable. The clean energy market is not only there for the low carbon transition, but as it matures, it is also becoming one of the critical financial markets.

The clean energy market is embedded in an intricate network of markets, and it is inevitably influenced by many factors. The interconnection between crude oil and clean energy is one of the richest topics in the literature. Haug (2011) points out that while clean energy does not quickly reverse the demand for oil, clean energy accelerates the market readiness for oil alternatives. Therefore, clean energy and oil are the two representative sources of energy that are often compared to each other. In the last decade, a large number of academics have studied the linkage between oil price volatility or oil stocks and clean energy stocks.

After that, many researchers, for example, Dutta and Dutta (2022) and Geng et al. (2021), have further explored the connection between the oil price shocks and clean energy stocks. The conclusion of these studies is almost unanimous, i.e., changes in oil prices significantly affect clean energy stock prices and are a catalyst for higher share prices. These studies confirm the importance of the dynamics of crude oil for clean energy, and for the time being, the one-way impact of oil on clean energy is more significant. Clean energy may still be in a position to be an alternative market to crude oil.

In addition, clean energy, as an environmentally friendly energy source strongly backed by the government, can sometimes play a pivotal role in its development compared to the industrial demand-driven nature of traditional energy sources (Ge and Zhi, 2016).

The most direct impact of policies for clean energy advocacy and investment is the rapid development of clean energy infrastructure (Lee, 2013). And in addition to this, any policy of green development will also bring about an acceleration of clean energy. Zahan and Chuanmin (2021) find that the implementation of green investment policies has significantly stimulated the development of clean energy with an autoregressive distributed lag (ARDL) method. The survey confirms that institutional and political factors play a key role in facilitating the renewable energy transition and shows that improving these factors can lead to decarbonisation.

The development of clean energy is also inseparable from the competition and cooperation between different regions, and geopolitics is gradually becoming a factor that cannot be ignored. Sivaram and Saha (2018) and Su et al. (2021) argue that the development of clean energy is influenced by geopolitics and, in turn, it brings opportunities and adjustments such as institutional reforms that have an impact on geopolitics. For instance, Zhao et al. (2021) find that geopolitical risks asymmetric impact energy use and carbon emissions in different countries and regions. Additionally, geopolitical risks have also been shown to have a significant impact on a number of aspects, such as clean energy stocks, related capital investment, and energy restructuring in various regions (Vakulchuk et al., 2020; Flouros et al., 2022). Geopolitical risks can therefore be both an opportunity and a challenge, and it is impossible to say which role it plays.

It is certain that, similar to many other financial or energy markets, the clean energy market is vulnerable to the unpredictability brought about by numerous external factors. Nevertheless, there is still a lack of comparison in terms of the effect of external uncertainty on the clean energy market in different aspects. This paper provides an innovative viewpoint in comparison to existing literature to examine the impact of external uncertainty on clean energy indices arising from both crude oil price shocks and political factors.

3. Methodology

3.1. Oil price shocks decomposition

This paper applied the method proposed by Ready (2018) to decompose oil price shocks into three more specific sub-shocks: supply,[1] demand[2], and risk[3] shocks. Taking the practice of Uddin et al. (2018) and Ren et al. (2022a) as a reference, we conducted the decomposition as follows:

$$X_t = AZ_t \tag{3-1}$$

where $X_t = [\Delta oil_t, R_t^{prod}, \zeta_{VIX,\ t}]^T$, whose components denote oil price change, the World Integrated Oil and Gas Producer index returns, and VIX innovations. Vector $Z_t = [s_t, d_t, v_t]^T$, and its elements are supply, demand, and risk shocks of oil price (Ready, 2018; Malik and Umar, 2019). The matrix A is as follows:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

$$A^{-1}\sum_X \left(A^{-1}\right)^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

where $\sum_X$ means the covariance matrices of the components of X_t. The σ_s, σ_d and σ_v represent the variances of corresponding shocks.

3.2. Wavelet transformation

In order to analyse from the different temporal dimensions, we adopt a wavelet decomposition approach by referring to the study by Kumah and Mensah (2022) and Ren et al. (2022a). This method could do a good job of breaking down the data into different frequencies and eliminating some of the noise simultaneously. It is a good data processing tool that helps in the analysis of this paper. The brief process is as follows:

It catches the different information through two kinds of wavelets:

$$\varphi_{\mu k} = -2^{-j/2}\varphi\left(\frac{t-2^{jk}}{2^j}\right), \int \varphi(t)dt = 1, \tag{3.1}$$

$$\psi_{jk} = -2^{-j/2}\psi\left(\frac{t-2^{jk}}{2^j}\right), \int \psi(t)dt = 0, \tag{3.2}$$

where $\{j = 1, \ldots, J\}$ denotes scale levels and $\{k = 1, \ldots, K\}$ denotes translation, the translation coefficients of $\varphi_{\mu k}$ and $\varphi_{\mu k}$ are defined as:

$$S_{J,k} = \int f(t)\varphi_{J,k}, \tag{3.3}$$

$$d_{jk} = \int f(t)\psi_{J,k} \tag{3.4}$$

The function $\{f(.)\}$ in the equations above is defined as:

$$f(t) = \sum_k S_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t)\ldots + \sum_k d_{J,k}\psi_{J,k}(t)\ldots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{3.5}$$

$$f(t) = S_J + D_J + D_{J-1} + \ldots + D_j + \ldots + D_1 \tag{3.6}$$

with its components are defined as:

$$S_j = \sum_k S_{J,k}\varphi_{J,k(t)}, \tag{3.7}$$

$$D_j = \sum_k d_{J,k}\psi_{J,k(t)}, j = 1, 2, \ldots, J. \tag{3.8}$$

Then we used the maximum overlapping discrete wavelet transform (MODWT) with perfect flexibility (Percival and Walden, 2000) to continue the decomposition process. The first step of the MODWT method is to set the wavelet filter $\widetilde{h}_l = h_1/\sqrt{2}$ and scale filter $\widetilde{g}_l = g_1/\sqrt{2} = (-1)^{l+1}\widetilde{h}_{L-1-t}$, satisfying the equations below:

$$\sum_{l=0}^{L-1}\widetilde{h}_l = 0, \sum_{l=0}^{L-1}\widetilde{h}_l^2 = \frac{1}{2}, \sum_{l=0}^{L-1}\widetilde{h}_l\widetilde{h}_{l+2n} = 0, \tag{3.9}$$

$$\sum_{l=0}^{L-1}\widetilde{g}_l = 1, \sum_{l=0}^{L-1}\widetilde{g}_l^2 = \frac{1}{2}, \sum_{l=-\infty}^{\infty}\widetilde{g}_l\widetilde{g}_{l+2n} = 0, \tag{3.10}$$

$$\sum_{l=-\infty}^{\infty}\widetilde{g}_l\widetilde{h}_{l+2n} = 0. \tag{3.11}$$

where n denotes the number of original time series. The second step is to determine the MODWT coefficients as follows:

$$\widetilde{W}_{1,t} = \sum_{l=0}^{L-1}\widetilde{h}_l X_{t-1\ modN}, \tag{3.12}$$

$$\widetilde{V}_{1,t} = \sum_{l=0}^{L-1}\widetilde{g}_l X_{t-1\ modN}, t = 0, 1, \cdots, N-1. \tag{3.13}$$

$\widetilde{W}_{1,t}$ and $\widetilde{V}_{1,t}$ are the first layer wavelet and scale coefficients of the MODWT, and we extend it to the j-th level wavelet:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L-1}\widetilde{h}_{j,l}X_{t-lmodN}, \tag{3.14}$$

$$\widetilde{V}_{j,t} = \sum_{l=0}^{L-1}\widetilde{g}_{j,l}X_{t-lmodN}, t = 0, 1, \cdots, N-1. \tag{3.15}$$

[1] Supply shock is presented by the residual component of oil price changes.
[2] Demand shock is the proportion of returns on a worldwide stock index of oil-producing companies.
[3] Risk shock is proxied by the volatility index innovations, its innovation component is the corresponding residuals after capturing unexpected changes, using ARMA (1,1) model.

$$\widetilde{h}_{j,l} = h_{j,l} \Big/ \left(2^{j/2}\right), \widetilde{g}_{j,l} = g_{j,l} \Big/ \left(2^{j/2}\right). \tag{3.16}$$

$\widetilde{h}_{j,l}$ and $\widetilde{g}_{j,l}$ are wavelet filter and scale filter for layer $\{j\}$ and $\{j\}$ corresponds to time scale $\{2^j - 2^{j+1}\}$. The width L_j corresponds to $\{(2^j\text{-}1)(L\text{-}1) + 1\}$. The time frequencies {2–4, 4–8, 8–16, 16–32, 32–64 and 64–128 days} are represented by wavelet scales $\{d_1, d_2, d_3, d_4, d_5, d_6\}$. We take d_1, d_4 and d_6 represent short-, medium- and long- terms, respectively, referring to Ren et al. (2022a).

3.3. Quantile granger causality test

We used quantile Granger causality tests to make a preliminary determination of the predictive relationship between different types of uncertainty (X_t) and the clean energy market (Y_t). Specifically, setting that vector $I_t \stackrel{\text{def}}{=} (I_t^Y, I_t^X)' \in R^d$, $d = s + q$, and $I_t^X := (X_{t-1}, \dots, X_{t-q})' \in R^q$ is the lag collections of X_t. The null hypothesis of no Granger causality is that:

$$H_0 : F_Y\left(y|I_t^Y, I_t^X\right) = F_Y\left(y|I_t^Y\right), \forall y \in R. \tag{3.17}$$

where $F_Y(y|I_t^Y, I_t^X)$ stands for the conditional distribution with the given (I_t^Y, I_t^X). The X_t does not Granger cause Y_t if:

$$E\left(Y_t|I_t^Y, I_t^X\right) = E\left(Y|I_t^Y\right), a.s. \tag{3.18}$$

The function E(•) denotes the average value. Then we followed the study of Troster et al. (2018) to make Granger causality test with quantiles. Defining $Q_T^{Y,X}(\bullet|I_t^Y, I_t^X)$ as the τ-th quantile of $F_Y(.|I_t^Y, I_t^X)$, the same with the meaning of $Q_T^Y(\bullet|I_t^Y)$ to $F_Y(.|I_t^Y)$. The null hypothesis of Granger causality changes to the form below (T denotes the compact set and $T \subset [0,1]$):

$$H_O : Q_T^{Y,X}\left(Y_t|I_t^Y, I_t^X\right) = Q_T^Y\left(Y_t|I_t^Y\right), a.s. \forall \tau \in \mathrm{T}. \tag{3.19}$$

The conditional τ-th quantile of Y_t meets these conditions:

$$Pr\left\{Y_t \le Q_T^Y\left(Y_t|I_t^Y\right) |I_t^Y\right\} := \tau, a.s. \forall \tau \in \mathrm{T}. \tag{3.20}$$

$$Pr\left\{Y_t \le Q_T^{Y,X}\left(Y_t|I_t^Y, I_t^X\right) |I_t^Y, I_t^X\right\} := \tau, a.s. \forall \tau \in \mathrm{T}. \tag{3.21}$$

Given I_t, probability$\Pr\{Y_t \le Q_T(Y_t|I_t)|I_t\} = E\{1[Y_t \le Q_T(Y_t|I_t)]|I_t\}$, creating an example for function $1[Y_t \le Y]$. The null hypothesis then is as follows:

$$E\left\{1\left[Y_t \le Q_T^{Y,X}\left(Y_t|I_t^Y, I_t^X\right)\right] |I_t^Y, I_t^X\right\} = E\left\{1\left[Y_t \le Q_T^Y\left(Y_t|I_t^Y\right)\right] |I_t^Y\right\}, a.s. \forall \tau \in T. \tag{3.22}$$

Assuming that $Q_T(\bullet|I_t)$ is properly specified through a parametric model that defined by$M = \{m(.|\theta(\tau))|\theta(.) : \tau \to \theta(\tau) \in \Theta \subset R^p$, then the zero assumption of Granger non-causality relationship can be set that:

$$H_O : E\left\{1\left[Y_t \le m\left(I_t^Y, \theta_0(\tau)\right)\right] |I_t^Y, I_t^X\right\} = \tau, a.s. \forall \tau \in \mathrm{T}. \tag{3.23}$$

The function $m(I_t^Y, \theta_0(\tau))$ stands for real conditional quantile of $Q_T^Y(.|I_t^Y)$. Rewriting the null hypothesis of non-Granger causality again as follows:

$$H_O : E\left\{1\left[Y_t - m\left(I_t^Y, \theta_0(\tau)\right) \le 0\right] - \tau\right\} exp(i\omega' I_t)\} = 0. \tag{3.24}$$

Finally, we assessed the test statistic and got that:

$$S_T := \int_\tau \int_W |v_T(\omega, \tau)|^2 dF_\omega(\omega) dF_\tau(\tau). \tag{3.25}$$

$$v_T(\omega, \tau) := \left(1 \Big/ \sqrt{T}\right) \sum_{t=1}^{T} \left\{1\left[Y_t - m\left(I_t^Y, \theta_0(\tau)\right) \le 0\right] - \tau\right\} exp(i\omega' I_t) \Bigg\}. \tag{3.26}$$

Setting $\varphi_{\tau_j}(.)$ be a function and $\varphi_{\tau_j}(\varepsilon) := 1(\varepsilon \le 0) - \tau_j$, combining with the test statistic and getting that:

$$S_T = \frac{1}{Tn} \sum_{j=1}^{n} \left|\vartheta_j' W \vartheta_j\right|. \tag{3.27}$$

where W is defined as the TxT matrix and ϑ_j is the j-th column of φ. The measurement process of the values of S_T and more details can be seen in the practice of Troster (2018).

