Energy Economics 121 (2023) 106657

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

The role of the COVID-19 pandemic in time-frequency connectedness between oil market shocks and green bond markets: Evidence from the wavelet-based quantile approaches

Ping Wei [a], Yinshu Qi [a], Xiaohang Ren [a,*], Giray Gozgor [b,c,d]

[a] Business School, Central South University, Changsha 410083, China
[b] School of Management, University of Bradford, Bradford, United Kingdom
[c] Faculty of Political Sciences, Istanbul Medeniyet University, Istanbul, Turkey
[d] Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon

ARTICLE INFO

JEL classification:
C1
C5
F3
F6
G1
Q4

Keywords:
Green bond market
Oil market shocks
The COVID-19 pandemic
Quantile coherency
Quantile Granger causality

ABSTRACT

This study contributes to the existing literature on the relationship between oil market shocks and the green bond market by investigating the impact of the COVID-19 pandemic on their dynamic correlation. We first decompose the oil market shocks into components using a time-frequency framework. Then, we combine wavelet decomposition and quantile coherence and causality methods to discuss changes during the COVID-19 era. We observe positive effects of both supply-driven and demand-driven oil shocks on the green bond market at most quantile levels. However, supply-driven oil price changes play a major role. The results also indicate that long-term changes have a greater impact than short-term changes on the connection between oil and green bond markets. Nevertheless, the COVID-19 pandemic changed the nature of the causal relationship, as we observed no relationship under extreme market conditions during the pandemic era. We argue that the economic and social impacts of the COVID-19 pandemic have left investors focusing on the short-term substitution between oil and green bond markets.

1. Introduction

Oil is the “blood of the modern economy” since it is the world’s most vital energy and chemical raw material. When the oil market experiences turbulence, it affects all levels of the national economy through the industrial chain. However, since the global financial crisis in 2007–8, the volatility of international crude oil prices has increased dramatically. The phenomenon of linkage effects with the price fluctuations of various markets, such as copper, gold, and stocks, has made the uncertainty of crude oil prices (Semeyutin et al., 2021). There are potential sources of oil price movements. As the most widely traded commodity globally, oil combines three attributes: commodity, financial and political. These characteristics make every crude oil move have a far-reaching “butterfly effect”. In recent years, there has been a proliferation of research exploring the relationship between crude oil prices and financial markets.

Hamilton (1983) argues that the impact of oil on the economy is exogenous. Still, Barsky and Kilian (2004) disagree, arguing that oil prices are an endogenous factor. Using a Vector Autoregression (VAR) model, Kilian (2009) demonstrates that oil price rises may be ascribed to supply-driven shocks from oil output, demand-driven shocks from global economic development, and the need for extra oil to safeguard against any disruptions in the oil output. There are, however, certain drawbacks to this approach. This model is flawed in many ways.

The first is monthly data, making it impossible to collect more precise data (Ready, 2018a); the second flaw is that it is difficult to determine what causes demand shocks, in particular for oil (Malik and Umar, 2019). And last but certainly not least, it understates the impact of oil-specific demand shocks (Demirer et al., 2020; Duan et al., 2023). Researchers have investigated oil price decomposition in more depth to address the issues above. Some breakthroughs, such as the technique described by Ready (2018b), were widely acknowledged and applied. Use daily data to examine more detailed findings and the capacity to separate supply-driven, demand-driven, and risk-driven shocks to

* Corresponding author.
E-mail addresses: domrxh@outlook.com, domrxh@csu.edu.cn (X. Ren).

https://doi.org/10.1016/j.eneco.2023.106657
Received 6 June 2022; Received in revised form 17 March 2023; Accepted 27 March 2023
Available online 6 April 2023

determine the link between petroleum and financial markets in more detail.

However, green financial markets have not received enough attention in these discussions, especially when the general public gradually accepts sustainable development. The huge demand for green investment has also stimulated green bonds' continuous expansion and innovation to speed up. Green Bonds (henceforth GB) have grown by leaps and bounds in the last decade. The global investment risks associated with environmental resource issues, the increasingly widespread influence of responsible investment concepts, and the continued concern of international investors about climate change, climate policy uncertainty, and environmental issues are the backdrop driving the rise of the green bond market. In 2020, international green bond issuance continued the growth since 2013. Worldwide green bond issuance now hit a record high of $269.5 Billion, up from $266.5 Billion the previous year. By the first half of 2021, 85 market entrants from 24 countries will bring the total number of Green Bond issuers to 1056.

Because of their unique environmental and clean attributes, the linkage between green bonds and oil shocks is noteworthy. This financial asset has attracted market participants and academic attention (Huynh, 2020). Compared with green credit, green bonds, as a direct financing tool, can reduce the cost of corporate financing. In the context of energy conservation and the green economy advocated by countries worldwide, green bond financing is an essential pillar in the transition from energy-intensive industries to a cleaner sector. Its unique environmental and clean attributes have brought attention to the correlation between green bonds and traditional energy sources, especially oil. Because of the fungibility of renewable energy and oil resources, higher oil prices are likely to spur investment in renewable energy, which creates a close correlation with green bonds.

Conversely, if the oil market turns weak and prices fall, resulting in less incentive to promote renewables, people will continue to rely on existing fossil fuels. In addition, shocks and volatility in the oil market can affect investment in green technologies, impacting the green bond market. The link between the oil market and clean assets, principally represented by green bonds, is crucial to examine the effect of these shocks on the green bond markets. In addition, investors need to know how oil volatility works and how the interaction affects green bond prices to profit from a diverse portfolio (Lee et al., 2021; Ren et al., 2022b).

The energy sector has been one of the sectors most affected by the pandemic due to liquidity constraints, resulting in a sharp reduction in oil demand and a sharp decline in oil prices due to oversupply (Lin and Su, 2021). Additionally, the first wave of the devastating COVID-19 outbreak severely impacted the world economy and destabilised global financial markets in early 2020 (Elsayed et al., 2022). The outbreak seriously impacted the oil market, and in April 2020, the price per barrel of West Texas Intermediate (WTI) crude oil became negative (Chen, 2021). While the oil market may recover through Organisation of the Petroleum Exporting Countries (OPEC) negotiations, the correlation between oil and the green bond market during the COVID-19 pandemic remains a short- and long-term concern for policymakers.

Therefore, the primary goal of this research is to examine the association between various shocks that affect oil prices and GB markets and the impact of the COVID-19 pandemic on this. Furthermore, this article adds to previous literature in a multitude of ways. First, we apply quantile coherency and quantile Granger causality tests developed by Baruník and Kley (2019) and Jeong et al. (2012) and then incorporate wavelet decomposition to explore the connection between oil prices and the green bond market by analysing correlation, long-run and short-run asymmetries.

Second, we analyze the influence of oil price shocks on the green bond markets by decomposing them into three components: risk-driven, demand-driven, and supply-driven (Ready, 2018b). According to Umar et al. (2021), the drivers of oil-price volatility can cause financial variables to respond differently to oil shocks. Consequently, this method will determine if demand-driven (or supply-driven) shocks and risk shocks contribute to the COVID-19 pandemic. In addition, considering the intrinsic dynamics of oil price fluctuations reveals potential interconnections between the green bond market and petroleum obscured when the effects are considered in aggregate.

Third, most articles on the link between oil and financial markets concentrate only on the stock or commodities markets. At the same time, only a few academics examine the green bond market. Therefore, we chose the most comprehensive global GB index during the sample period to explore the abovementioned connection more objectively and systematically. For the relationship between oil shocks and the green bond market, which is our focus, the correlation is not exactly normally distributed, with asymmetry and spikes and thick tails. Our study has to observe the association between the two at different quantiles. In particular, extreme quartiles should not be neglected. These quantile points will often represent some extreme market situations of particular interest and allow us to describe more fully the relationship between oil shocks and the green bond market. The combination of wavelet decomposition and quantile methods allows us to observe exciting relationships between the two variables of interest on different time scales and at different quantile levels. And in terms of methodology, our study is progressive. Moving from correlation to specific causality is a more rigorous exploration.

The remainder of the paper is laid out as follows. Section 2 composes the relevant literature. Section 3 represents the methodologies we employed and the data description. Section 4 reports empirical results and discussion. Section 5 concludes the paper with policy implications.

