Time-Frequency Correlation Between Crude Oil Market and New Energy Stock Market: A Wavelet-Based Analysis

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Abstract. Against the backdrop of accelerating energy structure transition and deepening global carbon emission reduction policies, the dynamic link between the crude oil market and the new energy stock market has grown increasingly complex. To reveal the correlation structure and transmission mechanism of the two markets across multiple time scales, this paper constructs a time-frequency analysis framework that integrates continuous wavelet transform, wavelet coherence, and multi-scale quantile Granger causality test. It systematically investigates the interaction between Brent crude oil futures and China's five major new energy sub-sectors from March 2018 to September 2025. The empirical results show three key findings. First, the volatility energy of the crude oil market is mainly concentrated in the low-frequency band, while new energy sectors also display significant volatility energy in medium- and high-frequency bands. Second, wavelet coherence analysis indicates that crude oil and new energy sectors have a structural correlation in the medium and long term, but their short-term correlation is weak and unstable, with obvious time-frequency heterogeneity in the linkage pattern. Third, multi-scale quantile Granger causality tests further reveal that the causal effects of crude oil on different new energy sectors differ significantly in both time scale and market state. This study provides a new time-frequency perspective for understanding the complex interaction between traditional and emerging energy markets during energy transition, and offers empirical evidence for differentiated policy-making and multi-scale investment strategy design.

Keywords: Crude oil market, New energy stock market, Wavelet coherence, Granger causality test, Time-frequency correlation.

1. Introduction

In the context of addressing global climate change and accelerating the transition of energy structure, the international community has continuously strengthened policy coordination and implementation. The 29th UN Climate Change Conference in 2024 further promoted the global process of clean energy transition. Many countries have successively raised their carbon neutrality targets and increased policy support and capital investment in renewable energy. Meanwhile, guided by the 15th Five-Year Plan for a modern energy system, China has steadily promoted the green and low-carbon transition of energy. The coverage of the national carbon emission trading market has been gradually expanded, and the green power trading mechanism has been continuously improved. Driven by both policies and markets, the new energy industry has achieved large-scale and high-quality development. The advancement of international carbon pricing instruments such as the EU Carbon Border Adjustment Mechanism (CBAM) has also exerted a profound impact on global energy trade and investment flows, further highlighting the complexity and dynamics of the interaction between traditional and new energy markets.

Against this background, the new energy market is expanding at an unprecedented speed and has become the core engine driving global sustainable development and achieving carbon neutrality goals. At the same time, the traditional fossil energy market represented by crude oil is undergoing profound internal structural adjustment. According to the *China Oil & Gas and New Energy Market Development Report*, China's oil consumption turned from growth to decline for the first time in 2024, and refined oil demand peaked and declined, marking a historic turning point in the market. The new energy industry is predicted to maintain rapid development in the next five years. This dynamic pattern of shift and change highlights that the global energy system is in a critical stage of transition between old and new driving forces.

The relationship between traditional and new energy markets is not a simple substitution, but a complex and dynamically changing interaction. Existing empirical studies show that the correlation between crude oil and various renewable energy stock indices is nonlinear and multi-dimensional. This interaction features remarkable heterogeneity, time-variation, and scale dependence. The correlation strength varies across different new energy sub-sectors with crude oil prices[1]. Major events such as the COVID-19 pandemic have significantly changed the co-movement pattern between markets[2]. More importantly, the correlation between the two often shows different strength and patterns in the long run and the short run[3]. Understanding such dynamic correlation across multiple time scales is crucial for grasping the path of energy transition, optimizing asset allocation, and early warning systemic risks.