3.4. Quantile-on-quantile regression method

This study applied the quantile-on-quantile (QQ) regression method proposed by Sim and Zhou (2015) to test for specific associations between different uncertainties and clean energy market performance. The QQ method is modified by traditional quantile regression and non-parametric estimation methods (Ren et al., 2022a; Dou et al., 2022). QQ method could find the actual marginal influence and can fully capture the interesting responses on different distributions (Duan et al., 2021). Firstly, setting the regression equation for clean energy return (CE_t) in time t as a function of each kind of uncertainty (U_t) as[4]:

$$CE_t = \beta^\theta(U_t) + \varepsilon_t^\theta. \tag{3.28}$$

where U_t represents uncertainty at time t, θ denotes the θ-th quantile of each variable. ε_t^θ stands for the residual term; β^θ represents the impact of uncertainty on clean energy index return. To examine the impact of the τ-quantile of uncertainty on the θ-quantile of the clean energy index return, we Taylor expand the function β^θ at first order level around U^τ:

$$\beta^\theta(U_t) \approx \beta^\theta(U^\tau) + \dot{\beta}^\theta(U^\tau)(U_t - U^\tau) \equiv b_0(\theta, \tau) + b_1'(\theta, \tau)(U_t - U^\tau). \tag{3.29}$$

Combining Eq. (3.28) and Eq. (3.27), then get the final equation that:

$$CE_t = \beta^\theta(U^\tau) + \dot{\beta}^\theta(U^\tau)(U_t - u^\tau) + \varepsilon_t^\theta. \tag{3.30}$$

Then solve Eq. (3.29) by considering

$$\begin{pmatrix} \widehat{b}_0(\theta, \tau) \\ \widehat{b}_1(\theta, \tau) \end{pmatrix} = arg \min_{b_0, b_1, \alpha^\theta} \sum_{t=1}^{T} \rho_\theta[CE_t - b_0 - b_1(U_t - U^\tau)] K\left(\frac{F(U_t) - \tau}{h}\right). \tag{3.31}$$

where $\rho_\theta(y) = y(\theta - I_{\{y<0\}})$ and $\{I_A\}$ stands for an indicator function of "A". K is a Gaussian kernel function on **R.** h: $h > 0$ means the bandwidth used in this process. The empirical distribution function is defined as $F(U_t) = \frac{1}{T}\sum_{k=1}^{T} I(U_k < U_{T-1})$.

Furthermore, we use the cross-validation (CV) method to obtain the optimal bandwidth following Stone (1984) and Duan et al. (2021) as follows:

$$IEE = \int \rho_\theta\{m(x) - \widehat{m}(x)\} dx. \tag{3.33}$$

$$M(h) = \sum_{k=1}^{T} \rho_\theta\left(CE_k - \widehat{b}_{0,-k} - \widehat{b}_{1,-k} U_{k-1}\right). \tag{3.34}$$

$$h_{cv} = \underset{h}{argmin} M(h) \tag{3.35}$$

[4] Quantile-based regression is essentially a combination of linear regression at different quantile levels. And the quantile levels represent the data arranged in order. In this paper, we use the returns of the S&P Global Clean Energy Index, so the quantile levels are ranked in order of its return series. The level of return series then directly represents the market performance, or the current state of the market.

4. Data resources

The basic data for oil price shocks decomposition, such as the WTI crude oil futures price and VIX index, is from the DataStream, the Intercontinental Exchange, and the Chicago Board Options Exchange. Apart from that, we collect the S&P global clean energy index from Bloomberg, and the daily data on the American economic policy uncertainty and the geopolitical risk index is obtained from the website of Economic Policy Uncertainty. This paper uses the returns for all data series except for the oil price decomposition shocks (i.e., difference after

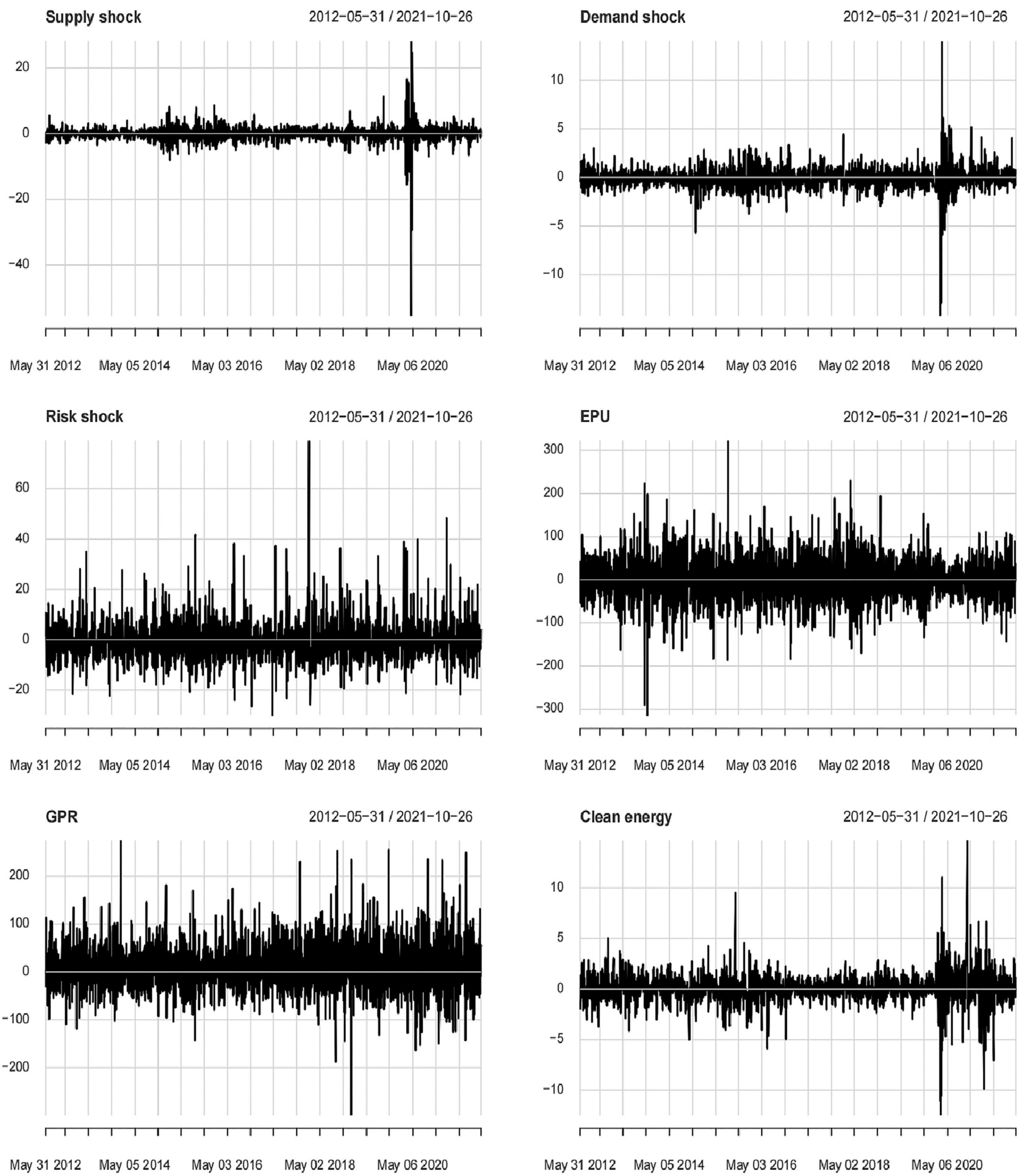


Fig. 1. Time series plots of main variables from 2012 to 05-31 to 2021-10-26.
This figure shows the density plots of the main variables in this paper. It includes three kinds of oil shock (supply shock, demand shock, and risk shock), returns of Standard & Poor's global clean energy index, economic policy uncertainty index (EPU), and geopolitical risk index (GPR).

logarithm). Fig. 1. displays the time series plots of the main variables in this paper from May 31, 2012, to Oct 26, 2021. Intuitively, the supply and demand shocks disaggregated by the oil price shock follow very similar paths, with both having a very sharp swing in mid-2020. However, there is no similar pattern for the risk shock of oil price. The time series plots of the other data series-the economic policy uncertainty, the geopolitical risk index, and the clean energy index, do not vary regularly. So we further employ density plots (Fig. 2.) to draw the true distribution of each series, and the descriptive Statistics of all of our variables are shown in Table 1.

The density plot shows that the true distribution of the individual series (indicated by the solid line) does not agree with the normal distribution (indicated by the dashed line). Therefore the data are non-normally distributed, and this conclusion is again confirmed by the results of the Jarque-Bera test in Table 1. Additionally, the test results of the Augmented DickeyFuller (ADF) test show that three oil price shocks and other data return series are all stationary, indicating the appropriateness of applying quantile-based approaches.

5. Empirical results and discussion

5.1. Maximum overlap discrete wavelet transforms

Before the regression process, we decompose the series of all variables into six waves of different frequencies using the MODWT method, and the results plots can be seen in the Appendix end of this study. We find that the trend of the data is smoother as the number of decomposition levels increases. The time scales after wavelet decomposition are 2–4, 4–8, 8–16, 16–32, 32–64, 64–128 trading days (corresponding to decomposition levels d_1 to d_6). To simplify the analysis process, we take 2–4, 16–32, and 64–128 trading days as representatives of the short-, medium- and long-term time dimensions, drawing on Kumah and Mensah (2022). This breakdown is based on the reality that financial markets do not trade and change every single day. Moreover, economic-related activities such as portfolio and market research are often scheduled in different time frames.