2. Literature review

Concerning green (clean) financial products, especially green bonds, a portion of the literature examines the relationship between green bonds and other assets, finding evidence of causality, correlation, and volatility spillovers (Elsayed et al., 2022; Kanamura, 2020; Ren et al., 2023b). For example, Hammoudeh et al. (2020) examined the time-varying causal relationship between green bonds and other assets. Pham (2021) investigates the frequency connectedness and cross-quantile dependence between the green bond and green equity markets. Reboredo (2018) investigates co-movement between the green bond and capital markets, concluding that the green bond market coupled with corporate and treasury bond markets weakly co-moves with stock and energy commodity markets. There is also some literature exploring the different sources of influence on green bond markets, with previous studies examining the relationship between stock prices, commodity markets, virtual currencies, and other markets and green bond markets.

Since Hamilton (1983), academics have strived for the connection between petroleum and macroeconomic indicators. Some previous studies have focused on the relationship between oil price shocks and equity markets, offering varied results (Apergis and Miller, 2009; Conrad et al., 2014; Dutta, 2017; Fatima et al., 2018; Hedi Arouri and Khuong Nguyen, 2010; Ren et al., 2023a; Wang et al., 2023a). Because of the importance of oil markets to the economy, the detrimental effects of oil price changes have been extensively explored (Hamilton, 1996). However, most of the available literature has been studied and interpreted in the correlation between the energy (oil) and clean (or renewable) stock markets. Little research is conducted on the connection between the oil price and GB dynamics. Reboredo et al. (2017) explored the co-movement and causality between oil and renewable energy stock prices using continuous and discrete wavelet methods. Starting with the financial instability brought about by the global crisis, Shahbaz et al. (2021) investigate how energy and stock markets affect the dynamics of green stock price returns, arguing that market mechanisms are important determinants of this effect. Naeem et al. (2021) investigate the asymmetric and severe tail correlations between five energy markets (including crude oil) and green bonds by employing a copula model and conclude that green bonds can effectively hedge most energy commodities. Kassouri and Altıntaş (2021) also use quantile approaches to analyze clean energy companies' equity dependence on different oil shocks to guide investing in clean assets.

Similarly, Dutta (2017) focused on the relationship between oil prices and clean energy stock returns, but unlike other scholars who used traditional oil price series, they used the crude oil volatility index (OVX) and constructed the realized volatility (RV) of stock returns in the clean energy sector. In examining the factors affecting the green bond market, Chi-Chuan Lee and Li (2021) considers the dimensions of the oil price and geopolitical risk in uncertainty, while Pham and Nguyen (2022) examine oil shocks and economic policy uncertainty. Azhgaliyeva et al. (2022) contribute to the existing literature by investigating the impacts of crude oil price shocks on financial markets. Their findings implied that the association between oil and GB varies with time. These studies have yielded some preliminary conclusions but have not explored this time-varying relationship sufficiently. The analysis of crude oil prices has been more superficial.

Our research is motivated by concerns about the impact of energy prices on the performance of environmental investments. Intuitively, decreasing oil prices will increase oil consumption, which may simultaneously weaken incentives for socially responsible investment. Considering the alternative relationship between conventional and alternative energy sources, we expand our emphasis on the GB market. The literature lacks a proper decomposition of the sources driving oil price changes to understand how oil prices affect green bonds. There is a lack of research in the existing literature that deconstructs the sources of oil price volatility and utilises them as a starting point to investigate the association between oil and the GB market. Most studies of the impact of crude oil on other markets have looked at prices, which are driven by various factors, including supply and demand. Forhad and Alam (2021) examine the effect of supply-driven and demand-driven oil shocks using the structural VAR model commended by Kilian (2009). The structural vector autoregressive (SVAR) model of the global oil market is largely used as the workhorse model to identify oil market shocks. A structural decomposition of the VAR disaggregates oil price shocks into oil supply shocks, global aggregate demand shocks, and oil precautionary demand shocks (Kolodzeij and Kaufmann, 2014; Ren et al., 2022a; Wang et al., 2023b). One weakness of this framework is that the data included in the SVAR needs to correlate with contemporaneous or future changes in oil prices to effectively identify shocks (Ready, 2018a). To provide motivation for the classification strategy used here, a model of a competitive commodity-producing sector is introduced, and the model is highly stylized to provide clear intuition for the identification strategy. To better understand oil price risk, Ready (2018a) offers fresh evidence on the connections between oil consumption, oil pricing, and economic growth, and Ready (2018b) develops a novel method for classifying oil price changes as supply- or demand-driven using the information in asset prices. In the existing literature, there isn't much research that breaks down the causes of oil price volatility and uses them as a starting point to look into the relationship between oil and the GB market.

3. Data and methodology

3.1. Methodology

It is well known that financial time series often exhibit thick tails. Still, it is noteworthy that causal links in the tail region may differ significantly from those based on the midpoint of the distribution. Moreover, to further understand the interactive movement between crude oil shocks and green bond markets, we chose the Discrete Wavelet Transform (DWT), Quantile Coherency and Quantile Granger Causality tests after comparing and analysing various advantages and disadvantages of the related empirical literature.

3.1.1. Separating oil-price shocks into supply, demand, and risk-driven factors

Ready (2018b) employs a model that separates oil prices into supply-SS, demand-DS, and risk-RS. The orthogonality theory is used extensively throughout the design. First, oil-producing enterprises are directly influenced by oil demand. It is suggested that this will result in the direct definition of oil demand shocks. This article uses a portion of oil producers' worldwide stock index returns as a proxy for oil demand shocks. Next, orthogonal to the preceding index, is the abnormal variation component of the logarithm of the VIX, which captures the total change in the market discount rate and essentially reflects the market's attitude toward risk and is therefore described as a proxy for risk shocks. Finally, oil supply shocks are represented by the remainder of oil price fluctuations orthogonal to these two indicators.

3.1.2. Discrete wavelet transform (DWT)

Compared to the ordinary wavelet transform, the discrete wavelet transform (DWT) produces less repetitive information and has more explanatory power (Li et al., 2020). Moreover, since the data collected for this work are time series, a discrete wavelet transform is more appropriate.

A time series $x(t)$ can be decomposed as follows:

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

where φ and ψ are two basic functions, representing the low frequency and high frequency. J denotes the number of multi-resolution levels, and k shows the ranges from 1 to the number of coefficients at each level.

Thus, using J-level multi-resolution decomposition analysis, a time series $x(t)$can be expressed as

$$x(t)=S_J(t)+D_J(t)+D_{J-1}(t)+\ldots+D_1(t) \tag{2}$$

where D_J, D_{J-1}, …, D_1indicate short, medium, or long term variations explained by shocks arising on time scale 2^J. In our study, we apply the orthogonal Discrete Wavelet Transformation (DWT) on daily series at different scale (j) as follows: d1 (2–4 days), d2 (4–8 days) days, d3 (8–16 days), d4 (16–32 days), d5 (32–64 days), and d6 (64–128 days).

3.1.3. Nonlinear Granger causality test

The conventional Granger causality test implicitly assumes linear data. Moreover, when time series are manifestly nonlinear, the conventional Granger causality test may provide extremely biased findings. Diks and Panchenko (2006) proposed a new nonparametric test. This test solves the previously problematic issue of over-rejection and adds a new statistic, T_n, which effectively compensates for concentration fluctuations.

A VAR (($d = p + m$) model is used to represent the relationship between two variables, X_t and Y_t as follows:

$$X_t=A_1(L)X_t+B_1(L)Y_t+U_{1t} \tag{3}$$

$$Y_t=A_2(L)X_t+B_2(L)Y_t+U_{2t}\, for\ t=1,2,\ldots,T \tag{4}$$

According to Diks and Panchenko (2006), considering two stationary time series, X_t and Y_t, and $X_t^{l_x}$ and $Y_t^{l_y}$ denoted as shown below:

$$X_t^{l_x}=(X_{t-l_x-1},\ldots,X_t) \text{ and } Y_t^{l_y}=\left(Y_{t-l_y-1},\ldots,Y_t\right) \text{ for } l_x,l_y\geq 1$$

If $k = 1$ in Eq.(3), then the following is the null hypothesis, which states that X_t does not Granger-cause Y_t:

$$H_0: Y_{t+1}|\left(X_t^{l_x};Y_t^{l_y}\right)\sim Y_{t+1}|Y_t^{l_y} \tag{5}$$

Assume $Z_t = Y_{t+1}$, then $K_t = (X_t^{l_x}, Y_t^{l_y}, Z_t)$. When $l_x = l_y = 1$ is assumed, and the time indices are removed. The joint and marginal probability density functions should follow this relationship, providing the null hypothesis is true:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{f_{Y,Z(y,z)}}{f_Y(y)} \tag{6}$$

As a result, H_0 may be written as:

$$q \equiv E\left(f_{X,Y,Z}(x,y,z)f_Y(y) - f_{X,Y}(x,y)f_{Y,Z}(y,z)\right) = 0 \tag{7}$$

Then, $T_n(e)$ may be written as:

$$T_n(e) = \frac{n-1}{n(n-2)}\sum_i \widehat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(X_i,Y_i)\widehat{f}_{Y,Z}(Y_i,Z_i) \tag{8}$$

The expression for $\widehat{f}_K(K_i)$, the local density estimate of K_i, is as follows:

$$\widehat{f}_K(K_i) = \frac{(2e)^{-d_k}}{n-1}\sum_{i,j\neq i} I_{ij}^K \tag{9}$$

$I(\bullet)$ is the indicator function described by $I_{ij}^K = I(\|K_i - K_j\| < e)$ in which e is the bandwidth such that $e = Cn^{-\beta}$, $C > 0$, $\frac{1}{4} < \beta < \frac{1}{3}$.