Price fluctuations in the crude oil market provide key signals for investment decisions and risk judgment in the new energy sector. Conversely, the performance of the new energy stock market reflects market expectations about the long-term role of crude oil in the energy system and the substitution process[4-5]. Therefore, an in-depth study of their dynamic correlation can not only reveal the pricing mechanism of energy transition in financial markets, but also provide a basis for policy formulation and portfolio management. This paper aims to systematically analyze the correlation structure and causal orientation of the two markets across multiple time scales by constructing a time-frequency analysis framework. It fills the gaps of existing research in depicting scale heterogeneity and nonlinear dynamics, and offers a new methodological perspective and empirical evidence for understanding the complex interaction between energy and financial markets.

The rest of the paper is structured as follows. Section 2 systematically reviews the literature on the correlation mechanism between crude oil and new energy stock markets and time-frequency research methods. Section 3 details the research design and methods, including data description, continuous wavelet transform, wavelet coherence, and multi-scale nonlinear Granger causality test model. Section 4 presents the empirical analysis, including the results of multi-scale correlation and causality tests. Section 5 summarizes the full paper and puts forward policy recommendations.

2. Literature Review

Early research on the correlation between crude oil and new energy stock markets focused on the price transmission from crude oil prices to the stock market. In recent years, the research scope has gradually expanded. Scholars generally recognize that their correlation is not a simple price co-movement. From the perspective of supply and demand shocks, global crude oil market fluctuations exert dynamic impacts on the US clean energy trends, and shocks of different natures have heterogeneous effects[6]. In addition, geopolitical risks have become a non-negligible core variable. Events such as the Russia-Ukraine conflict not only directly impact crude oil supply and prices, but also indirectly affect the rhythm of strategic investment in new energy in various countries[7-8]. Furthermore, recent studies have refined the micro-mechanism of correlation using the VARMA-DCC-GARCH-in-mean model. They find that stock market uncertainty negatively affects the traditional energy market and positively affects the renewable energy market, highlighting the role of financial market sentiment as a key link[9]. Heterogeneity analysis within the new energy sector shows that firms listed at different times differ significantly in their correlation with oil prices and volatility: established firms show two-way correlation, while newly listed firms show insignificant correlation[5]. Overall, although the above international studies reveal the complex interaction between crude oil and new energy markets from multiple dimensions, most are based on mature markets, and research on market structural differences is relatively limited.

As China plays an increasingly critical role in global energy consumption and green transition, research targeting the uniqueness of the Chinese market has become an important branch. Studies find that China's green energy stock market can dominate the price changes of domestic crude oil futures to a certain extent. This influence becomes more prominent especially after the strengthening of the "dual carbon" policy and the launch of the national carbon market[10]. Furthermore, international carbon-related factors, domestic industrial support policies, and government-guided media tone can significantly affect the market performance and risk-return characteristics of China's new energy sector, thereby modulating the correlation strength and direction with the traditional crude oil market[10-11]. Notably, the interaction mechanism between China's new energy and crude oil markets presents significant asymmetry. Studies find that the correlation structure between the two has undergone a structural mutation before and after the proposal of the "dual carbon" goal. In the early stage of carbon market launch, the sensitivity of the new energy sector to oil price volatility increased significantly. With the gradual improvement of the green power trading mechanism, this sensitivity shows a dynamic attenuation trend[12]. In addition, the causal relationship between China's new energy sub-sectors and the crude oil market has a threshold effect: significant predictability exists only when oil prices are in a specific range or market sentiment is extreme[13]. However, most of the above China-focused studies adopt full-sample models with daily data. Although they can clarify the average correlation, they fail to fully reveal the heterogeneity of correlation patterns under different investment cycles and the time-frequency localized impacts of exogenous shocks such as policies and the pandemic.

