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A study on the correlation between green bond market, coal market and crude oil market - an empirical analysis based on wavelet coherence

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Abstract. Achieving carbon peaking and carbon neutrality represents a green industrial revolution with immense and far-reaching significance, and the "dual-carbon" goal plays a crucial role in China's realization of high-quality economic development and comprehensive green transformation of economic and social development. In this paper, the wavelet model is employed to extract dynamic correlation information across different time periods and time scales using wavelet coherence. For the overall and sectoral renewable energy indices for the period of 2014-2024, the results of wavelet coherence show that: short-term dependence between crude oil prices and coal prices, and coal prices and green bond indices is relatively weak, but long-term dependence is gradually strengthened, mainly around 2018. As for crude oil and green bond index, there is an extremely significant positive correlation between the two at any frequency. These findings carry significant implications for China's policy decisions regarding investor support and the development of renewable energy, as well as for the sustainable growth of the carbon market.

Keywords: Crude oil prices; Coal prices; green bonds; Wavelet analysis.

1. Introduction

Energy serves as a crucial material foundation for national economic development, and fluctuations in energy prices typically impact the overall output of the national economy. In recent years, due to the superimposed impact of climate change, the Russia-Ukraine conflict and the Palestinian-Israeli conflict, international energy prices have continued to rise, and compared with the low point in 2021, WTI crude oil futures prices have risen by more than 50% [1]. The scarcity of energy further reinforces its attributes as a financial product. The rise in energy prices has driven the growth of the renewable energy sector, which is widely considered the most effective approach to addressing the challenge of climate change, resolving global conflicts over resources, and ensuring a stable energy supply [2].

In order to further promote the above process, China has issued a series of policies on green finance, among which green bond, as a bond tool specially used to fund green projects in compliance with regulations, plays an indispensable role in promoting the process of realizing the above goals. In recent years, China has introduced a series of policies to support the development of green bonds, and on April 2, 2021, Sinopec issued the first carbon neutral bond for a domestic oil and gas company. In 2023, the China Securities Regulatory Commission and The State Council, in collaboration with relevant authorities, issued a notice titled "On Supporting Central Enterprises in Issuing Green Bonds. In the same year, The People's Bank of China, in conjunction with other ministries and commissions, issued the "Guiding Opinions on Further Strengthening Financial Support for Green and Low-Carbon Development".

The generation of green bonds provides a new financing channel for the traditional energy market and helps these industries add green financial products to their portfolios. At the same time, the consumption of fossil fuels represented by crude oil is one of the main factors leading to carbon emission and environmental pollution. The green bond market, carbon market and crude oil market have a natural information transmission mechanism. Therefore, there is an objective linkage effect among crude oil market, green bond market and carbon market. By examining the dynamic evolution of financial markets and risk trends from the perspective of correlation, the mainland financial market is a net importer of risk spillovers [2]. Therefore, when the energy market is hit, all three markets are affected to varying degrees.

Scholars have discovered that green assets exhibit a high sensitivity to oil shocks [3], with the resulting volatility in the green bond market being notably persistent, leading to market inefficiencies [4]. Anupam Dutta et al [5]. studied the response of oil price shocks on green bonds using Markov transformation mechanism regression considering WTI oil returns. The authors first find that crude oil prices do not have a significant effect on green bonds, while further analysis suggests that green bonds switch between low and high volatility regimes.C.-C. Lee et al [6]. used quantile analysis to study Granger causality and obtained a two-way causal relationship between crude oil shock and green bond index. We also found that changes in oil prices can affect renewable energy consumption, which may in turn lead to changes in traditional energy market prices [7]. Exploring the relationship between the energy market and the green bond market is therefore of great significance, as it aids in investor risk management and informs the development of relevant policies.

The existing literature primarily examines the relationship between individual energy sources and the overall clean energy index, with limited research investigating the connections between multiple energy markets and the clean energy market. Additionally, due to the more stringent measures implemented by the Chinese government in response to the COVID-19 pandemic compared to other countries, studies utilizing Chinese data may yield different conclusions than those based on data from other regions. The main objective of this study is to examine the relationship between the green bond market, the crude oil market, and the coal market and to provide insights into: (1) How are green financial markets (especially green bonds) affected by energy market prices compared to other assets? (2) How do various types of clean energy sources have different hedging effects on the green bond market? (4) How have the interplay between markets evolved over time?