5.2. Quantile granger causality test

Based on the wavelet decomposition, we were able to analyse

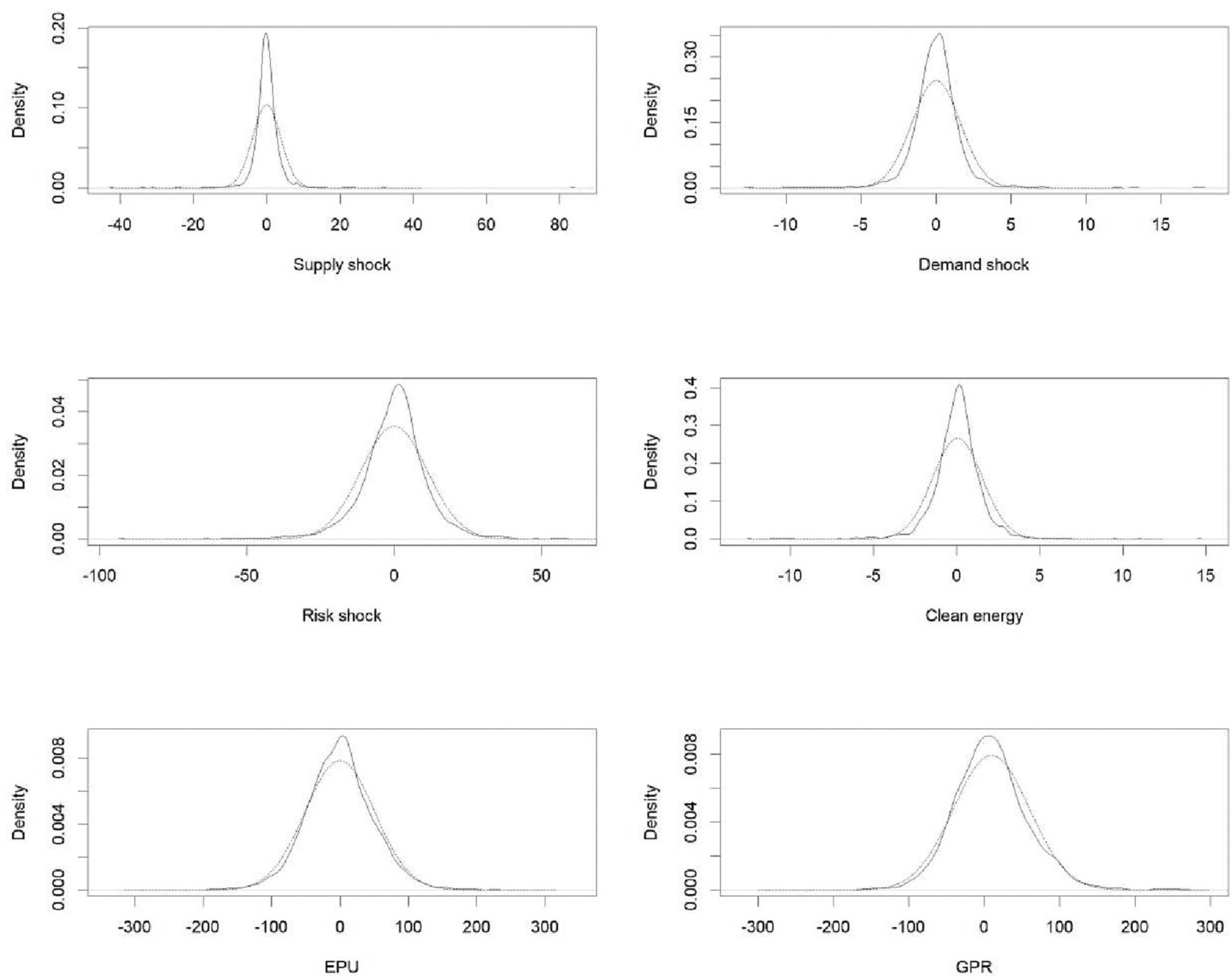


Fig. 2. Density plots of main variables from 2012 to 05-31 to 2021-10-26.
This figure shows the density plots of the main variables in this paper. It includes three kinds of oil shock (supply shock, demand shock, and risk shock), returns of Standard & Poor's global clean energy index, economic policy uncertainty index (EPU), and geopolitical risk index (GPR). The solid line shows the true density distribution of the variable series, and the dashed line shows the normal distribution.

Table 1
Descriptive statistics.

	Oil supply shock	Oil demand shock	Oil risk shock	Clean energy index return	EPU return	GPR return
Minimum	−42.3838	−12.4776	−92.5740	−12.4971	−314.8325	−299.5883
Maximum	83.5996	17.5810	57.2828	14.6326	303.2457	273.6160
25th Quartile	−1.4123	−0.7609	−5.6801	-0.6367	−36.9654	−22.0862
75th Quartile	1.37462	0.7492	5.8166	0.7478	20.1589	37.0870
Mean	0.0010	0.0003	0.0014	0.0553	−7.4269	9.6630
Stdev	3.8422	1.6226	11.2531	1.4966	49.1977	50.3090
Skewness	3.8793	0.9527	−0.4832	−0.2738	−0.0704	0.4233
Kurtosis	117.7607	20.3054	5.1490	13.9678	2.5313	2.4276
JB test	1285478***	38,397.82***	2535.581***	18,001.21***	594.7014***	611.5271***
ADF test	−20.1809***	−20.3609***	−22.4459***	−11.0410***	−13.6118***	−12.6473***

This table shows the basic information of the main variables in this paper. It includes three kinds of oil shock (supply shock, demand shock, and risk shock), returns of Standard & Poor's clean energy index, economic policy uncertainty index (EPU), and geopolitical risk index (GPR). The sample period is from May 31, 2012, to Oct 26, 2021. *** denotes the 1% significance level.

different temporal frequencies. The Granger causality between different "uncertainties" and the performance of the clean energy market is examined from multiple time scales and quantile levels by combining the wavelet series with the quantile-based approach.

Firstly, the quantile Granger test results of three oil price shocks with the clean energy index are presented in Figs. 3, 4, and 5, respectively. It can be observed that both supply shock, demand shock, and risk shock yield a Granger effect (Granger causality between variables implies a predictive or correlational relationship rather than an actual causal relationship) on the clean energy index. Additionally, the first two oil price shocks have a roughly consistent time trend about the Granger causality effect: in the short term, the predictive ability of oil price supply and demand shocks for clean energy markets is more significant in the middle quartile. However, in the medium and long-term scenarios, the interquartile range with significant Granger causality widens, reaching a maximum in the long term (significant results in almost all quartiles). This suggests that in the short term, three oil price shocks are more significant in predicting clean energy market performance, which is in normal market conditions. While in the long term, even when clean energy markets are extreme, they also cause a Granger effect. That is, the performance of clean energy returns also brings different levels of sensitivity to external oil shocks. It is quite interesting that the performance of the risk shock did not differ significantly across frequencies, unlike the other two oil price shocks. Even in the long-term case, risk shocks do not have a significant Granger effect on the clean energy index in the extreme quantile (i.e., when the clean energy market is in an extreme market state).

Conversely, the clean energy index is not predictive of any of these three oil price shocks (as shown in the right half of Figs. 3 to 5, where the solid black line is largely below the solid red horizontal line representing 5% significance). However, two exceptions exist. In the long run, the Clean Energy Index has a strong Granger effect on oil price supply shocks around the 0.7 quantiles (Fig. 3). Further, it partially affects oil price risk shocks in the short term (Fig. 5). This suggests that the specific association of different shocks with the clean energy index also varies considerably, with specific shocks potentially having a stronger two-way effect in certain time intervals.

This reciprocal Granger effect also appears in the test results of the clean energy index with economic policy uncertainty and geopolitical risk (Figs. 6 and 7). What is clearly visible is that uncertainty from economic policy or geopolitics can have as significant a predictive effect on clean energy index returns as uncertainty from oil prices. And similarly, the interquartile range with significant Granger effects gradually widens as the time horizon increases (short-term progressively to long-term). In the long-term scenario, the clean energy index has a "partial quantile" Granger effect on both economic policy uncertainty and geopolitical risk.

Summing up the results of all the tests, it can be seen that uncertainty, whether caused by oil prices or by economic policy making and geopolitics, significantly affects the clean energy market (at least proving a significant one-way Granger causality for it). With increasing time horizons, this effect can cover the clean energy index in almost all market states (i.e., represented by different quartiles). At some frequencies, clean energy may also have an inverse Granger effect on these uncertainties, but these cases are negligible in comparison to all combinations of frequencies and quantiles.

Overall, we can argue that the clean energy index can be significantly shaken or disrupted by these uncertainties, but it does not strongly shake or influence these uncertainties. In the subsequent analysis, we further used the quantile-on-quantile method to perform tests of the effects under the joint distribution.

5.3. *Quantile-on-quantile regression*

This section conducts the quantile-on-quantile regression to test the impact of each uncertainty on the clean energy index, and the results are illustrated by Figs. 8 to 12. The factors $b_1(\theta,\tau)$and $b_0(\theta,\tau)$represents the impact coefficient and regression constant term of the τ-th quantile of uncertainty return on the θ-th quantile of clean energy return. Comparing the three oil price shocks, the impact coefficient of the risk shock is negative, while the coefficients of the supply and demand shocks are mainly positive.

For supply shock, the coefficient of the impact of supply shocks on clean energy fluctuates around 0.04 in the short term. Only for extreme combinations (supply shock below the 0.2 quantile and clean energy indice above the 0.8 quantiles) appears an impact coefficient below zero. This result suggests that supply shocks from oil price changes can positively affect the clean energy index returns in most cases. In the medium term, the influence of supply shock on the clean energy index is largely determined by the quantile of the clean energy index (i.e., the state of the clean energy market). When the clean energy market is in the middle quartile (0.4–0.8 quartile), the impact coefficient is relatively small and sometimes negative. When it is in the extreme quartile range, the impact coefficients of supply shock on it are all greatly positive. This suggests that in the range of 16 to 32 trading days, the impact of supply shocks is significantly positive for clean energy markets in extreme states, while for it in relatively smooth market states, the influence is smaller and may appear to be negative.

The dramatic performance in extreme quantiles is consistent with the findings of Elie et al. (2019). And over a longer time horizon (bottom of Fig. 8.), the impact coefficient for supply shocks increases overall, above 0.1 under most joint distributions, reaching a maximum of around 0.35 (essentially appearing in the 0.7 to 0.9 interquartile range of the clean energy index). This suggests that the impact of supply shocks will be more pronounced in the long term, even leading to a high boom in clean energy markets. To sum up, the influence of supply shock is significant in all time scales and most of quantile levels. However, our results show that the impact of supply shocks is evident in medium term, which is

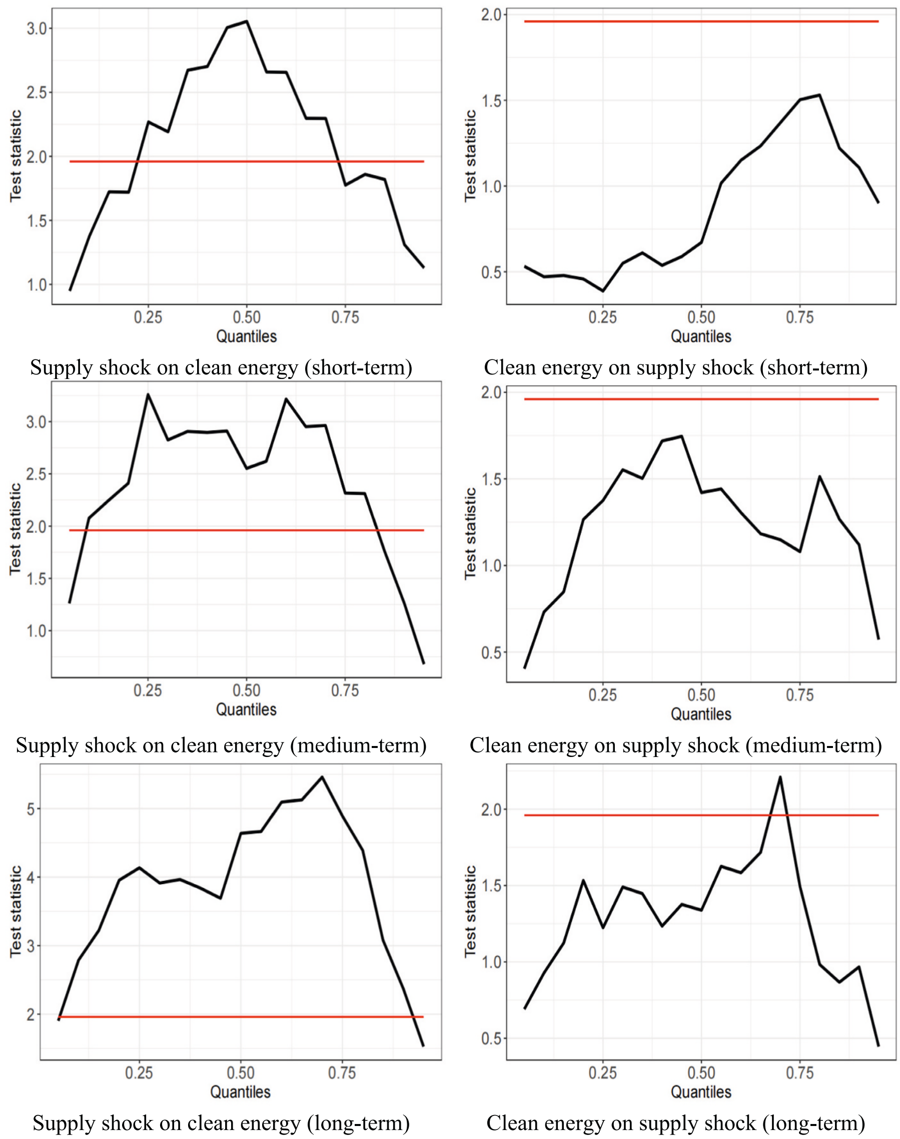


Fig. 3. Quantile granger test results between the supply shock (crude oil) and clean energy return.
This figure shows the results of the Granger causality test between oil supply shock and the clean energy index. The red line stands for the 5% critical level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