Such methodological limitations are not unique to China-focused research, but reflect a more general challenge. Traditional econometric models gradually expose their reliance on the single time-scale assumption when dealing with complex financial time series. Methods represented by vector autoregression and its extensions, such as Diebold and Yilmaz's spillover index, are good at depicting linear mean and volatility spillover networks between markets[14]. The subsequently developed time-varying parameter VAR model further improves flexibility[15]. The Copula function breaks through the assumption of linear correlation by separating marginal and joint distributions, and has advantages especially in depicting asymmetric tail dependence between markets[16]. Multivariate GARCH models, such as DCC-GARCH, have become one of the mainstream tools for capturing dynamic correlation by allowing time-varying conditional correlation coefficients[17]. However, these methods share a common underlying assumption: the market correlation pattern operates homogeneously on a single time scale. This assumption faces challenges in reality. The correlation structure may differ drastically across investment cycles. The interaction mechanism between short-term shocks and long-term trends can hardly be integrated into a unified framework. Meanwhile, preprocessing methods such as differencing for non-stationary series may lose long-term information or structural breakpoints, making the analysis results sensitive to scale selection.

Due to the limitations of the above traditional methods in integrating time and frequency domains, scholars have introduced wavelet analysis into financial correlation research in recent years. As a time-frequency analysis tool, wavelet analysis can decompose non-stationary series into different time scales without distortion through its multi-resolution capability. This allows researchers to examine the characteristics and evolution of correlation on independent scales such as short, medium, and long term. For example, wavelet coherence analysis can accurately visualize the correlation strength and phase relationship between oil prices and green bond indices in specific time-frequency domains, which is difficult for traditional time-domain methods[18]. On this basis, scholars have further extended wavelet methods to multivariate market co-movement analysis. They use wavelet local multivariate correlation coefficients to measure time-frequency dependence between financial systems and real estate markets, providing a new analytical tool for identifying risk spillover windows among multiple markets[19]. More advanced applications have gone deep into market microstructure. For instance, multivariate wavelet coherence and partial wavelet coherence are used to systematically investigate time-frequency co-movement among pandemic risk, geopolitical risk, crude oil, gold, Bitcoin, and other assets. They reveal differentiated impact paths of different risk sources on different financial assets across short, medium, and long-term scales[20]. In addition, unsupervised classification of stock price jumps using multi-scale wavelet representation can not only distinguish jumps driven by exogenous news and endogenous factors, but also identify new jump categories dominated by mean reversion or trends. This shows the advantage of wavelet analysis in revealing complex nonlinear dynamics and contagion paths[21]. In practical applications, structurally decomposing the original series before applying GARCH or Copula models to each component can effectively improve the robustness and explanatory power of model estimation[22]. Meanwhile, wavelet Granger causality tests can judge the lead-lag relationship between variables on multiple scales[23]. These studies provide an important methodological basis for this paper. However, existing literature mostly focuses on bivariate coherence description or single-scale causality tests, and has not yet formed an analysis framework that can simultaneously integrate continuous wavelet transform, wavelet coherence, and multi-scale quantile Granger causality test.

In summary, existing studies have made significant progress in revealing the correlation between crude oil and new energy stock markets and the evolution of methods, but still have three limitations. First, most studies rely on traditional time-domain models, which are difficult to capture the multi-scale, nonlinear, and time-varying characteristics of correlation, and insufficiently depict the heterogeneous correlation of sub-industrial chains. Second, although time-frequency methods have been initially applied, most are based on linear or static assumptions and fail to systematically reveal dynamic causality and phase evolution across different scales. Third, the analysis of time-frequency localized impact mechanisms of exogenous shocks is insufficient, lacking a unified analytical framework for multi-scale interaction effects.

In view of this, this paper constructs a time-frequency analysis framework integrating continuous wavelet transform, wavelet coherence, and multi-scale quantile Granger causality test. Compared with existing research, the marginal contributions of this paper are as follows. In terms of analysis dimension, it deepens from overall correlation to sub-scale correlation and identifies differentiated interaction patterns between different new energy sectors and crude oil across short, medium, and long-term scales. In terms of causality identification, it reveals the scale dependence and dynamic evolution of lead-lag relationships between markets through phase analysis and nonlinear causality tests. In terms of method integration, it embeds external shocks into time-frequency localization analysis, providing a new methodological perspective and empirical evidence for understanding the complex market mechanism in energy transition.