2. Literature review

Crude oil has become an essential economic barometer, drawing considerable global focus. A substantial amount of research has explored the connection between fluctuations in crude oil prices and the returns of green or renewable energy shares. Initial studies concentrated on assessing the presence and stability of this relationship. For example, Broadstock [8] have shown that rising oil prices can positively stimulate the green bond market. In addition, both Reboredo and Ugolini and Shah [9], among others, confirm the view that NEP stock price changes are mainly influenced by oil price fluctuations.

Previous research has examined the interconnections between the crude oil market and the green bond market. According to Dutta et al [10] [11] , it has been found that the connectivity between the crude oil and green bond markets is weaker during low-frequency periods and stronger during high-frequency periods. Similarly, Braga et al. [12] demonstrate a weak correlation between the oil market and green bonds. Kanamura's [13] findings reveal that the MSCI and S&P green bond indices exhibit a positive correlation with oil prices, whereas the Solactive green bond prices show a negative correlation with oil prices. The recent study by Yousaf et al. [14] identified a negative one-way volatility transmission effect from petroleum to the international eco-friendly bond sector, suggesting that green bonds possess a hedging capability against oil price fluctuations.

Studies have demonstrated that the connection between eco-friendly bonds and the renewable energy sector is low or even negative, implying that green bonds could provide a safeguard against fluctuations in the renewable energy market's pricing[15]. In addition, green bonds are becoming increasingly popular with investors because of their higher average returns compared to traditional bonds [16]. Nevertheless, the majority of existing literature primarily emphasizes the association between singular energy sources and the comprehensive green energy benchmark, whereas a limited number of studies explore the interconnections among various conventional energy trading and its renewable energy analogues.

Eco-friendly bond sector and renewable energy marketplace have recently undergone substantial expansion in both scope and scale. Analyzing the interactions between these markets is essential for investors and policymakers with a focus on environmental sustainability. In addition, studies have shown that green bonds have a greater positive than negative impact on clean energy markets. For instance, research has shown that the positive spillover effect of green bonds on clean energy markets is stronger than the negative spillover effect.[17].

The increasing linkages between energy markets make each market vulnerable to the rapid dissemination of market information in the event of an unknown shock. These events may disrupt the existing market structure [18]. Therefore, It is of utmost importance for investors and policy makers to understand the potential risks, time-varying characteristics and risk-aversion properties of clean energy markets [19]. In conditions of extreme market volatility, green bonds catalyze a short-term expansion within the clean energy domain and, over time, increasingly impose a more substantial positive impact. However, there are few investigations into the association and structural correlation between clean energy markets and primary energy markets, and China's strict financial market strategy leads to differences in its market correlation with other countries.

The contribution of this study to the existing literature is mainly in the following three aspects: (1) It reveals the association between the coal market and the crude oil market, which provides a valuable reference for investors' behavior in the green bond market. (2) The study confirms the interplay between the renewable energy sector and the eco-friendly bond marketplace, perfecting the status quo that most of the current studies are only linked to a single energy market. (3) The innovative use of wavelet analysis explores the association in the time-frequency domain, providing more detailed empirical evidence.

3. Methodology

We utilize uninterrupted and interactive wavelet analysis transforms to demonstrate the evolution of regional variability and correlation between dual temporal sequences, and utilize spectral concurrence and phase examination to assess their area-specific conjoint motion in the temporal-spectral plane. In addition, we employ discrete wavelets to investigate both linear and nonlinear causal relationships between the returns of crude oil, coal, and green bonds across various time scales. Later in the paper, we provide a concise explanation of core wavelets and their application in our analysis.

3.1. Continuous wavelet

A wavelet is a function generated by a individual wavelet known as the mother wavelet, characterized by a real-valued, square-integrable function via:

$$\psi_{\tau,s} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right), \tag{1}$$

Here, $\frac{1}{\sqrt{s}}$ represents a normalized variance ensuring that the wavelet is characterized by unitary variance, while t and s denote the position and scale parameters, respectively, which control the specific location of the wavelet and its expansion or stretching. A wavelet must fulfill the admissibility criterion, meaning it possesses effective temporal-spectral positioning across both temporal and spectral dimensions.