The statistics above satisfy:

$$\sqrt{n}\,\frac{(T_n(e) - q)}{S_n} \overset{D}{\to} N(0,1) \tag{10}$$

Asymptotic expectation estimator and standard error are represented by q and S_n, (respectively).

3.1.4. Quantile coherency approach

According to Baruník and Kley (2019) quantile coherency methodology, the following is our description of quantile coherency in the oil shock and green bond markets:

$$\Re^{OIL,GB}(\omega;\tau_1,\tau_2) = \frac{f^{OIL,GB}(\omega;\tau_1,\tau_2)}{\left(f^{OIL,OIL}(\omega;\tau_1,\tau_2)f^{GB,GB}(\omega;\tau_1,\tau_2)\right)^{1/2}} \tag{11}$$

where $-\pi < \omega < \pi$, τ_1,$\tau_2 \in (0,1)$. $f^{OIL,\ OIL}$ and $f^{GB,\ GB}$, these two quantile cross-spectral densities are obtained from the Fourier transform of the matrix of quantile cross-covariance kernels, while $f^{OIL,\ GB}$ is the quantile cross-spectral of the oil shock and green bond markets, respectively.

In the multifrequency research, the τ-th quantile cross-spectral density kernels are as follows:

$$\mathfrak{f}(\omega;\tau_1,\tau_2) := (2\pi)^{-1}\sum_{k=-\infty}^{\infty}\gamma_k^{OIL,GB}(\tau_1,\tau_2)exp^{-ik\omega} \tag{12}$$

where

$$\gamma_k^{OIL,GB}(\tau_1,\tau_2) := COV\left(I\{GB_{t+k} \le q_{GB}(\tau_1)\}, I\{OIL_t \le q_{OIL}(\tau_2)\}\right) \tag{13}$$

and where τ_1 and τ_2 represent the quantile levels of the GB markets and the oil shock, and the function $k \in Z$, $I\{\psi\}$ serves as an indicator of event ψ.

We can evaluate reliance during regular and torturous periods by analysing these different percentiles. We also have three frequencies for band allocation: short-term (1 week), mid-term (1 month), and long-term (1 year).

3.1.5. Quantile Granger causality test

The linear Granger causality test can't give an accurate picture of an explanatory factor's ability to predict because it can only measure that factor's ability to predict the conditional means of the response variable and is less useful when dealing with the upper and lower tails of the response variable. This problem can be remedied with the quantile Granger causality test. It integrates quantile regression and linear Granger causality tests to determine the precise locations (quantile intervals) where causal relationships between variables are established and to capture causal relationships missed by Granger causality tests.

Using the quantile Granger causality test developed by Jeong et al. (2012), we analyze the possible dependent relationship between the oil shock and the GB markets. Consider the price of green bonds as y_t and oil shock as x_t.Using the lag vector of $\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\}$, quantile causality may be written as: x_t does not cause y_t in the θ-th quantile if:

$$Q_\theta\left(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\right) = Q_\theta\left(y_t y_{t-1},\ldots,y_{t-p}\right) \tag{14}$$

where $Q_\theta(y_t|)$ is the θ-th quantile of y_t depending on t and $0 < \theta < 1$.

Let $Y_{t-1} \equiv (y_{t-1},\ldots,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},\ldots,x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|Z_{t-1}}(y_t \mid Z_{t-1})$ represent the conditional distribution functions for y_t provided Z_{t-1}. The hypotheses are:

$$H_0 = P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|Z_{t-1}\} = \theta\right\} = 1 \tag{15}$$

$$H_1 = P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|Z_{t-1}\} = \theta\right\}\langle 1 \tag{16}$$

Jeong et al. (2012) go on to use the following distance measure to calculate their results:

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|Z_{t-1}\} - \theta\right\}^2 f_z(Z_{t-1})\right] \tag{17}$$

$Z_{t-1}{}'s$ marginal density function is denoted by $f_Z(Z_{t-1})$. Notable is the fact that $J \ge 0$ if and only if H_0 is true. Thus, we may use J to repeatedly verify H_0. The test statistic based on the kernel for J is

$$\widehat{J_T} = \frac{1}{T(T-1)h^{2p}}\sum_{t=p+1}^{T}\sum_{s=p+1,s\neq t}^{T} K_{ts}\widehat{\varepsilon}_t\widehat{\varepsilon}_s \tag{18}$$

$$= \frac{1}{T(T-1)h^{2p}}\sum_{t=p+1}^{T}\sum_{s=p+1,s\neq t}^{T} K_{ts}[1\{y_t \le \widehat{Q}_\theta(x_t)\} - \theta][1\{y_S \le \widehat{Q}_\theta(x_s)\} - \theta] \tag{19}$$

here, $K_{ts} = K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)$ represents the kernel function, h indicates the bandwidth, T defines the sample size, p represents the lag order, $\widehat{\varepsilon_t}$ is the regression error estimate.

3.2. Data

As part of our empirical study, we examined the correlation between the oil shock and the return of green bonds at different time scales using the daily data of NYMEX Oil Futures Contract 1 to represent oil prices, the volatility index (VIX) from the Chicago Board Options Exchange's website to show financial market risk, and the S&P Dow Jones Green Bond index for measuring the performance of global green bond markets. The graph description of crude oil price changes, three shocks, and DJ_GB from September 30, 2011, to September 30, 2021, is shown in Fig. 1.

Using daily frequency data, Table 1 summarizes the descriptive statistical characteristics of the DJ_GB and the oil price shocks, decomposed into three parts: risk shock (RS), demand shock (DS), and supply shock (SS). The variables in this part are given an initial study to determine how they will behave. Overall, the oil-related data are all relatively similar in order of magnitude. The standard deviation of the VIX shows its high degree of dispersion. As for skewness, we can note that it is positive for all variables, indicating that they have varying degrees of right deviation. The demand- and supply-shocks have substantially larger kurtosis coefficients than the VIX component. Using the Augmented Dickey-Fuller (ADF), it was determined that there is no unit root and, as a consequence, that the variables are stationary. High scores on the J-B test indicate the non-normality of the variables.

Fig. 1. Crude oil price changes, three shocks and the DJ_GB from September 30, 2011, to September 30, 2021.

Table 1
Descriptive statistics of the variables.

Variable	Mean	Median	Min	Max	Std.Dev	Skew.	Kurt.	Q()	Q(75)	ADF-test	JB-test
OPC	0.00164	0.09572	−60.16758	31.96337	2.966	−3.102	89.875	−1.09067	1.16873	−12.803***	797762***
SS	−0.01228	0.04504	−55.44434	28.15524	2.521	−3.742	117.017	−0.93731	0.95109	−13.232***	1373045***
DS	−0.03998	−0.06989	−14.21779	14.01063	1.153	−0.643	31.792	−0.59220	0.50884	−14.562***	87354***
RS	−0.2627	−1.0481	−30.1349	78.9412	7.873	1.379	10.61	−4.6770	3.0353	−15.314***	6891.5***
DJ_GB	7.745e-05	1.300e-04	−2.424e-02	2.573e-02	8.436	0.827	3.235	−1.775e-03	1.973e-03	−13.998***	4288.1***

Note: This table reports the descriptive statistics of the OIL shock and Global green bond return. JB Stat. represents the statistics of the Jarque-Bera test for normality. *** denotes statistical significance at the 1% level.

4. Empirical results

4.1. Discrete wavelet analysis

This section serves as a precursor for follow-up research. We used the MODWT with the Daubechies wavelet filter to deconstruct oil-price change, demand shock, supply shock, risk shock, and daily GB indexes. Decomposition into six scales occurs initially. Each of them corresponds to a different time horizon: D1 (2–4 days) and D2 (4–8 days) are short-term; D3 (8–16 days) and D4 (16–32 days) are medium-term; D5 (32–64 days) and D6 (64–128 days) represent the long term. After wavelet decomposition of the data, further relationship judgment can be conducted.