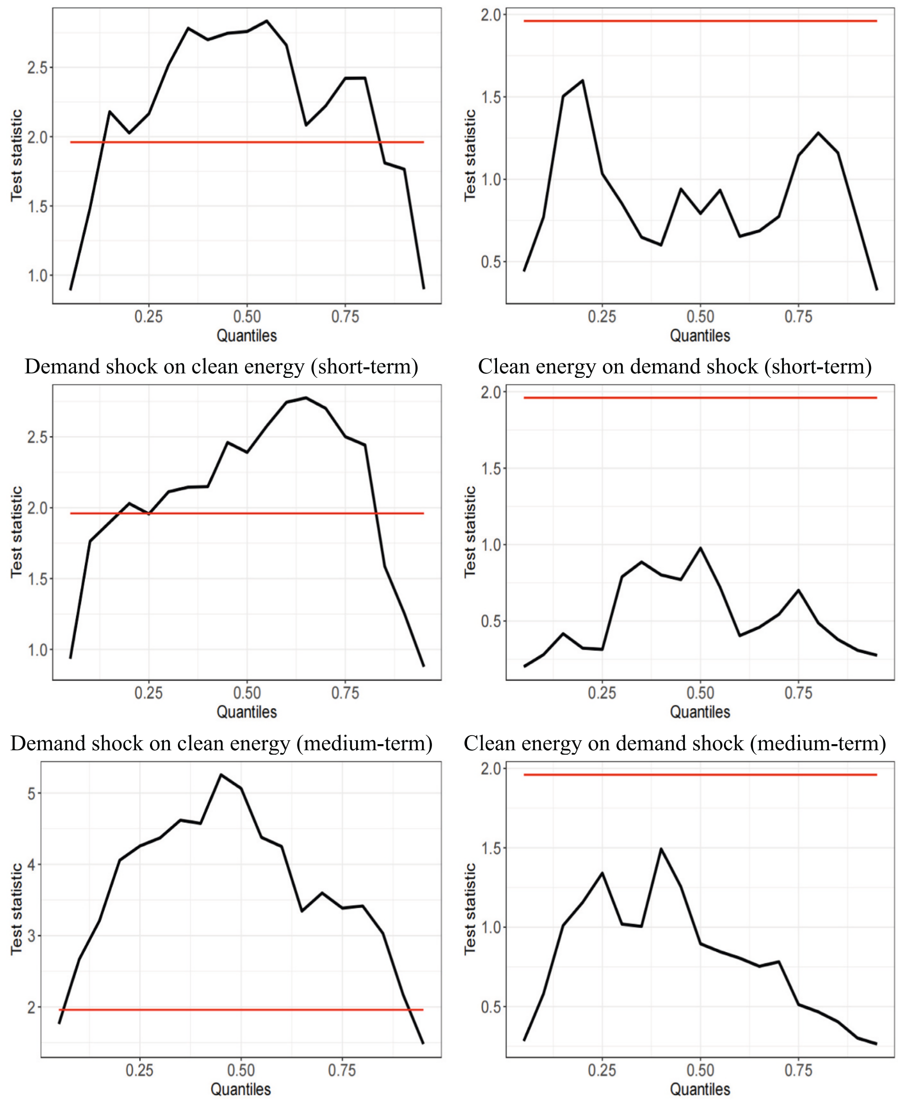
opposite to the conclusion of Zhang et al. (2020).

In terms of the oil demand shock, it is clear that the demand shock highly positively affects the clean energy index return, no matter in which time scales and quantile levels (Fig. 9). There is still a slight difference between the three frequencies, though. In the short term, demand shock mainly plays a role when the clean energy market is in a bull market condition (above the 0.5 quantiles). The effect of the demand shock on clean energy is relatively stable in the medium term, while the effect is greatly complex and has no rule in the long term (but also in the long term, it has the highest mean impact factor). The impact of the oil price risk shock on the clean energy index is negative and slight compared to the former two oil shocks (Fig. 10). Additionally, its effect does not change dramatically with the expansion of the time scale; instead, there is a steady increase of the negative impact.

The results of the three oil price shocks are complicated but also follow some logical lines. Generally, crude oil, the archetypal traditional highly polluting fossil energy source, and clean energy, an environmentally friendly energy source, are both commonly used today and are to some extent substitutes for each other. The supply shock disaggregated by oil price fluctuations represents the uncertainty caused by changes on the supply side. Changes in the volatility of crude oil supply are likely to indirectly affect changes in the supply of one of its substitutes, clean energy, and thus the performance of the clean energy market. The demand shock in oil price fluctuations represents more of a ‘demand’ for energy from consumers around the world, while oil is a fossil energy source that is not renewable in the short term and is semi-monopolised by many suppliers. So the more extensive the shock, the more likely it is to lead to a focus on clean energy, as clean energy is an alternative to traditional energy sources such as crude oil, and its production process is faster. This may be one reason for our result-the impact of demand-side shocks on clean energy is much more dramatic.

Risk shock measures a psychological expectation of market investors, and when such shocks occur too frequently, investors are likely to feel pessimistic about the market as a whole (so clean energy is also negatively affected), but the market volatility index takes into account many factors and is not limited to energy markets, so the absolute power of the impact on clean energy could be relatively smaller.

As for two kinds of uncertainty related to political factors (i.e., economic policy uncertainty and geopolitical risk), the results of their influence on the clean energy market seem relatively uneventful but still



Demand shock on clean energy (short-term) Clean energy on demand shock (short-term)

Demand shock on clean energy (medium-term) Clean energy on demand shock (medium-term)

Demand shock on clean energy (long-term) Clean energy on demand shock (long-term)

Fig. 4. Quantile granger test results between the demand shock (crude oil) and clean energy return.
This figure shows the results of the Granger causality test between oil demand shock and the clean energy index. The red line stands for the 5% critical level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

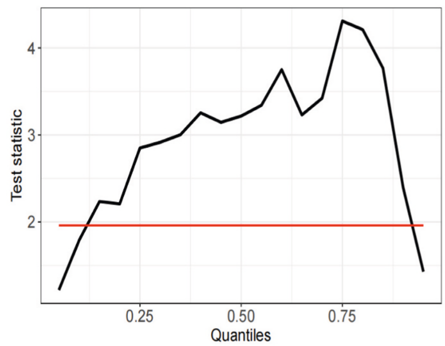
worth watching. From Fig. 11, we can get an interesting result that the impact of EPU on clean energy index return is basically positive in the short term but changes to all negative in the medium to long term. This suggests that in a state of less-than-clear economic policy trends, for the clean energy market, speculation may have prevailed in the short term, with more active clean energy trading and potentially more lucrative returns. However, over time, the fog of economic policy uncertainty may worry or deter investors, which in turn may cause a downturn in the clean energy market. These interesting results are similar to the results of Adedoyin and Zakari (2020), they claimed that EPU could improve the carbon emissions or the consumption of clean energy in the short term, while its impact in the long term will turn out to be very unfavorable.

In contrast, geopolitical risk has a mostly negative effect on clean energy markets in the short term on most joint distributions. Its impact is relatively flat in the medium term, while in the long term, the impact is largely positive. This reflects the slightly strange phenomenon that, for clean energy markets, the risk posed by geopolitical conflict surprisingly contributes to higher returns over a longer period of time, almost the opposite of the outcome of economic policy uncertainty. But there are reasons to explain. The deployment of clean energy can affect national energy security or energy competitiveness between countries, so conflicts brought about by geopolitics can also lead to a struggle over clean energy (Sivaram and Saha, 2018; Sweidan, 2021). On the other hand, when geopolitical tensions increase, clean energy as an alternative is up for grabs due to the many limitations of commodities such as crude oil (Dutta and Dutta, 2022). Overally, the results of these two politically relevant uncertainties form a very interesting contrast, allowing for a new addition to the politically relevant risk-resistant nature of the clean energy market.

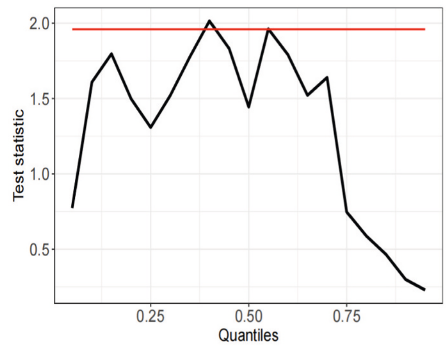
To sum up all the results above, we obtained that external uncertainty will have a significant impact on the clean energy market, and this will become greater as the time horizon expands. In addition, clean energy markets in extreme market conditions can be more susceptible to dramatic disruptions.

6. Conclusion

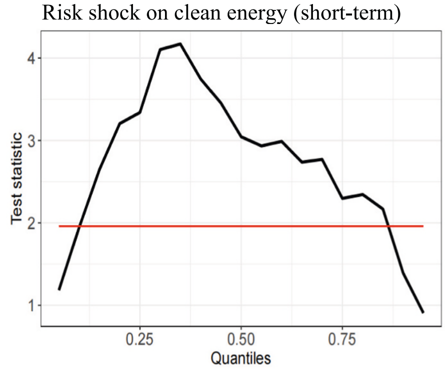
The clean energy market has become one of the most crucial energy markets and is highly visible to global stakeholders and policymakers.



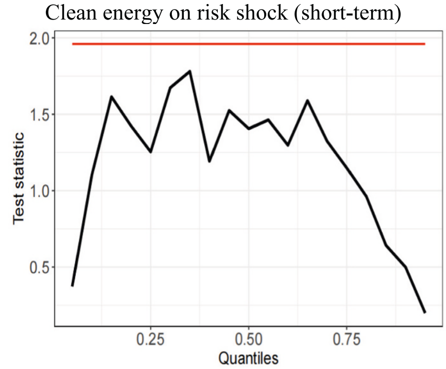
Risk shock on clean energy (short-term)



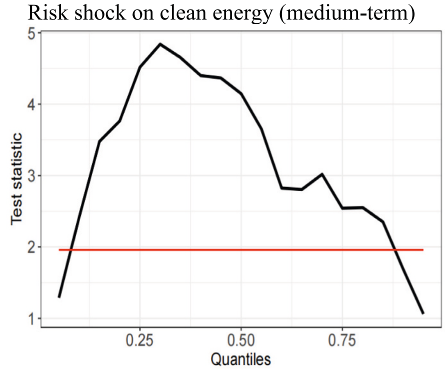
Clean energy on risk shock (short-term)



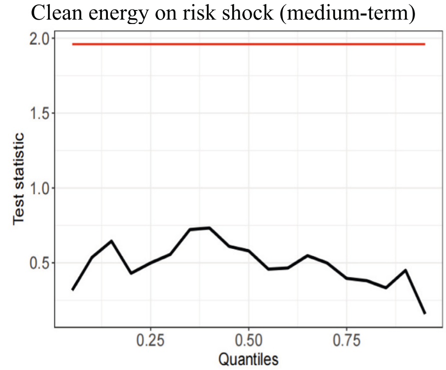
Risk shock on clean energy (medium-term)



Clean energy on risk shock (medium-term)



Risk shock on clean energy (long-term)



Clean energy on risk shock (long-term)

Fig. 5. Quantile granger test results between the risk shock (crude oil) and clean energy return.
This figure shows the results of the Granger causality test between oil risk shock and the clean energy index. The red line stands for the 5% critical level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To clarify how resilient the clean energy market is to external disturbances, this paper examines the impact of various external uncertainties on it and makes a comparison of them. We used three shocks derived from the decomposition of oil price changes (i.e., supply, demand, and risk shocks) and two political shocks (i.e., economic policy uncertainty and geopolitical risk) as core confounders and evaluated their effects on the clean energy index separately.