Each wavelet possesses distinct properties that are valuable for delineating various datasets. Within the scope of our experiential examination, the Morlet wavelet is used to uncover the data's inherent fluctuations, which is frequently employed in economic and financial studies for examining magnitude and phase. The Morlet wavelet is expressed as follows:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}, \tag{2}$$

In this study, $\omega_0 = 6$ is chosen to balance time and frequency localization. Here, $\pi^{-\frac{1}{4}}$ serves as the normalization factor to ensure the wavelet maintains unit energy, while $e^{-\frac{t^2}{2}}$ represents a Gaussian distribution characterized by a unit standard deviation.

3.1.1. Continuous wavelet transform.

The continuous wavelet transform $W_x(s)$ enables the analysis of the frequency content's temporal evolution within a given time series and is defined as:

$$W_x(s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi^*(\frac{t}{s}), \tag{3}$$

Where $*$ denotes the conjugate transpose, the scale parameter dictates the wavelet's ability to identify either the high or low components of the sequence $\mathrm{x(t)}$, provided that the requisite conditions are satisfied.

3.1.2. wavelet coherence.

To analyze the interdependence of two temporal sequences across time and spectral dimensions, we utilize three key concepts: the wavelet spectral density, wavelet cross-spectral power, and bivariate wavelet transform. The wavelet spectral density quantifies the variance contribution of the sequence across different temporal resolutions, while the wavelet cross-spectral power assesses the covariance impact across the temporal-spectral field. The wavelet interaction of two time series, denoted as $\mathrm{x(t)}$ and $\mathrm{y(t)}$, with their respective wavelet decompositions, $W_n^X(s)$ and $W_n^Y(s)$, is defined as follows:

$$W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s), \tag{4}$$

The symbol $*$ represents the complex conjugate. Wavelet coherence, as defined by Torrence and Webster [20], quantifies the coordinated movement between two sequences through temporal and freqency dimensions. It is calculated as the square of the wavelet coherence coefficient:

$$R_n^2(s) = \frac{\left|(s^{-1} W_n^{XY}(s))\right|^2}{(s^{-1}\left|W_n^X(s)\right|^2)(s^{-1}\left|W_n^Y(s)\right|^2)} \tag{5}$$

Where s is a smoothing operator acts on both time and scale. $R^2(s)$ is similar to the correlation coefficient, it ranges from 0 to 1, where figures close to 0 indicate a feeble association, and figures close to 1 indicate a firm association.

3.1.3. Phase.

To analyze the associations among two time-stamped progressions within time-frequency dimensions, we apply the wavelet coherence phase difference, which allows us to identify and measure negative correlation, positive correlation, and overshoot-lag effects. The concept of wavelet coherence phase difference, as outlined by Torrence and Webster, provides a framework for this analysis:

$$\varphi_{xy}(s) = tan^{-1}(\frac{\Im(s^{-1} W_n^{XY}(s))}{\Re(s^{-1} W_n^{XY}(s))}) \tag{6}$$

In this analysis, the imaginary component $\Im$ and the real component $\Re$ of the smoothed power spectrum are considered. The directional orientation of the arrows provides insight into the phase correspondence within the two time-stamped progressions. Specifically: (1) An arrow pointing to the right (left) indicates that the series are either in phase (out of phase), which corresponds to a positive (negative) correlation; (2) An arrow pointing downward (upward) signifies that the second (first) time series leads the first (second) time series by a phase difference of 90°.

3.2. discrete wavelet

Using discrete wavelet transforms, it is possible to break down a time series $y(t)$ into its constituent components across various time scales:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(k) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (7)$$

In the context of wavelet analysis, functions ϕ and ψ are referred to as the parent wavelet and mother wavelet, respectively. These functions play crucial roles in emblematic of the sub-harmonic frequencies, smooth components ϕ and the upper spectral range, detailed components ψ of a given series. The parameters, denoted as $s_{J,k}, d_{J,k}, \ldots, d_{1,k}$, represent the wavelet analysis factors, which quantify the influence of individual wavelet functions on the cumulative signal. Through a J-level multiresolution decomposition process, a time series $y(t)$ can be decomposed and expressed using these functions and coefficients.