4.2. Multiscale nonlinear Granger causality analysis

To test for Granger causality, use the nonparametric test that Diks and Panchenko (2006) recommended (DP test). After wavelet decomposition, we used the multifrequency data to do a nonlinear causality test on the time series for each time scale (See Table 2). The link between initial OPC and GB markets suggests that causality is stronger in the medium and long term, especially at about one month. The causal relationship between supply shocks and the green bond market is found at short-, medium-, and long-term scales. However, the significance is weaker in the short and medium terms, and the causality is stronger on the long-term scale. This suggests that the impact from supply factors is inevitable. The causality tests for the causality between demand shocks and the green bond market show that this effect appears in the short and medium terms and is not strong. In the nonlinear Granger causality test, the effect of risk shock and green bond was not found. However, this is only a preliminary result, and more research is needed to get definitive results. Overall, the results of the nonlinear Granger causality test show that the cause-and-effect relationship between the price of crude oil and the market for green bonds can be seen at different scales and from different sources.

Table 2
Nonlinear Granger causality test for time-scaled components.

Time scales	*t*-test	*p*-value	Results
H_0: OPC≠ > DJ_GB			
D1	0.751	0.22628	No causality
D2	1.378	0.08411*	OPC → DJ_GB
D3	1.718	0.04287**	OPC → DJ_GB
D4	2.076	0.01894**	OPC → DJ_GB
D5	0.653	0.25687	No causality
D6	1.47	0.07072*	OPC → DJ_GB
H_0: SS≠ > DJ_GB			
D1	1.722	0.04257**	SS → DJ_GB
D2	0.528	0.2989	No causality
D3	1.016	0.15478	No causality
D4	1.489	0.06821*	SS → DJ_GB
D5	1.225	0.11024	No causality
D6	2.355	0.00926***	SS → DJ_GB
H_0: DS≠ > DJ_GB			
D1	0.638	0.26163	No causality
D2	1.343	0.08965*	DS → DJ_GB
D3	0.927	0.17692	No causality
D4	2.059	0.01973**	DS → DJ_GB
D5	0.653	0.25689	No causality
D6	0.477	0.31676	No causality
H_0: RS≠ > DJ_GB			
D1	−0.688	0.75421	No causality
D2	0.048	0.48092	No causality
D3	−1.006	0.84285	No causality
D4	0.346	0.36452	No causality
D5	0.302	0.38141	No causality
D6	−0.869	0.80764	No causality

4.3. Quantile coherency analysis

Quantile coherency analysis over multiple time horizons can be used to figure out how much the tails of the joint distribution (or any other part) depend on each other. For reasons of economic significance, we use the results of the real part as the main evidence. Fig. 2 shows the results of the quantile coherency analysis of the original oil price changes and oil price changes from different shocks to the green bond market, respectively. Below are estimates of how well the extreme and middle quantiles of the joint distribution match up at different frequencies (0.05|0.05, 0.95|0.95, 0.5|0.5, and 0.05|0.95). The quantile coherency method can give a much more accurate picture of what's going on than the nonlinear Granger causality tests. In addition to the previously identified patterns of reliance between the oil and green bond markets, more noteworthy discoveries have been made. There is a positive correlation between OPC (oil price change) and DJ_GB in the long term. The curves at different time scales show some changes around the 0.2-quantile. For the supply shock, the quantile coherency analysis is more similar to the previous images obtained using OPC, proving Ready (2018b) claim that the supply shock is the one that plays a major role among the three shocks. The shocks from supply and demand show different trends. Overall, the connection between the oil and GB markets can be more affected by long-term and persistent influences than short-term fluctuations.

4.4. Multiscale quantile Granger causality analyses

The causality test based on the quantile approach may show the nonlinear and asymmetric causality better and find any possible nonlinearity. We divide this section into two parts for elaboration. The first provides a specific explanation of the quantile causality exhibited by the full sample interval. The second part provides a comparative analysis of the changes in the relationship between crude oil shocks and the green bond market before and after the COVID-19 outbreak.

4.4.1. Full period analysis

Fig. 3 shows the results of the quantile Granger causality test, which uses the full sample interval (2011−2021) for the data selected for this paper. Overall, the quantile intervals showing causality on the long-term scale are wider than those on the short-term scale. The black curves in

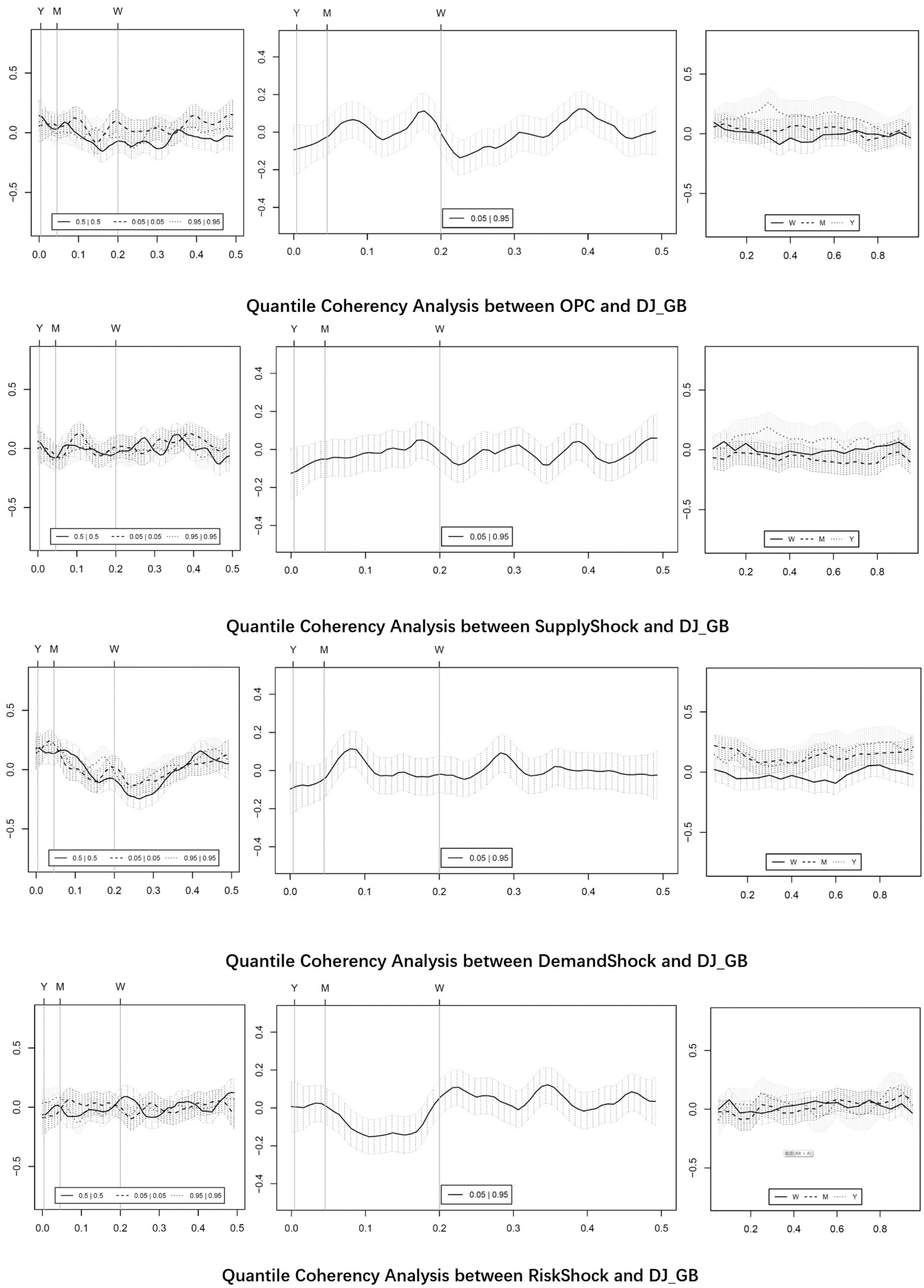

Fig. 2. The results of the quantile coherency analysis.
Note: The quantile coherency analysis was estimated for the 0.05, 0.5 and 0.95 quantiles. Note: The letters W, M and Y indicate weekly, monthly and yearly periods.