Our analysis process is based on a framework of multiple frequencies (representing the time dimension) and multiple quantiles (representing the state of the market or shocks). This study decomposed the individual variables into six time frequency series by means of wavelet decomposition and divided them into short-, medium-, and long-term cases. Then this paper used the quantile Granger causality test method to verify the specific connection between each uncertainty and clean energy index. We find that all kinds of uncertainty can significantly Granger cause the clean energy index, but the clean energy index only Granger causes these uncertainties in rare cases. On the basis of the quantile Granger test results, this paper examed the specific impact of these uncertainties on the clean energy market performance through the quantile-on-quantile regression method. The outcomes of the QQ method affirmed the remarkable effect of these external perturbations on the clean energy market across diverse frequencies and distributions, thereby elucidating the importance of the uncertainty analysis in maintaining stability in the clean energy market.

The results of this research reflect the fact that clean energy markets are less resilient to external uncertainties and that it is difficult for clean energy markets to in turn have a significant impact on these external factors. Fluctuations in either traditional energy or political factors can be strongly disruptive to clean energy markets, and their impact increase with the increase of time horizons overall (and interestingly, sometimes a shift in the direction of influence can occur). Our findings also reflect the inconsistency of the impact of different external uncertainties on clean energy markets. Among the three kinds of oil price shocks, demand shock has the greatest impact on the clean energy market compared with supply and risk shocks. The influence of oil price fluctuations on clean energy market is far more conspicuous than economic policy uncertainty and geopolitical risks. This is not only due to the discrepancies in frequencies and quantiles of the distribution, but also because the sources and pathways of action of different shocks can be notably disparate. When operating in the clean energy market, it is important to

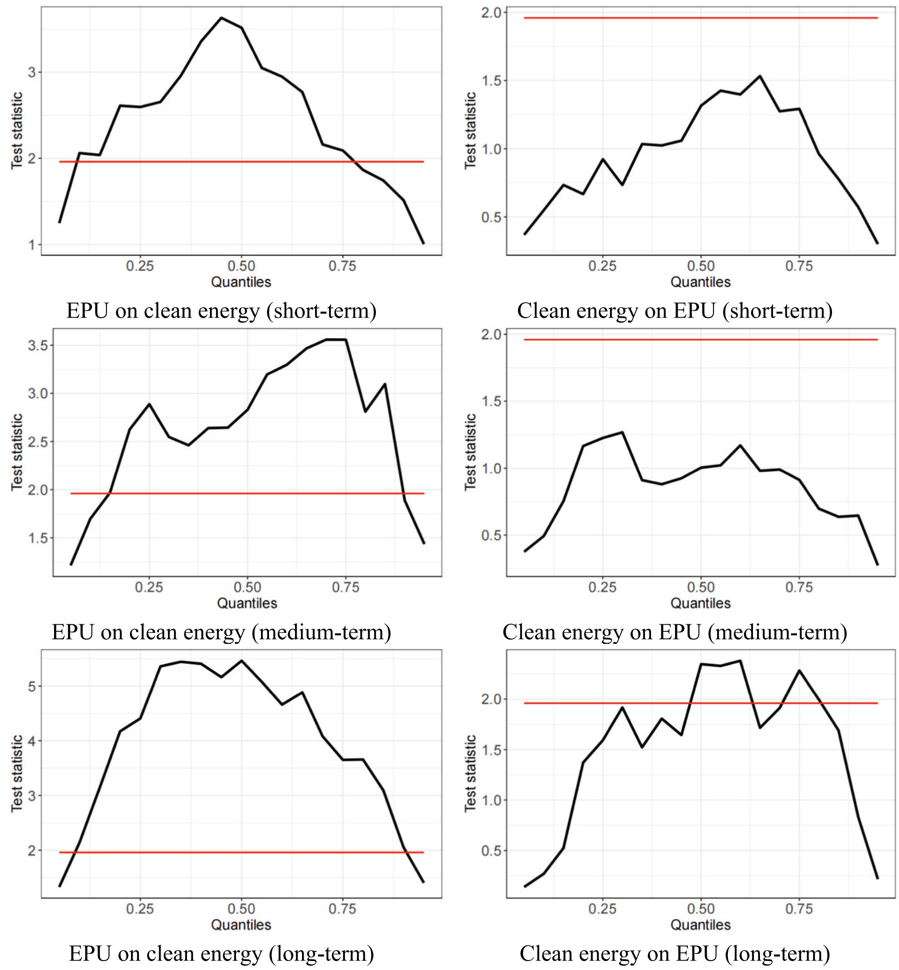


Fig. 6. Quantile granger test results between the economic policy uncertainty (EPU) and clean energy return.
This figure shows the results of the Granger causality test between economic policy uncertainty and the clean energy index. The red line stands for the 5% critical level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

differentiate between various sources of uncertainty in order to be better equipped to come up with coping strategies.

Focusing on clean energy that has the potential to balance economic development and environmental protection, this article reminds stakeholders of their concerns about the resilience of the clean energy market and looks to promote a more rational and scientific investment model. In addition, this article can also provide a more dimensional picture of the real performance of the clean energy market, which can inform the systemic arrangements of policymakers and regulators. Finally, this paper shows an intuitive link between external uncertainty and clean energy market performance, the channels of influence and more need to be explored by more scholars together.

CRediT authorship contribution statement

Yiying Li: Conceptualization, Validation, Writing – original draft. **Cheng Yan:** Data curation, Methodology, Writing – review & editing. **Xiaohang Ren:** Methodology, Writing – review & editing, Supervision.

Appendix A. Appendix[5]

[5] Note: d_j corresponds to the time scale 2^j to 2^{j+1} trading days (i.e., removing of weekends, holidays and other times when various transactions do not take place).

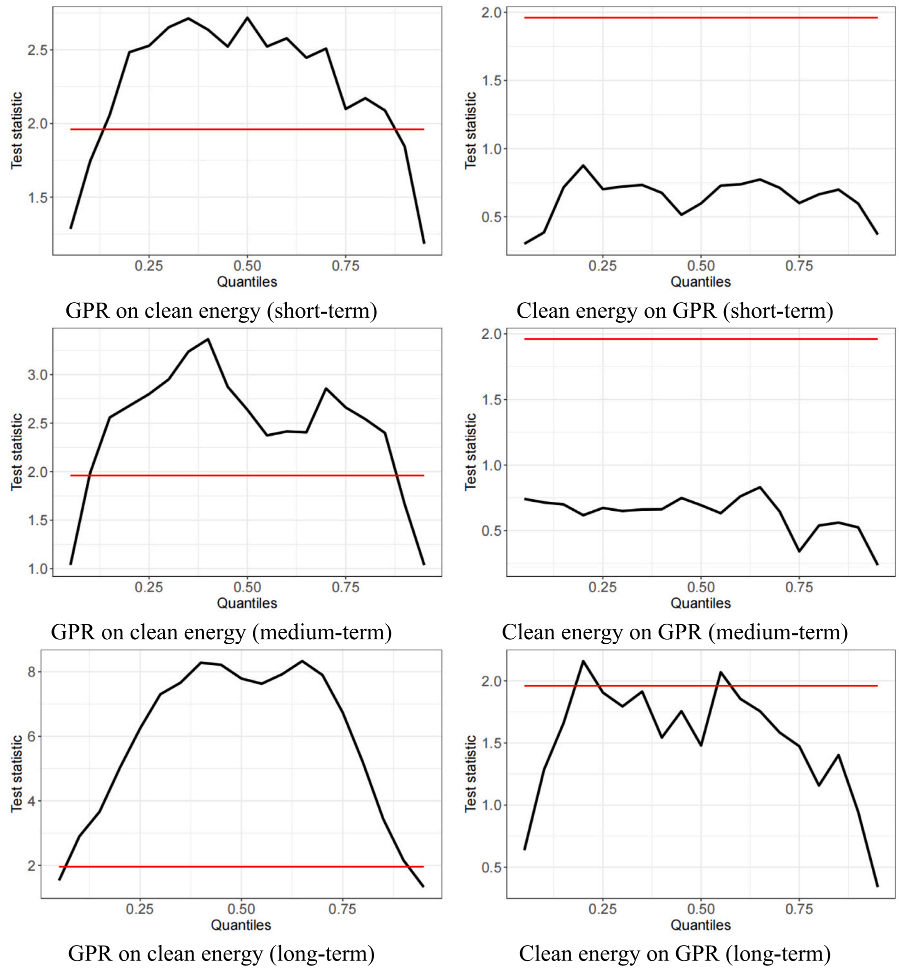
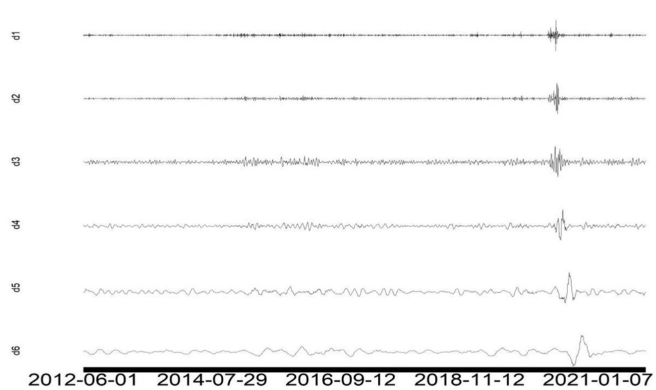


Fig. 7. Quantile granger test results between the geopolitical risk (GPR) and clean energy return.
This figure shows the results of the Granger causality test between geopolitical risk and the clean energy index. The red line stands for the 5% critical level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



Maximum overlapping discrete wavelet decomposition results of the Supply shock from 2012 to 05-31 to 2021-10-26.[6]

[6] From the graphical representation of the wavelets at different levels we can also see the underlying regularities of putting these data series at different time frequencies. This helps us to capture the movement of market returns under different scenarios, or the degree of volatility of different shocks.