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) \ldots + D_1(t) \quad (8)$$

In this context, frequency component D_j is associated with variations over short, medium, and long terms, which are driven by the shocks occurring at the time scale defined by 2^j. The residual, denoted as S_j, is obtained by extracted $D_1, \ldots, D_j$ from the initial time series. Our empirical study employs daily data to construct $j = 8$ with multiple levels of resolution j, consistent with prior research indicating that the medium filter is well-suited for financial data [21]. This decomposition results in eight levels of detail: (1) the highest frequency component, D_1, captures fluctuations at the duration scale of $2^1 = 2$ days (daily effect); (2) the constituent D_2 reflects changes over a duration scale of $2^2 = 4$ days (weekly effect); and (3) constituent D_3, D_4, D_5, D_6, D_7 and D_8 correspond to intermediate and prolonged fluctuations, covering $2^3 = 8$ and $2^8 = 256$ days, respectively.

4. Data

We used daily spot prices to conduct an practical investigation into the reliance and causation between prices under different time scales using the following indices: (1) CSI Green Bond Daily Price Index. (2) China Carbon Emission Allowance Spot Composite Price Index. (3) WTI Crude Oil Index. The time span is 2014-2024, and the statistics are extracted from the Wind database.

Figure I shows the association between the CSI Green Bond Index and the different energy price indices, showing that the major recession occurred mainly in 2018 in the context of the world economic crisis, with a sharp fall in oil prices with an expected decline in petroleum rates and fluctuation in the international economic landscape. Visual Figure 1 also shows that the price volatility of the petroleum cost indicator, coal price index and green bond index are not exactly synchronized, with the petroleum cost indicator and coal price index being slightly more volatile than the green bond index.

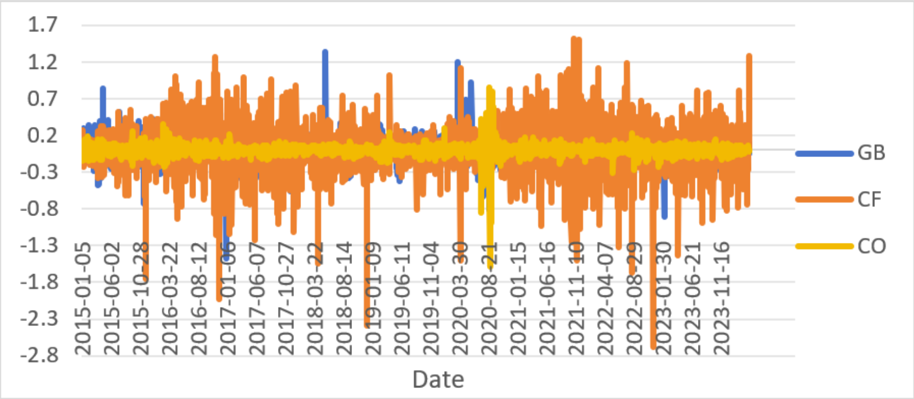

Figure 1. Crude oil, coal and green bond index data from 2015 to 2024

Table 1 reports descriptive statistics for the petroleum cost indicator, the coal price index and the green bond index. The daily financial gains are all roughly nonexistent, and the maximum and minimum values indicate that the magnitude of volatility is similar for all series of variables, except for the green bond index, which is less volatile. The skewness of all three variables is negative, while the kurtosis statistics indicate that the distributions of all indices exhibit thick tails. Table 2 shows that the correlation among the three is at a low level, so we carry out the analysis in this paper under this precondition.

Table 1. Descriptive statistics

	Full distance	minimum value	maximum value	average value	standard deviation	variance	skewness	kurtosis
CO	2.431	-1.581	0.850	0.00089	0.087	0.008	-2.604	72.686
CF	4.185	-2.674	1.511	0.00588	0.342	0.117	-0.718	5.536
GB	2.799	-1.468	1.331	0.00299	0.142	0.020	-0.283	14.958