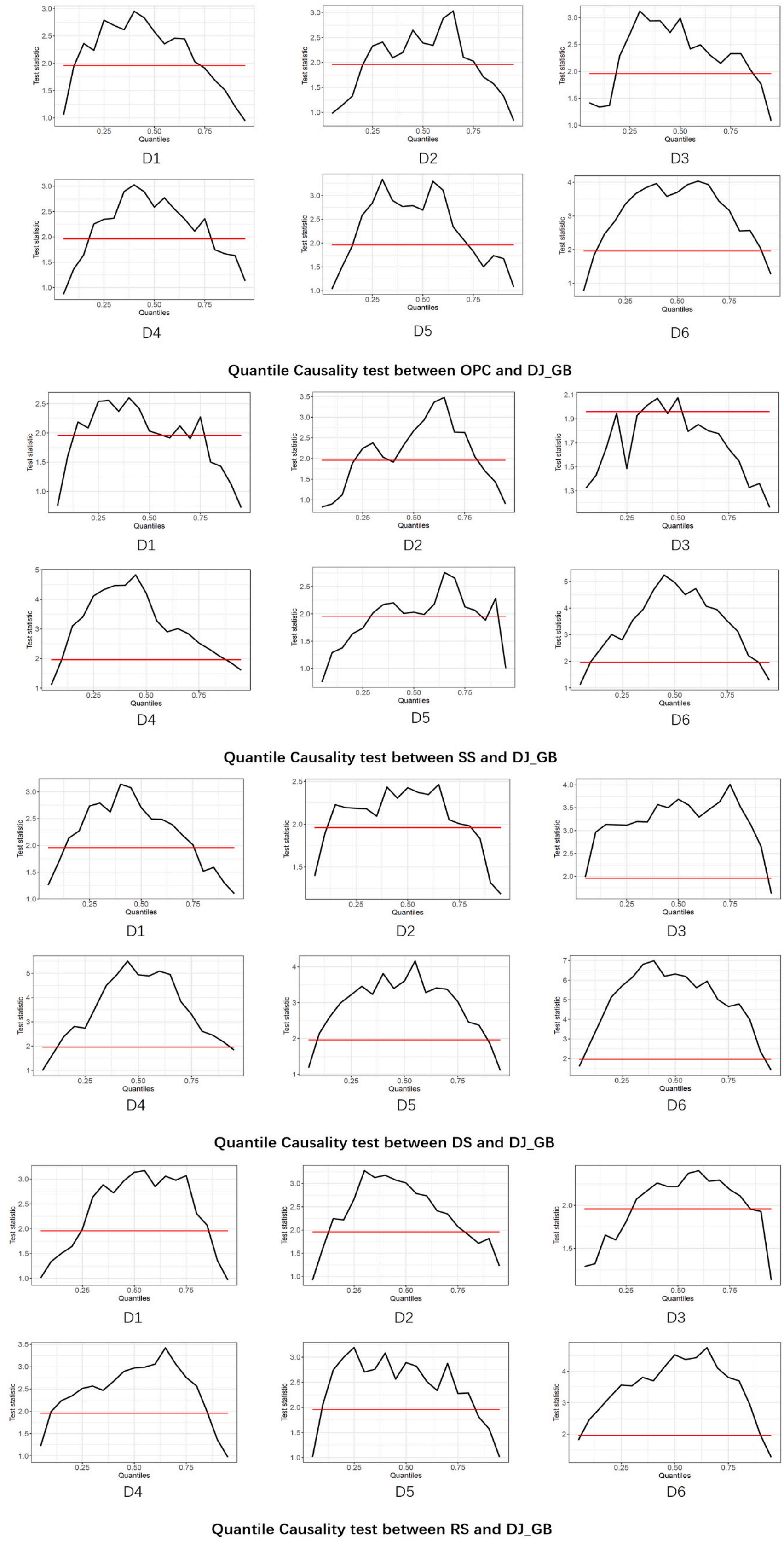

Fig. 3. The quantile Granger causality test results.
Notes: (i) The Fig plots results of the nonparametric causality-in-mean test from different quantiles of OPC (SS, DS, RS) to green bond markets, and the corresponding estimate of the 5% critical value (SJ) is represented as the horizontal red solid line.

almost every graph are arch-shaped, so focusing on differences at the extreme quantile levels is more informative. We can do a comparative analysis based on these output results in two ways. First, we can look at how the causes of oil price shocks from one source change over different time scales. The second is a cross-sectional comparison, i.e., the change in the impact of oil price shocks from different sources on the green bond market at the same time scale.

The first-group plots in Fig. 3 show the quantile Granger causality of crude oil price changes with DJ_GB on different time scales. As mentioned earlier, each subplot has an arch in the black curve. Specifically, the most significant causality is reached in the quantile range of [0.25, 0.75]. As the time scale increases, the quantile range that appears significant shifts to the right and gradually widens. Next, decomposing the OPC changes the picture dramatically. The second-group plots show how OPC affects the GB market due to demand shocks. The comparison between time scales demonstrates that the quantile range expands in tandem with the extension of the time scale, which is significant. The causality curves of supply-side oil price shocks and DJ_GB show significant oscillations. The significance is both strong and stable at the D4 and D6 scales, implying a more robust causal relationship between price changes motivated by the oil supply side and the green bond market relationship at both the one-month and one-quarter scales. This issue may be related to the monthly or quarterly delivery of crude oil futures contracts in the market. The fourth-group plots show that oil price volatility directly affects the green bond market. Extreme quantile levels can lead to large changes, suggesting that volatility in extreme market conditions can severely affect the link between the OPC and GB markets. However, this phenomenon changes as the time scale expands. A comparison of the four sets of plots shows that the oil supply shock is the weakest of the three shocks. This suggests that oil demand shocks and market risk shocks reduce the uncertainty of investment in the green bond market compared to supply shocks. It is important to note that the impact of COVID-19 on green investment will not be permanent and may only require a longer recession.

4.4.2. The pre- COVID-19 vs the COVID-19 periods

When we do not divide the long-, short-, and medium-term time scales, we can roughly observe the changes in the causal relationship between different shocks to oil prices and the green bond market before and after the COVID-19 outbreak. The black curves in the eight subplots of Fig. 4 are all arched, and the curves all have a left-skewed pattern. The intervals with the most significant causal relationships are all in [0, 0.5]. Before the COVID-19 outbreak, there was a strong correlation at essentially all quantile levels between fluctuations in oil prices and movements in the green bond markets, regardless of the source. However, after the COVID-19 global pandemic, the distance between the significant red line and the black curve shrank significantly. Except for the two RS-DJ-GB plots from market volatility, which don't change much, the causal relationship between changes in oil prices and the green bond market changes a lot because of both the supply and demand sides. From the graphs of the COVID-19 period, we can see that the supply-side causes of oil price shocks have the biggest effect on the overall changes in oil prices. The pandemic also impacts the market, and in the four graphs below in Fig. 4, the black curves at extreme quantiles are below the significant red line. This evidence indicates that, in severe market circumstances, the causal connection no longer exists.

The pandemic inevitably changed the relationship between oil as a traditional non-clean energy source and the green bond market, which represents sustainable development. Furthermore, we performed the same test before and after the COVID-19 outbreak, and the results are shown in Fig. 5. The multiscale results expose the hidden causal changes when no wavelet decomposition is performed. For the oil price without decomposition, the interval reflecting the connection between oil and GB is the largest on time scales D1 and D6 during the pre-COVID-19 period, implying that the relationship between oil and green debt is stronger immediately and for the next quarter or so. After the COVID-19 pandemic in the world, it can be seen that from D1 to D4, the relationship between oil prices and green bonds is not positive. The black curve is only above the significant red line at a few quantile levels. The economic and social impact of the pandemic left investors with no time to focus on the short-term substitution between oil and green bonds. Only some long-term investors will selectively consider investing in green bonds.