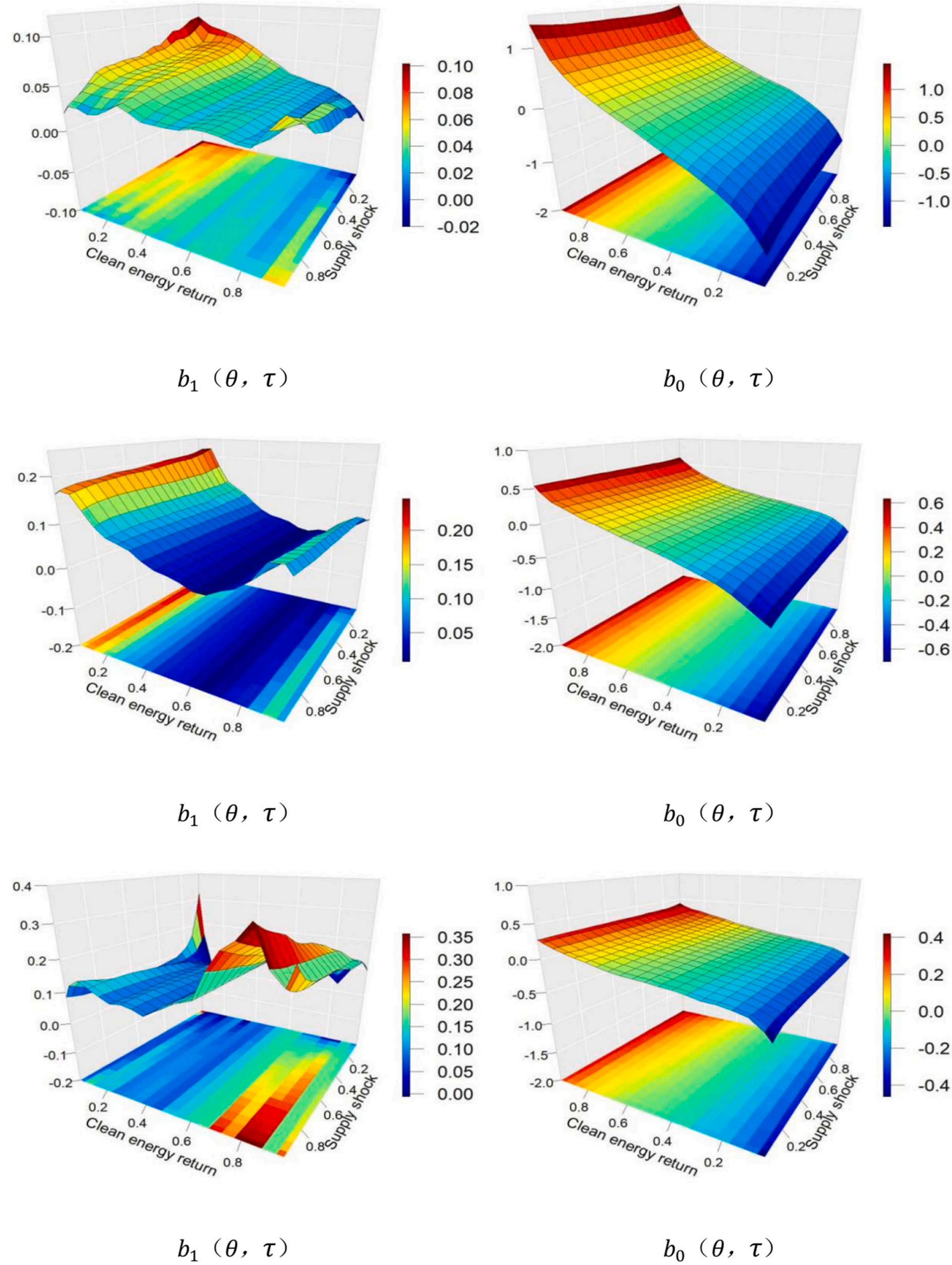


Fig. 8. Quantile-on-quantile regression results of the impact of the oil supply shock on clean energy (from top to bottom, in order of short, medium, and long term situation).
This figure shows the results of the impact of the oil supply shock on the clean energy index.
$b_0(\theta, \tau)$ is constant of the regression and $b_1(\theta, \tau)$ corresponds to the influence of the τ-th quantile of supply shock on the θ-th quantile of clean energy index.

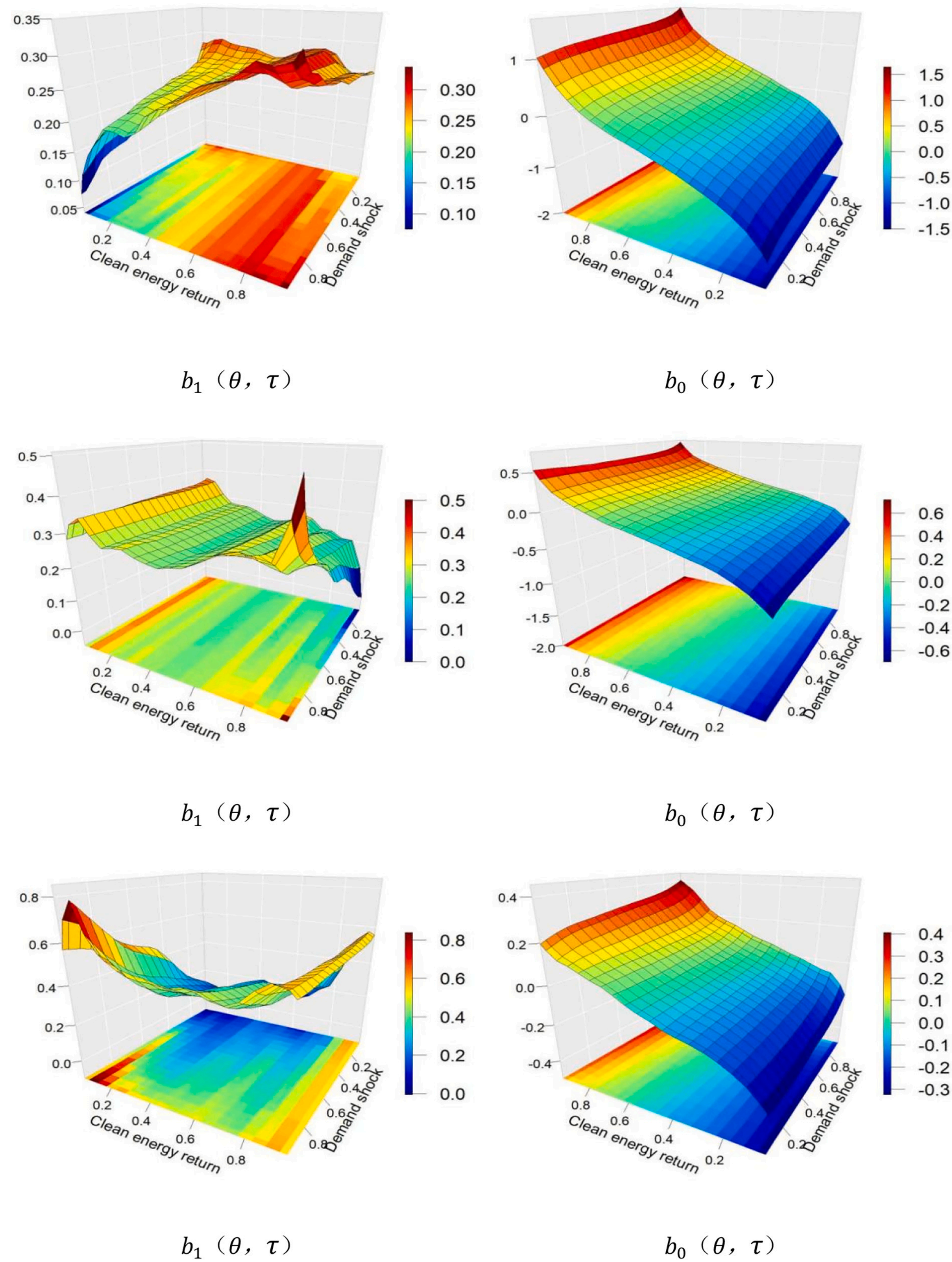


Fig. 9. Quantile-on-quantile regression results of the impact of the oil demand shock on clean energy (from top to bottom, in order of short, medium, and long term situation).

This figure shows the results of the impact of the oil demand shock on the clean energy index.

$b_0(\theta, \tau)$ is constant of the regression and $b_1(\theta, \tau)$ corresponds to the influence of the τ-th quantile of demand shock on the θ-th quantile of clean energy index.

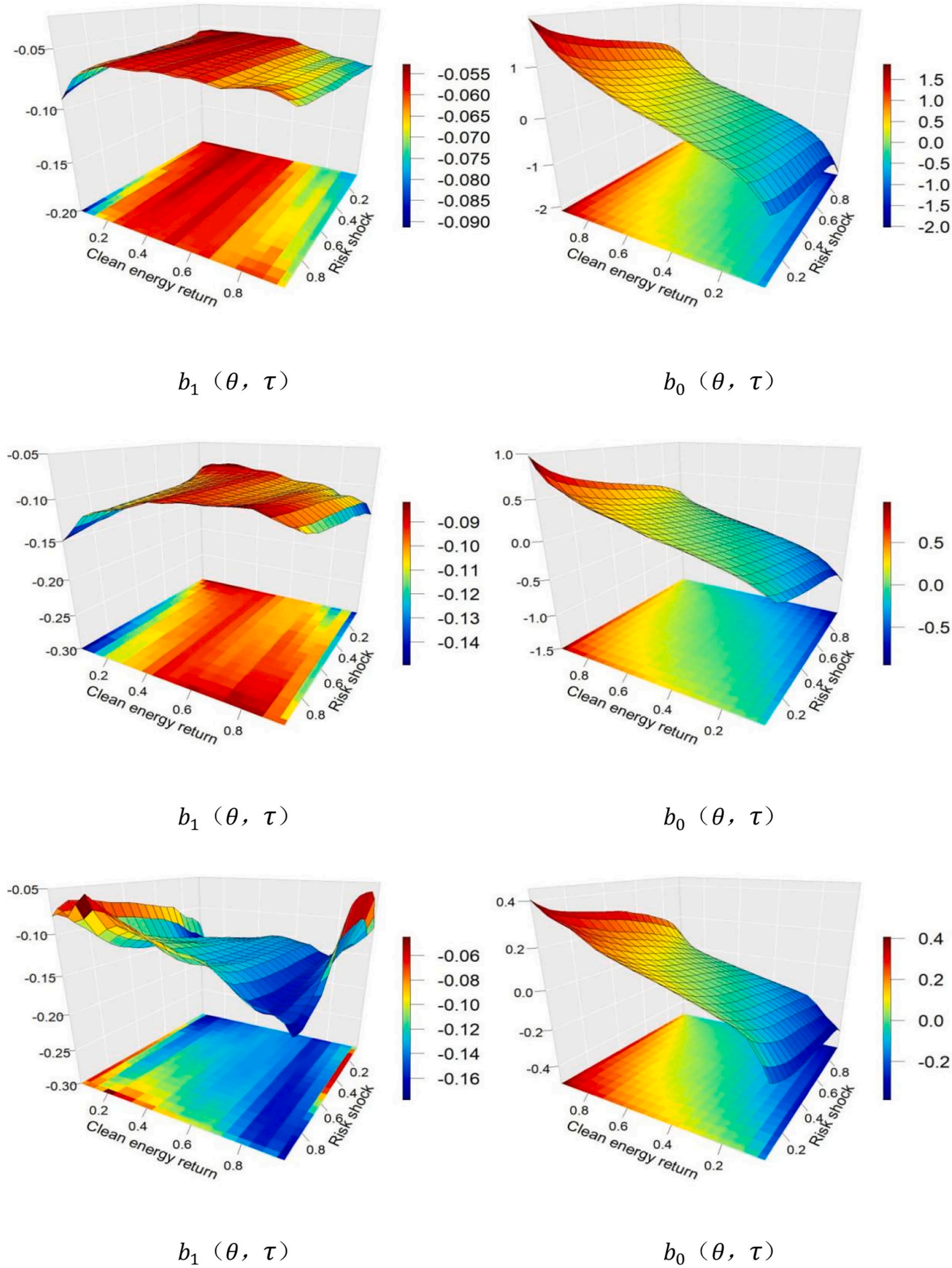


Fig. 10. Quantile-on-quantile regression results of the impact of the oil risk shock on clean energy (from top to bottom, in order of short, medium and long term situation).
This figure shows the results of the impact of the oil risk shock on the clean energy index.
$b_0(\theta,\tau)$ is constant of the regression and $b_1(\theta,\tau)$ corresponds to the influence of the τ-th quantile of risk shock on the θ-th quantile of clean energy index.