Table 2. Statistics of correlation

	CF	CO	GB
CF	1.000		
CO	0.0164	1.000	
GB	0.0160	0.0598	1.000

5. Empirical results

Under the premise that the CBSI represents the green bond market, the futures coal price represents the coal market, and the raw petroleum price represents the raw petroleum market, Figure 3 shows the estimated wavelet coherence and phase difference between the green-oriented bond sphere and the coal market, the green-oriented bond sphere and the raw petroleum market, and the coal market and the raw petroleum market, and shows the difference between the green bond market and the coal market, the green bond market and the raw petroleum market, the coal market and the raw petroleum market at differences in the dependence between returns in different frequency ranges and as time passes. Wavelet coherence works by identifying two sequences across the time-spectrum plane, plotting the region of higher dependence in warmer colors and the region of lower dependence in cooler colors. Given that the successive wavelet transforms use information about data points near a specific point, caution is needed in interpreting the regions at the beginning and end of the time span.

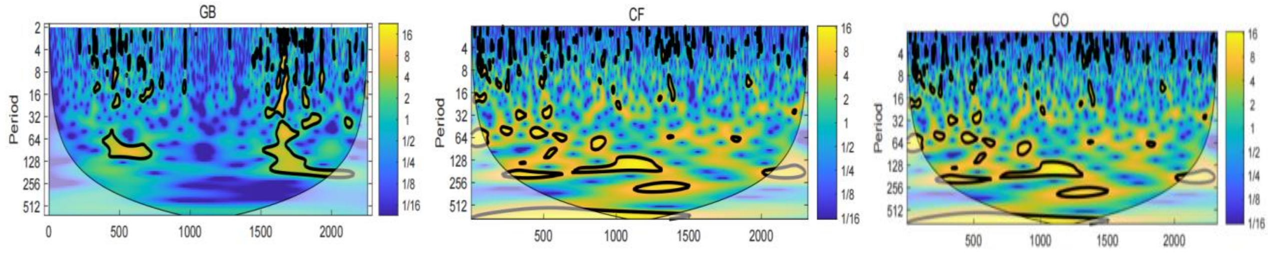

Figure 2. Continuous wavelet transform for crude oil, coal, and green bond indices

Figure 2 presents the uninterrupted wavelet transform spectral densities for three pairs of chronological series: CBSI and futures carbon, CBSI and crude oil, and futures carbon and crude oil. In these spectra, the horizontal scale represents the count of specimens ordered chronologically, while the vertical scale corresponds to frequency, which is converted into time units. Hachured lines indicate regions of notable at the 0.05 significance threshold, determined through Monte Carlo simulations using phased stochastic substitution sequences. Solid curves represent impact cones, marking areas influenced by edge effects. Warm colors denote areas of high power, whereas cool colors indicate low power. The time scale decomposition across all series depicted in the figure reveals that most of these series exhibit a response time to shocks within a two-year period. Notably, the medium and high-frequency power dominates over low-frequency power for the volatilities of crude oil, Chinese bonds, and futures carbon. Despite these observations, there is no noticeable shift in the framework of the series, as indicated by the intermingling of cool and warm colors throughout the chart.