The last three sets of subplots in Fig. 5 are a more detailed explanation of the research questions in this paper for different shocks. During the time before COVID-19, price changes caused by the supply of oil were linked to the green bond market at most quantile levels. However, the performance at the medium scale is quite ordinary. The COVID-19 period is largely insignificant from D1 to D5, when oil price fluctuations due to supply changes are decoupled from green bonds in both the short and medium terms. Only D6 is significant at the partial quantile level. After encountering the pandemic, demand-influenced oil prices behave somewhat similarly to the previous supply effects. However, the pandemic's effects are not particularly significant at D2 and gradually return to the pre-COVID-19 period relationship from D4 to D6. This evidence indicates that in the short run, the sudden outbreak of the pandemic will bring some panic to investors, decoupling oil prices from green bonds, and investors have no time to care about the green bond

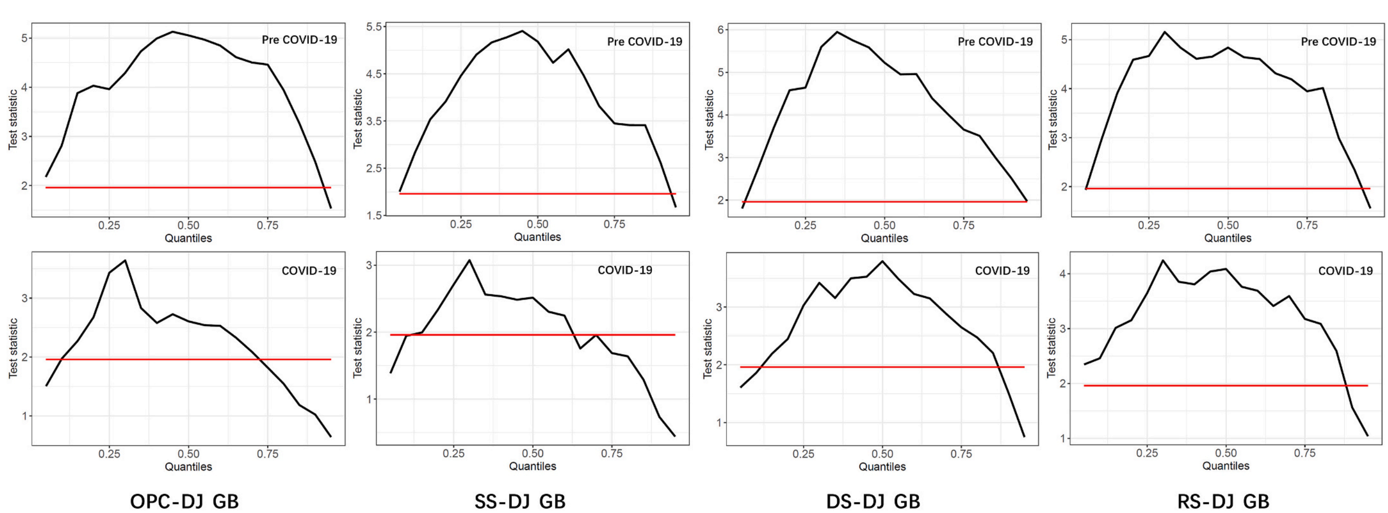

Fig. 4. Quantile Granger causality test results between oil and green bond returns before and during the COVID-19 pandemic periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

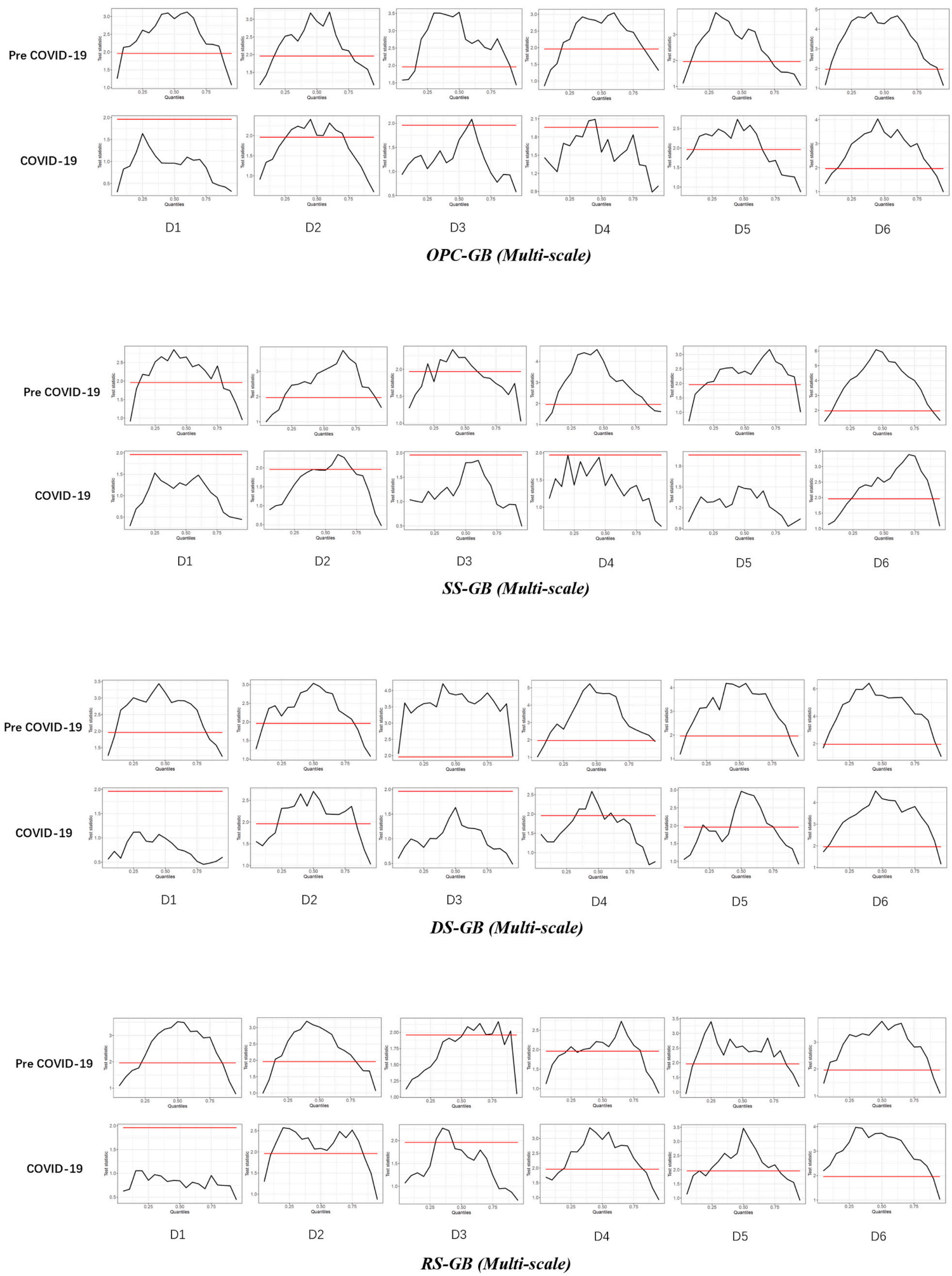

Fig. 5. Quantile Granger causality test results between oil and green bond returns before and during the COVID-19 pandemic periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

market at this time. But after a while, demand for oil is still one of the most important things that affects oil prices, and stable investors still link oil to the green bond market. The correlation between an oil price change and the green bond market due to risk shock is not very strong compared to supply shock and demand shock. Because its data comes from the VIX, it shows more market volatility and investor sentiment. So, as Wei et al. (2022) said, the emergence of COVID-19 gives green bonds a safe haven function and attracts investors to the relationship between oil and green bonds, and long-term investors increase their attention in this area. It also demonstrates that long-term and continuous fluctuations have a greater impact on the association between oil and sustainable energy-related markets than sudden shocks.

4.5. Robustness checks

4.5.1. Controlling geopolitical risk (GPR) and economic policy uncertainty (EPU)

This section tests the robustness of our key results. We test the robustness of the impact of oil price shocks on green bonds by controlling for geopolitical risk (GPR) and economic policy uncertainty (EPU), which are the two variables that have been focused on by current mainstream academic research (See Table 3). The results show that GPR and EPU do not play a significant role in the variable relationships we focus on, except in the RiskShock section, where geopolitics shows some significance. However, some of the associations presented here are not unusual because risk factors are already considered in RiskShock and therefore do not affect our results. The significance of the main study variables at the high-quantile level also supports our previous statement about the need to focus on tail risk. Overall, our results can be considered robust.

4.5.2. Variable substitution

For the VIX index chosen as the measure of market risk in this paper,

Table 3
Robustness checks.