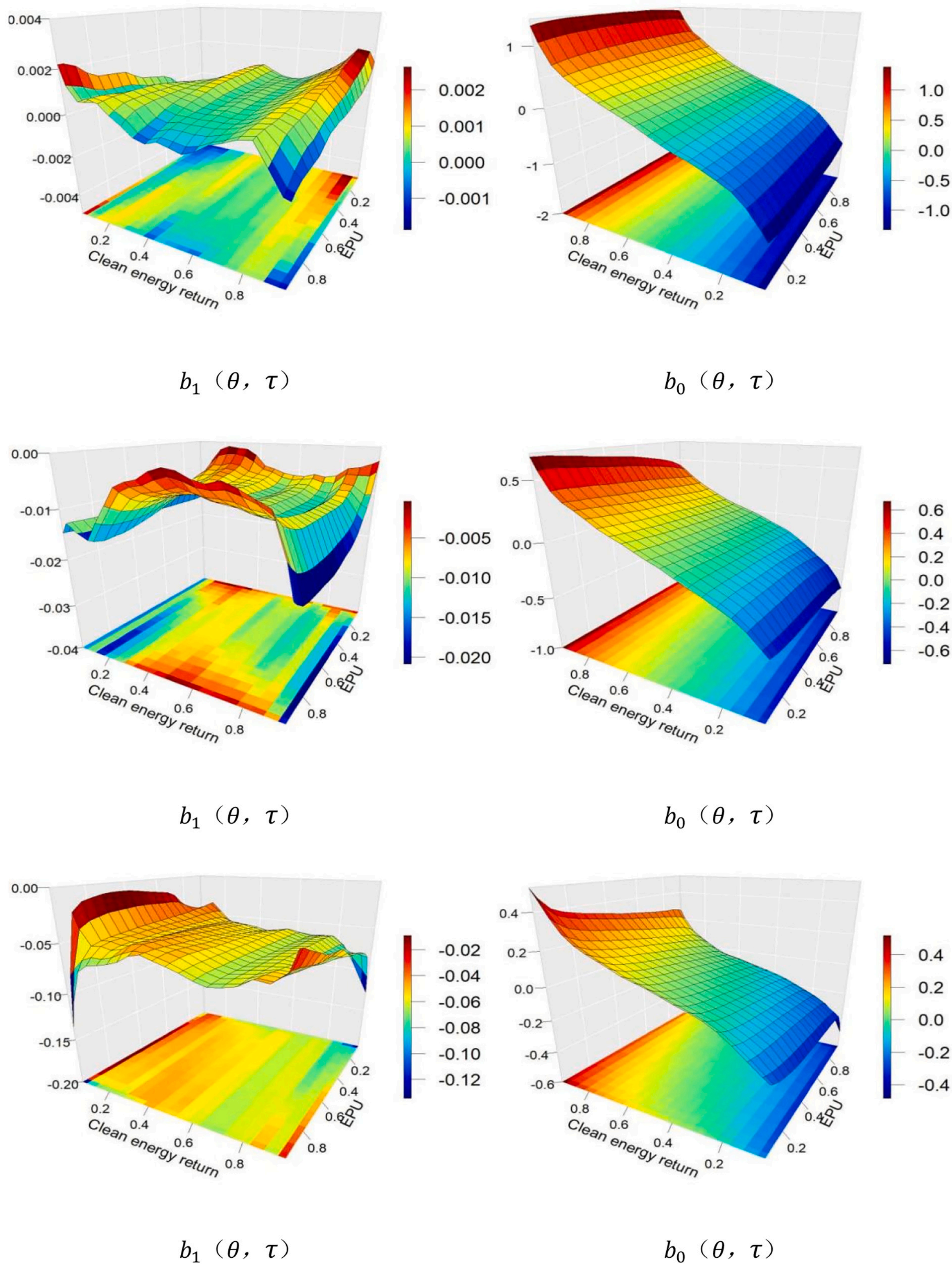


Fig. 11. Quantile-on-quantile regression results of the impact of the economic policy uncertainty (EPU) on clean energy (from top to bottom, in order of short, medium and long term situation).
This figure shows the results of the impact of the economic policy uncertainty on the clean energy index. $b_0(\theta, \tau)$ is constant of the regression and $b_1(\theta, \tau)$ corresponds to the influence of the τ-th quantile of economic policy uncertainty on the θ-th quantile of clean energy index.

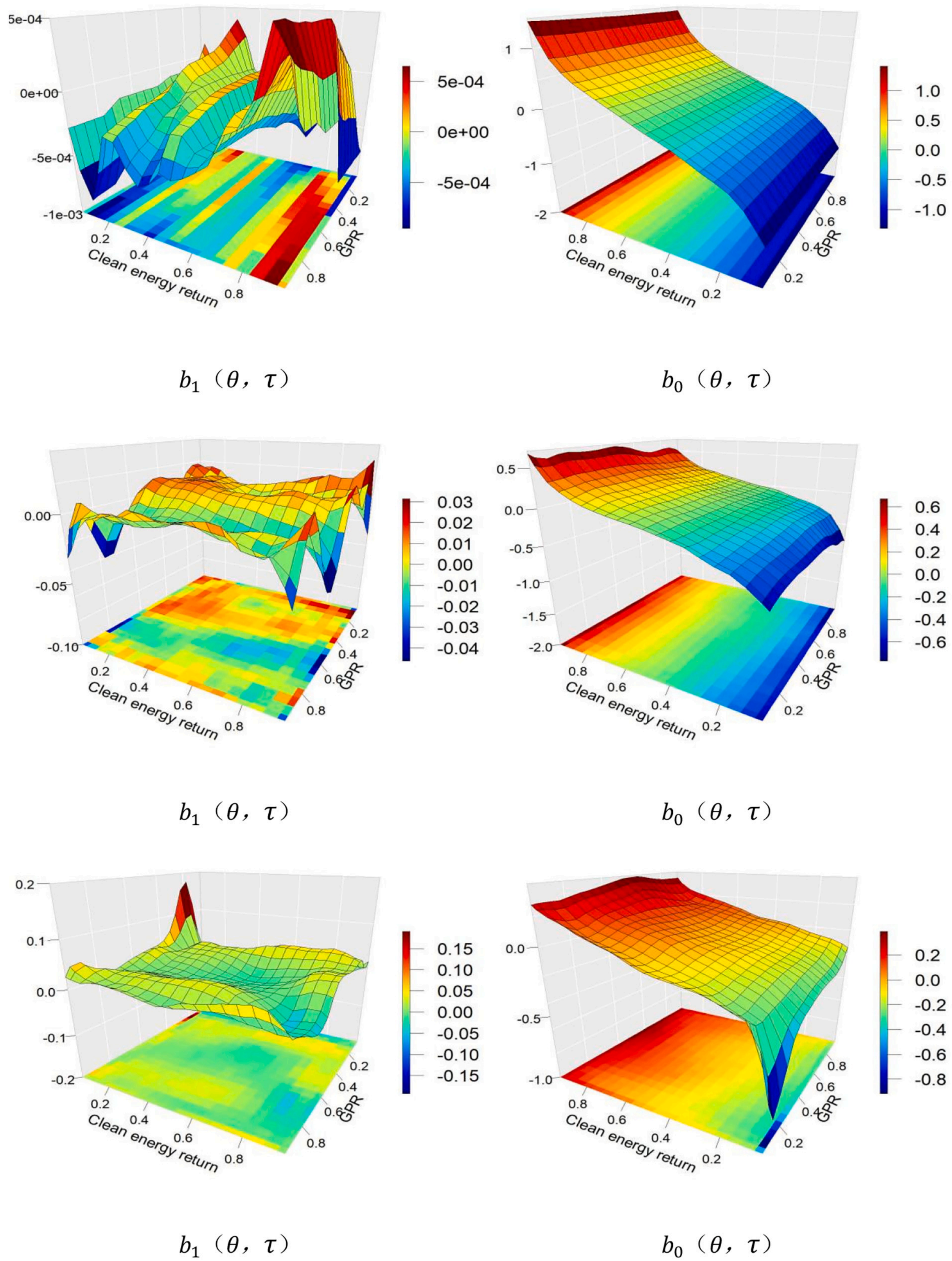
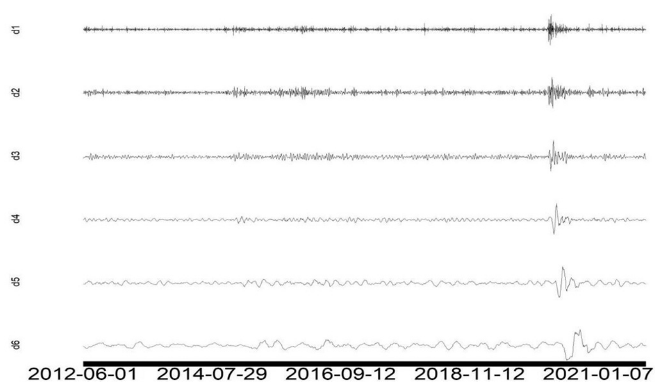


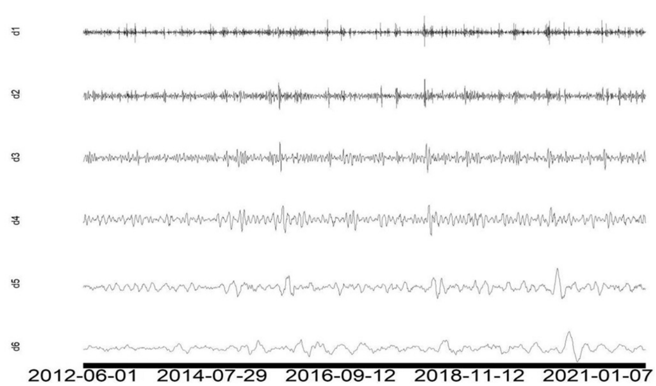
Fig. 12. Quantile-on-quantile regression results of the impact of the geopolitical risk (GPR) on clean energy (from top to bottom, in order of short, medium and long term situation).

This figure shows the results of the impact of the geopolitical risk on the clean energy index.

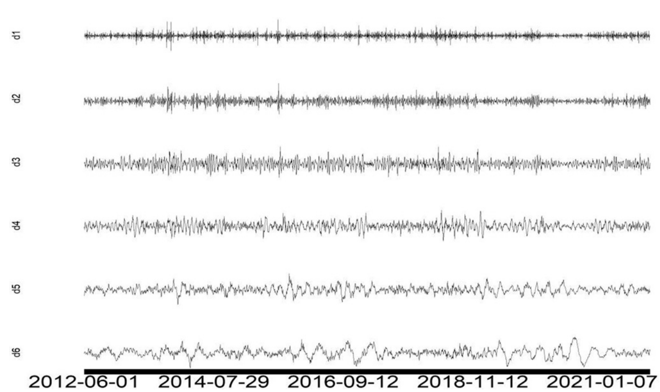
$b_0(\theta, \tau)$ is constant of the regression and $b_1(\theta, \tau)$ corresponds to the influence of the τ-th quantile of geopolitical risk on the θ-th quantile of clean energy index.



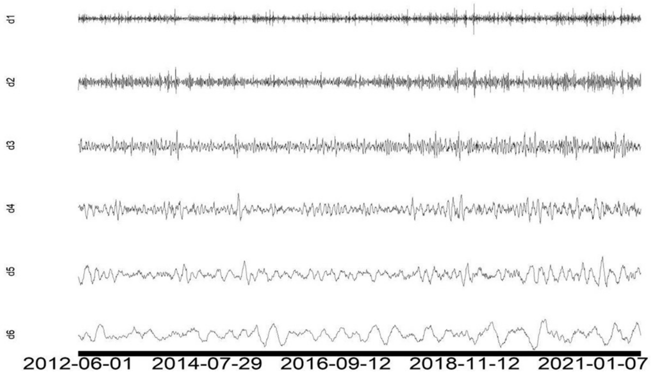
Maximum overlapping discrete wavelet decomposition results of the Demand shock from 2012 to 05-31 to 2021-10-26.