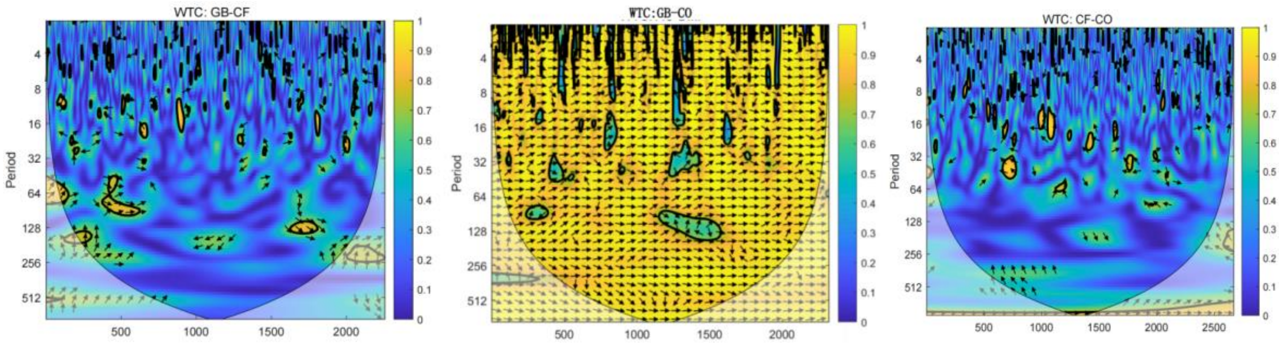

Figure 3. Cross-wavelet transforms for crude oil, coal and green bond indices

Through the above graphs we can find a weak correlation between the two variables represented by the two graphs at higher frequencies, except for the green-oriented bond sphere and the raw petroleum market, which show a high level of correlation irrespective of all frequencies versus time, and this phenomenon persists across the duration of the data set. However, in the lesser frequency intervals, the dependence of the CBSI on futures coal prices increases, especially at the onset of the world economic crisis (around 2018), ultimately attaining a considerable degree of reliance centered in the lesser frequency intervals (from 64 to 256 days) between 2019 and mid-2024; meanwhile the coal and crude oil markets reflect a high level of dependence at intermediate frequencies (from 16 to 64 days) dependence, culminating in a concentration of dependence in the ultra-long term (>512 days). Overall, the figure shows the dynamics of dependence between the green-oriented bond sphere and the raw petroleum market, and the coal market and the crude oil market over time and frequency, with firm interdependence at low frequency and slight interdependence at high frequency as of mid-2024; and slight interdependence in the elevated frequency intervals and low frequency from 2015 to mid-2018.

In addition, the phase relationship in phase among the pair of time series is indicated by arrows (1) when the arrow points to the right (left), the sequence is synchronized (inverted) or the correlation exhibits positively (negatively); and (2) when the arrow points down (up), the second (first) series leads the first (second) series by 90◦ . The arrows in the graph representing the CBSI and futures coal prices point to the right most of the time and frequency, indicating that the two show a positive correlation, while the absence of a lead-lag relationship suggests that the CBSI is not a cause of futures carbon prices; however, from 2015 to 2018, the arrows in the graph are shown to be facing downward to the left, indicating that futures coal prices changed ahead of the CBSI, and that this period of time was in the midst of a global economic bubble period, the real economy had a great impact on the green-oriented bond sphere, so the price changes in the coal market at this time had an impact on the green-oriented bond sphere.

Meanwhile, the gauged wavelet agreement and phase synchronization difference of the Chinese bond index and crude oil price reveal that they are not only highly correlated, but also the arrows point in the rightward direction at any frequency and time, indicating that there is an obvious positive correlation between the two, and that there is an obvious relationship of mutual positive influence on the changes between the two. This relationship implies that a rise in crude oil prices may result in an upward movement in the Chinese bond index. Consequently, this could stimulate significant growth in the green bond market. We explain this as follows: when the crude oil price increases, it will lead to a significant increase in the demand for non-fossil energy, which will lead to a rise in the valuation of green bonds; on the other hand, an increase in the consumption of non-fossil energy will also lead to an increase in the willingness of enterprises to green financing, which will indirectly lead to the number of green bonds in the demand side of the demand side is greater than that in the supply side, resulting in a direct increase in the Chinese Bond Index, which will lead to the thriving state of the green-oriented bond sphere.

6. Conclusion

In this study, we investigate the causality and direction between oil, coal, and green bonds using continuous and discrete wavelets, as well as obtaining dynamic correlation information from wavelets over time and across various durations. We used data from 2014 to 2024 for these three sectors, and the data reveal that the interactions between crude oil prices and coal prices and and coal prices and green bond indices are weakly correlated in the near term but increase gradually over an extended period, and the correlation is most significant in 2018 during the global economic crisis. Concurrently, the linkage between crude oil prices and the green bond index is very strong at all frequencies and time periods, and it can be considered that there is a strong positive influence between the two.

Grounded in the outcomes of the research, we put forward the following policy. Firstly, investors engaging in green bonds and the coal market should remain cognizant of the risks linked to crude oil price fluctuations and should strategically adjust their asset portfolios and allocations to optimize returns. As there are dynamic links between these markets, participants in one market must be fully cognizant of the prevailing conditions in other markets; second, policymakers should fully consider the interrelationship of the markets, maximize the advantages of each market, make the green bond market and carbon market cope with the impact of oil prices within a controllable range by establishing a risk early warning mechanism, vigorously strengthen the green-oriented bond sphere and increase its role in advancing the carbon market.

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