Variables	Q(5)	Q(25)	Q(50)	Q(75)	Q(95)
Panel A: OPC-DJ_GB					
OPC	0.049	0.010	0.072*	0.027	0.187***
	(1.17)	(0.13)	(1.69)	(0.38)	(2.97)
GPR	0.101	1.235**	0.157	0.302	0.358
	(0.41)	(2.55)	(0.62)	(0.70)	(0.96)
EPU	0.036	0.086	−0.003	−0.074	0.145
	(0.14)	(0.18)	(−0.01)	(−0.17)	(0.39)
Panel B: SupplyShock- DJ_GB					
SupplyShock	0.051	0.014	0.076	0.041	0.199***
	(1.09)	(0.14)	(1.51)	(0.48)	(2.67)
GPR	0.073	1.226**	0.170	0.278	0.435
	(0.31)	(2.53)	(0.67)	(0.65)	(1.15)
EPU	0.013	0.072	−0.057	−0.079	0.060
	(0.05)	(0.15)	(−0.22)	(−0.18)	(0.16)
Panel C: DemandShock- DJ_GB					
DemandShock	0.136	0.083	0.137	0.011	0.423***
	(1.18)	(0.39)	(1.25)	(0.06)	(2.67)
GPR	0.190	1.326***	0.172	0.270	0.215
	(0.71)	(2.70)	(0.68)	(0.63)	(0.59)
EPU	0.059	0.108	−0.077	−0.048	0.036
	(0.22)	(0.22)	(−0.31)	(−0.11)	(0.10)
Panel D: RiskShock- DJ_GB					
RiskShock	0.005	0.011	0.007	0.030	0.018
	(0.28)	(0.37)	(0.45)	(1.16)	(0.85)
GPR	0.110	1.285***	0.209	0.313	0.302
	(0.42)	(2.66)	(0.81)	(0.77)	(0.92)
EPU	0.014	−0.002	−0.126	−0.022	−0.005
	(0.05)	(−0.00)	(−0.49)	(−0.05)	(−0.01)

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

some scholars argue that it is more appropriate to use the variance risk premium, which can reduce the underestimation of demand shocks (Clements et al., 2019). It is shown that using an estimate of the variance risk premium (VRP) to identify risk shocks alleviates this issue.

In fact, there are many methods to calculate the VRP, and the more general method detailed by Bekaert and Hoerova (2014) is applied to construct the VRP, defined as

$$VRP_t = VIX_t^2 - E_t[RV_{t+1}] \tag{20}$$

Then we obtained an applicable variance risk premium. As a matter of caution, we performed the same wavelet decomposition of the VRP series before subjecting it to a quantile Granger causality test with green bonds. Fig. 6 shows the results.

Unlike the empirical results obtained by Clements et al. (2019) using VRP instead of VIX, VRP does not exhibit better performance than VIX in our test. The causality of the first three levels was not even detected. We can assume that the results are qualitatively robust.

5. Conclusion

This paper extends the literature on the association between the OPC and the GB markets. It examines the impact of neocrown pneumonia on the dynamic correlation between oil and green bonds. Using a time-frequency framework, we follow Ready (2018b) to decompose the oil shock into its components, combine wavelet decomposition and quantile methods, and discuss changes around the COVID-19 era. Thus, we present a more detailed account of the link between different driven petroleum shocks and the green bond market.

This analysis utilises data from September 30, 2011, to September 30, 2021. According to our research, the impact of oil shocks from both the supply and demand side on the GB markets is positive at most quantile levels. Supply-driven oil price changes are the shocks that play a significant role. At the same time, the results obtained from multiple approaches indicate that the connection may be more affected by continuous changes than by sudden effects. Significance changes at the extreme quantile level suggest that extreme market conditions are unstable, leading to a potentially highly influenced relationship. And this phenomenon changes as the temporal scale expands. In addition to the complete sample analysis, our subsample analysis before and after the outbreak of COVID-19 yielded essential findings. When we do not divide the long-, short- and medium-term time scales, significance decreases significantly after the COVID-19 global pandemic. Supply-side shocks most heavily influence oil price fluctuations. After the pandemic, the previously observed causal relationship no longer exists in severe market circumstances. We performed multiscale quantile Granger causality analysis before and after the COVID-19 outbreak. These results reveal hidden causal changes when wavelet decomposition was not made.

The pandemic has inevitably changed the relationship between oil as a traditional non-clean energy source and the GB markets. It leaves no time for investors to focus on the short-term substitution between oil and green bonds. Only some long-term investors will selectively consider investing in green bonds. In the short term, the sudden pandemic outbreak will create some fear among investors and decouple oil prices from green bonds for a short time. Leaving investors with no time to focus on the short-term substitution between oil and green bonds. However, after some time, oil demand remains one of the key factors influencing oil price movements, and stable and long-term inclined investors still associate oil with the green bond market and selectively consider investing in green bonds. As a result, a successful transition to green investments will depend on financial stability.

This research offers new information about the correlation between traditional non-clean oil energy and green bonds, a new green financial asset. This evidence is crucial to portfolio management and related policy-making, not only in regular times but also in times of crisis. When developing investment strategies and portfolio allocations, investors

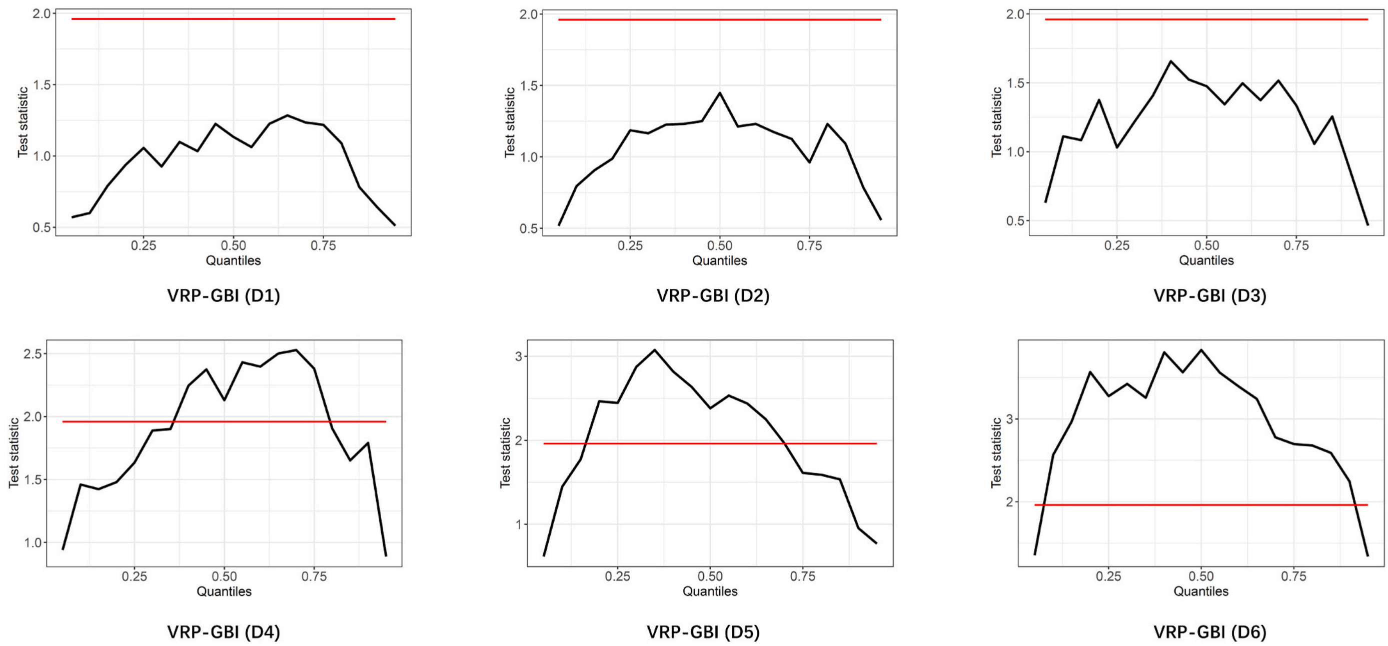

Fig. 6. The quantile Granger causality test results.
Notes: (i) The Fig plots results of the nonparametric causality-in-mean test from different quantiles of VRP to green bond markets, and the corresponding estimate of the 5% critical value (SJ) is represented as the horizontal red solid line.

should be cautious in the face of shocks to demand in the oil market. Optimising the green portfolio strategy is necessary for the context of oil shocks with different impacts. The green bond market can be a new option for investors when designing their portfolios.

On the one hand, in the process of the world economy moving toward low-carbon goals, it is necessary to fully consider the diversified financial asset allocation and incorporate cross-market linkage into the analysis and decision-making. On the other hand, when green financial assets are booming, policymakers should also maintain great attention and proper supervision to promote orderly economic transformation. The resilience of green bonds in times of market turmoil has proven as a facilitator for narrowing the gap between the economic growth initiative and evolution into an eco-friendly economic system after the COVID-19 pandemic, suggesting that governments need to focus on promoting the innovation of green financial products and the structure of green financial ecosystems to satisfy the various financial requirements of investors. This research also points to some directions for investors. First, given that green bonds serve as a source of financing for sustainable development and a safe haven against financial shocks, governments should work together to promote international convergence of green bond standards to improve reporting, thereby enhancing the diversification function of green bonds for different economies. Investors should be aware of the adverse effects on market stability and the resulting benefits during health crises such as a new crown pneumonia outbreak. And investors should be aware of the adverse effects on market stability and the resulting benefits during periods of health crises such as the new crown pneumonia outbreak.