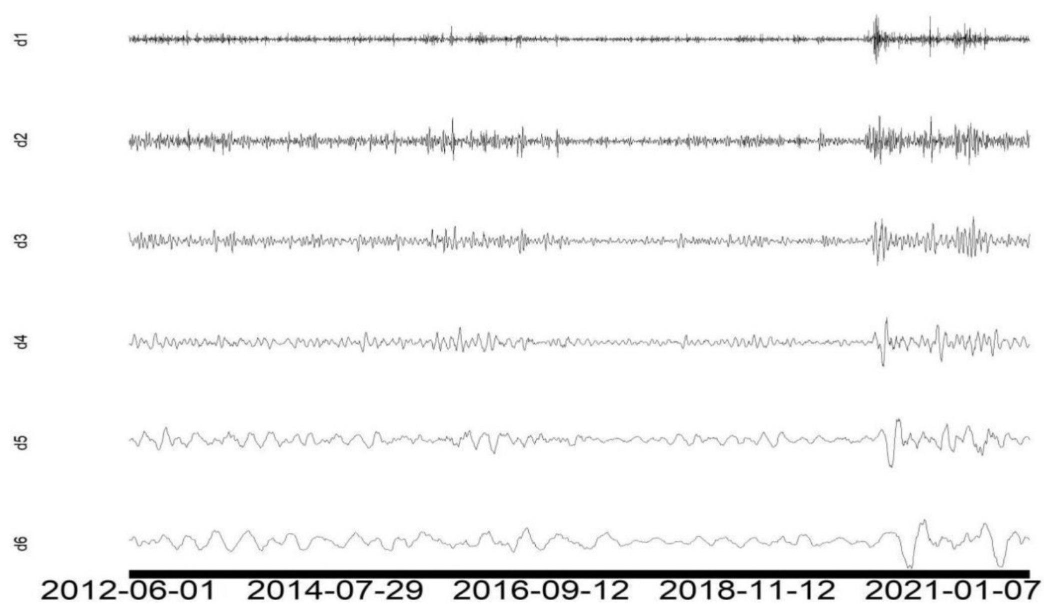
Maximum overlapping discrete wavelet decomposition results of the Risk shock from 2012 to 05-31 to 2021-10-26.



Maximum overlapping discrete wavelet decomposition results of the economic policy uncertainty (EPU) index return from 2012 to 05-31 to 2021-10-26.



Maximum overlapping discrete wavelet decomposition results of the geopolitical risk (GPR) index return from 2012 to 05-31 to 2021-10-26.



Maximum overlapping discrete wavelet decomposition results of the Clean energy index return from 2012 to 05-31 to 2021-10-26.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106679.

References

Adedoyin, F.F., Zakari, A., 2020. Energy consumption, economic expansion, and CO2 emission in the UK: the role of economic policy uncertainty. Sci. Total Environ. 738, 140014.

Aleluia, J., Tharakan, P., Chikkatur, A.P., Shrimali, G., Chen, X., 2022. Accelerating a clean energy transition in Southeast Asia: role of governments and public policy. Renew. Sust. Energ. Rev. 159, 112226.

Al-Thaqeb, S.A., Algharabali, B.G., 2019. Economic policy uncertainty: a literature review. J. Econ. Asym. 20, e00133.

Barrett, J.P., Hoerner, J.A., Bernow, S., Dougherty, B., 2002. Clean Energy and Jobs: A Comprehensive Approach to Climate Change and Energy Policy. Economic Policy Institute, Washington, DC.

Breetz, H., Mildenberger, M., Stokes, L., 2018. The political logics of clean energy transitions. Business Pol. 20 (4), 492–522.

Ćetković, S., Buzogány, A., 2019. The political economy of EU climate and energy policies in Central and Eastern Europe revisited: shifting coalitions and prospects for clean energy transitions. Pol. Govern. 7 (1), 124.

Ćetković, S., Buzogány, A., Schreurs, M., 2016. Varieties of Clean Energy Transitions in Europe: Political-economic Foundations of Onshore and Offshore Wind Development (No. 2016/18). WIDER Working Paper.

Chen, J., Wang, Y., Ren, X., 2022. Asymmetric effects of non-ferrous metal price shocks on clean energy stocks: evidence from a quantile-on-quantile method. Res. Policy 78, 102796.

de Abreu, M.C.S., Webb, K., Araújo, F.S.M., Cavalcante, J.P.L., 2021. From "business as usual" to tackling climate change: exploring factors affecting low-carbon decision-making in the canadian oil and gas sector. Energy Policy 148, 111932.

Dincer, I., Acar, C., 2015. A review on clean energy solutions for better sustainability. Int. J. Energy Res. 39 (5), 585–606.

Dou, Y., Li, Y., Dong, K., Ren, X., 2022. Dynamic linkages between economic policy uncertainty and the carbon futures market: Does COVID-19 pandemic matter? Res. Policy 75, 102455.

Duan, K., Ren, X., Shi, Y., Mishra, T., Yan, C., 2021. The marginal impacts of energy prices on carbon price variations: evidence from a quantile-on-quantile approach. Energy Econ. 95, 105131.

Dutta, A., Dutta, P., 2022. Geopolitical risk and renewable energy asset prices: implications for sustainable development. Renew. Energy 196, 518–525.

Elie, B., Naji, J., Dutta, A., Uddin, G.S., 2019. Gold and crude oil as safe-haven assets for clean energy stock indices: blended copulas approach. Energy 178, 544–553.
Flouros, F., Pistikou, V., Plakandaras, V., 2022. Geopolitical risk as a determinant of renewable energy investments. Energies 15 (4), 1498.
Ge, Y., Zhi, Q., 2016. Literature review: the green economy, clean energy policy and employment. Energy Procedia 88, 257–264.
Geng, J.B., Liu, C., Ji, Q., Zhang, D., 2021. Do oil price changes really matter for clean energy returns? Renew. Sust. Energ. Rev. 150, 111429.
Ghabri, Y., Ayadi, A., Guesmi, K., 2021. Fossil energy and clean energy stock markets under COVID-19 pandemic. Appl. Econ. 53 (43), 4962–4974.
Haug, M., 2011. Clean energy and international oil. Oxf. Rev. Econ. Policy 27 (1), 92–116.
He, Y.X., Jiao, Z., Yang, J., 2018. Comprehensive evaluation of global clean energy development index based on the improved entropy method. Ecol. Indic. 88, 305–321.
Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Econ. 30 (3), 998–1010.
Ji, Q., Liu, B.Y., Nehler, H., Uddin, G.S., 2018. Uncertainties and extreme risk spillover in the energy markets: a time-varying copula-based CoVaR approach. Energy Econ. 76, 115–126.
Kumah, S.P., Mensah, J.O., 2022. Are cryptocurrencies connected to gold? A wavelet-based quantile-in-quantile approach. Int. J. Financ. 27 (3), 3640–3659.
Lee, J.W., 2013. The contribution of foreign direct investment to clean energy use, carbon emissions and economic growth. Energy Policy 55, 483–489.
Liang, C., Wei, Y., Li, X., Zhang, X., Zhang, Y., 2020. Uncertainty and crude oil market volatility: new evidence. Appl. Econ. 52 (27), 2945–2959.
Lin, B., Li, Z., 2022. Towards world's low carbon development: the role of clean energy. Appl. Energy 307, 118160.
Malik, F., Umar, Z., 2019. Dynamic connectedness of oil price shocks and exchange rates. Energy Econ. 84, 104501.
Managi, S., Okimoto, T., 2013. Does the price of oil interact with clean energy prices in the stock market? Japan World Econ. 27, 1–9.
Naeem, M.A., Peng, Z., Suleman, M.T., Nepal, R., Shahzad, S.J.H., 2020. Time and frequency connectedness among oil shocks, electricity and clean energy markets. Energy Econ. 91, 104914.
Nilavongse, R., Michał, R., Uddin, G.S., 2020. Economic policy uncertainty shocks, economic activity, and exchange rate adjustments. Econ. Lett. 186, 108765.
Patnaik, B., Mishra, M., Bansal, R.C., Jena, R.K., 2021. MODWT-XGBoost-based smart energy solution for fault detection and classification in a smart microgrid. Appl. Energy 285, 116457.
Percival, D.B., Walden, A.T., 2000. Wavelet Methods for Time Series Analysis, 4. Cambridge University Press.
Ready, R.C., 2018. Oil prices and the stock market. Rev. Finance 22 (1), 155–176.
Ren, X., Cheng, C., Wang, Z., Yan, C., 2021. Spillover and dynamic effects of energy transition and economic growth on carbon dioxide emissions for the European Union: a dynamic spatial panel model. Sustain. Dev. 29 (1), 228–242.
Ren, X., Dou, Y., Dong, K., Li, Y., 2022a. Information spillover and market connectedness: multi-scale quantile-on-quantile analysis of the crude oil and carbon markets. Appl. Econ. 54 (38), 4465–4485.
Ren, X., Wang, R., Duan, K., Chen, J., 2022b. Dynamics of the sheltering role of Bitcoin against crude oil market crash with varying severity of the COVID-19: a comparison with gold. Res. Int. Bus. Financ. 62, 101672.
Ren, X., Li, J., He, F., Lucey, B., 2023. Impact of climate policy uncertainty on traditional energy and green markets: evidence from time-varying granger tests. Renew. Sust. Energ. Rev. 173, 113058.
Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. J. Bank. Financ. 55, 1–8.
Sivaram, V., Saha, S., 2018. The Geopolitical Implications of a Clean Energy Future from the Perspective of the United States. Geopolitics of Renewables, Springer, Cham.
Sohail, M.T., Majeed, M.T., Shaikh, P.A., Andlib, Z., 2022. Environmental costs of political instability in Pakistan: policy options for clean energy consumption and environment. Environ. Sci. Pollut. Res. 29 (17), 25184–25193.
Stone, C.J., 1984. An asymptotically optimal window selection rule for kernel density estimates. Ann. Stat. 1285–1297.
Su, C.W., Khan, K., Umar, M., Zhang, W., 2021. Does renewable energy redefine geopolitical risks? Energy Policy 158, 112566.
Sweidan, O.D., 2021. The geopolitical risk effect on the US renewable energy deployment. J. Clean. Prod. 293, 126189.
Tenaw, D., 2022. Do traditional energy dependence, income, and education matter in the dynamic linkage between clean energy transition and economic growth in sub-Saharan Africa? Renew. Energy 193, 204–213.
Troster, V., 2018. Testing for Granger-causality in quantiles. Econ. Rev. 37 (8), 850–866.
Troster, V., Shahbaz, M., Uddin, G.S., 2018. Renewable energy, oil prices, and economic activity: a Granger-causality in quantiles analysis. Energy Econ. 70, 440–452.
Uddin, G.S., Rahman, M.L., Shahzad, S.J.H., Rehman, M.U., 2018. Supply and demand-driven oil price changes and their non-linear impact on precious metal returns: a Markov regime switching approach. Energy Econ. 73, 108–121.
Vakulchuk, R., Overland, I., Scholten, D., 2020. Renewable energy and geopolitics: a review. Renew. Sust. Energ. Rev. 122, 109547.
Wang, K.H., Su, C.W., Umar, M., 2021. Geopolitical risk and crude oil security: a Chinese perspective. Energy 219, 119555.
Wang, X., Li, J., Ren, X., 2022a. Asymmetric causality of economic policy uncertainty and oil volatility index on time-varying nexus of the clean energy, carbon and green bond. Int. Rev. Financ. Anal. 102306.
Wang, Z.R., Fu, H.Q., Ren, X.H., 2022b. The impact of political connections on firm pollution: new evidence based on heterogeneous environmental regulation. Pet. Sci. https://doi.org/10.1016/j.petsci.2022.10.019.
Wang, X., Li, J., Ren, X., Bu, R., Jawadi, F., 2023a. Economic policy uncertainty and dynamic correlations in energy markets: assessment and solutions. Energy Econ. 117, 106475.
Wang, Z., Fu, H., Ren, X., 2023b. Political connections and corporate carbon emission: new evidence from Chinese industrial firms. Technol. Forecast. Soc. Chang. 188, 122326.
Zahan, I., Chuanmin, S., 2021. Towards a green economic policy framework in China: role of green investment in fostering clean energy consumption and environmental sustainability. Environ. Sci. Pollut. Res. 28 (32), 43618–43628.
Zhang, H., Cai, G., Yang, D., 2020. The impact of oil price shocks on clean energy stocks: fresh evidence from multi-scale perspective. Energy 196, 117099.
Zhao, W., Zhong, R., Sohail, S., Majeed, M.T., Ullah, S., 2021. Geopolitical risks, energy consumption, and CO2 emissions in BRICS: an asymmetric analysis. Environ. Sci. Pollut. Res. 28 (29), 39668–39679.