Additional studies might benefit from some of the flaws in our latest research. Our research is limited by the existing access to the Green Bond Index and the Crude Oil Index, focusing only on the global level. Future research could concentrate on the regional and national levels, and this analysis could provide more precise conclusions. In addition, our reliance on more rigorous indices representing a range of green bonds likewise opens up a broad path for new research.

CRediT authorship contribution statement

Ping Wei: Funding acquisition, Supervision, Writing – review & editing. **Yinshu Qi:** Software, Formal analysis, Writing – original draft. **Xiaohang Ren:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Giray Gozgor:** Writing – review & editing.

Declaration of Competing Interest

None.

Acknowledgements

This research was supported by the Major Projects of the National Natural Science Fund of China [NO. 71991483], the Natural Science Fund of Hunan Province [NO. 2022JJ40647] and the Fundamental Research Funds for the Central Universities of Central South University [NO. 2022ZZTS0353]. Certainly, all remaining errors are our own.

References

Apergis, N., Miller, S.M., 2009. Do structural oil-market shocks affect stock prices? Energy Econ. 31, 569–575.
Azhgaliyeva, D., Kapsalyamova, Z., Mishra, R., 2022. Oil price shocks and green bonds: an empirical evidence. Energy Econ. 112, 106108.
Barsky, R.B., Kilian, L., 2004. Oil and the macroeconomy since the 1970S. J. Econ. Perspect. 18, 115–134.
Baruník, J., Kley, T., 2019. Quantile coherency: a general measure for dependence between cyclical economic variables. Econ. J. 22, 131–152.
Bekaert, G., Hoerova, M., 2014. The VIX, the variance premium and stock market volatility. J. Econom. 183, 181–192.
Chen, Y., 2021. Evaluating the influence of energy prices on tight oil supply with implications on the impacts of COVID-19. Res. Policy 73, 102129.
Chi-Chuan Lee, C.-C.L., Li, Yong-Yi, 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. N. Am. J. Econ. Financ. 55, 101309.
Clements, A., Shield, C., Thiele, S., 2019. Which oil shocks really matter in equity markets? Energy Econ. 81, 134–141.
Conrad, C., Loch, K., Rittler, D., 2014. On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets. J. Empir. Financ. 29, 26–40.
Demirer, R., Ferrer, R., Shahzad, S.J.H., 2020. Oil price shocks, global financial markets and their connectedness. Energy Econ. 88, 104771.
Diks, C., Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric granger causality testing. J. Econ. Dyn. Control. 30, 1647–1669.
Duan, K., Ren, X., Wen, F., Chen, J., 2023. Evolution of the information transmission between Chinese and international oil markets: a quantile-based framework. J. Commod. Mark. 29, 100304.

Dutta, A., 2017. Oil price uncertainty and clean energy stock returns: new evidence from crude oil volatility index. J. Clean. Prod. 164, 1157–1166.
Elsayed, A.H., Naifar, N., Nasreen, S., Tiwari, A.K., 2022. Dependence structure and dynamic connectedness between green bonds and financial markets: fresh insights from time-frequency analysis before and during COVID-19 pandemic. Energy Econ. 107, 105842.
Fatima, T., Xia, E., Ahad, M., 2018. Oil demand forecasting for China: a fresh evidence from structural time series analysis. Environ. Dev. Sustain. 21, 1205–1224.
Forhad, M.A.R., Alam, M.R., 2021. Impact of oil demand and supply shocks on the exchange rates of selected southeast Asian countries. Glob. Financ. J. 54, 100637.
Hamilton, J.D., 1983. Oil and the macroeconomy since world war II. J. Polit. Econ. 91, 228–248.
Hamilton, J.D., 1996. This is what happened to the oil price-macroeconomy relationship. J. Monet. Econ. 38, 215–220.
Hammoudeh, S., Ajmi, A.N., Mokni, K., 2020. Relationship between green bonds and financial and environmental variables: a novel time-varying causality. Energy Econ. 92, 104941.
Hedi Arouri, M.E., Khuong Nguyen, D., 2010. Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. Energy Policy 38, 4528–4539.
Huynh, T.L.D., 2020. When 'green' challenges 'prime': empirical evidence from government bond markets. J. Sustain. Finance Investm. 12, 375–388.
Jeong, K., Härdle, W.K., Song, S., 2012. A consistent nonparametric test for causality in quantile. Economic Theory 28, 861–887.
Kanamura, T., 2020. Are green bonds environmentally friendly and good performing assets? Energy Econ. 88, 104767.
Kassouri, Y., Altıntaş, H., 2021. The quantile dependence of the stock returns of "clean" and "dirty" firms on oil demand and supply shocks. J. Commod. Mark. 28, 100238.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am. Econ. Rev. 99, 1053–1069.
Kolodzeij, M., Kaufmann, R.K., 2014. Oil demand shocks reconsidered: A cointegrated vector autoregression. Energy Econ. 41, 33–40.
Lee, C.-C., Lee, C.-C., Li, Y.-Y., 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. N. Am. Econ. Financ. 55, 101539.
Li, R., Li, S., Yuan, D., Yu, K., 2020. Does economic policy uncertainty in the U.S. influence stock markets in China and India? Time-frequency evidence. Appl. Econ. 52, 4300–4316.
Lin, B., Su, T., 2021. Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities? Res. Int. Bus. Financ. 56, 101360.
Malik, F., Umar, Z., 2019. Dynamic connectedness of oil price shocks and exchange rates. Energy Econ. 84, 104501.
Naeem, M.A., Bouri, E., Costa, M.D., Naifar, N., Shahzad, S.J.H., 2021. Energy markets and green bonds: a tail dependence analysis with time-varying optimal copulas and portfolio implications. Resourc. Pol. 74, 102418.
Pham, L., 2021. Frequency connectedness and cross-quantile dependence between green bond and green equity markets. Energy Econ. 98, 105257.
Pham, L., Nguyen, C.P., 2022. How do stock, oil, and economic policy uncertainty influence the green bond market? Financ. Res. Lett. 45, 102128.
Ready, R.C., 2018a. Oil consumption, economic growth, and oil futures: the impact of long-run oil supply uncertainty on asset prices. J. Monet. Econ. 94, 1–26.
Ready, R.C., 2018b. Oil prices and the stock market. Rev. Finance 22, 155–176.
Reboredo, J.C., 2018. Green bond and financial markets: co-movement, diversification and price spillover effects. Energy Econ. 74, 38–50.
Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A., 2017. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Econ. 61, 241–252.
Ren, X., Dou, Y., Dong, K., Yan, C., 2022a. Spillover effects among crude oil, carbon, and stock markets: evidence from nonparametric causality-in-quantiles tests. 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., An, Y., Jin, C., 2023a. The asymmetric effect of geopolitical risk on China's crude oil prices: new evidence from a QARDL approach. Financ. Res. Lett. 53, 103637.
Ren, X., Li, J., He, F., Lucey, B., 2023b. Impact of climate policy uncertainty on traditional energy and green markets: evidence from time-varying granger tests. Renew. Sust. Energ. Rev. 173, 113058.
Semeyutin, A., Gozgor, G., Lau, C.K.M., Xu, B., 2021. Effects of idiosyncratic jumps and co-jumps on oil, gold, and copper markets. Energy Econ. 104, 105660.
Shahbaz, M., Trabelsi, N., Tiwari, A.K., Abakah, E.J.A., Jiao, Z., 2021. Relationship between green investments, energy markets, and stock markets in the aftermath of the global financial crisis. Energy Econ. 104, 105655.
Umar, Z., Trabelsi, N., Zaremba, A., 2021. Oil shocks and equity markets: the case of GCC and BRICS economies. Energy Econ. 96, 105155.
Wang, Z., Fu, H., Ren, X., 2023a. The impact of political connections on firm pollution: new evidence based on heterogeneous environmental regulation. Pet. Sci. 20 (1), 636–647.
Wang, X., Li, J., Ren, X., Bu, R., Jawadi, F., 2023b. Economic policy uncertainty and dynamic correlations in energy markets: assessment and solutions. Energy Econ. 117, 106475.
Wei, P., Qi, Y., Ren, X., Duan, K., 2022. Does economic policy uncertainty affect green bond markets? Evidence from wavelet-based quantile analysis. Emerg. Mark. Financ. Trade 58 (15), 4375–4388.