3. Research Design and Methods

3.1. Data Description and Variable Definition

3.1.1 Data Sources

Considering the timeliness of data and the rationality of variable selection, the sample interval of this study is from March 27, 2018 to September 30, 2025, covering the key stage of accelerated energy transition. The crude oil market price is represented by the daily closing price of the continuous contract of Brent crude oil futures. The new energy stock market selects representative indices covering five core sub-fields: photovoltaic, wind power, nuclear power, hydropower, and new energy lithium batteries. Specifically, they include the CSI Photovoltaic Industry Index, CSI Wind Power Industry Index, CSI Nuclear Power Industry Index, CSI Hydropower Industry Index, and CSI Battery Theme Index. All index data are obtained from the National Bureau of Statistics and Wind Database. The variable selection is summarized in Table 1.

Table 1. Summary of Variable Selection

Variable Type	Variable Symbol	Indicator Name	Frequency
Crude Oil Market	OIL	Indicator Name	Daily
	PV	Daily Closing Price of Continuous Contract for Brent Crude Oil Futures	Daily
New Energy Market	WIND	CSI Photovoltaic Industry Index Closing Price	Daily
	NP	CSI Wind Power Industry Index Closing Price	Daily
	WP	CSI Nuclear Power Industry Index Closing Price	Daily
	NB	CSI Hydropower Industry Index Closing Price	Daily

3.1.2 Variable Processing

To ensure that the research conclusions are not disturbed by cross-border pricing units and exchange rate fluctuations, this study uses the monthly average exchange rate of RMB against USD to convert the price indicators denominated in USD into RMB through the corresponding exchange rate time series. Specifically, the daily central parity rate of RMB against USD published by the State Administration of Foreign Exchange is used as the exchange rate benchmark:

$$P_{CNY,t} = P_{USD,t} \times ER_t \tag{1}$$

On this basis, all price series are standardized. First, trading days are aligned and ST samples and missing values are eliminated to form a balanced panel. Then, all series are processed by natural logarithm, and their first differences are calculated to obtain stationary logarithmic return series:

$$R_t = ln(P_t) - ln(P_{t-1}) \tag{2}$$

3.2. Model Construction

3.2.1 Continuous Wavelet Transform (CWT)

Continuous wavelet transform is a basic tool for time-frequency analysis. Its core idea is to project a one-dimensional time series onto a two-dimensional time-frequency plane through a scalable and translational mother wavelet function, so as to obtain local information in both time and frequency domains simultaneously. For a given time series $x(t)$, its continuous wavelet transform $W_x(\tau,s)$ is defined as the convolution of the mother wavelet function $\psi(t)$ and the series:

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

where τ is the translation parameter controlling the position of the wavelet on the time axis; s is the scale parameter (s>0), which is inversely proportional to frequency (f≈1/s). A larger scale corresponds to a lower frequency (long term), and a smaller scale corresponds to a higher frequency (short term). $\psi^*(\cdot)$ denotes the complex conjugate of the mother wavelet function. The transform result $W_x(\tau,s)$ is a complex number. Its modulus $|W_x(\tau,s)|$ represents the energy intensity at a specific time-frequency point (τ,s), and the phase $\phi_x(\tau,s)=\arg\boxed{f()}(W_x(\tau,s))$ reflects the local periodic characteristics at that point.

The selection of the mother wavelet needs to meet the admissibility condition and usually has zero mean. In financial time series analysis, the complex Morlet wavelet is widely adopted due to its good time-frequency localization property and ability to provide phase information. Its expression is:

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

where ω_0 is the central frequency, usually set to 6 to ensure good frequency resolution.

3.2.2 Wavelet Coherence (WTC)

Wavelet coherence is used to quantify the local correlation strength between two time series in the time-frequency domain. It is similar to the correlation coefficient in the time domain but has the advantage of time-frequency localization. Given two series $x(t)$ and $y(t)$ and their wavelet transforms $W_x(\tau,s)$ and $W_y(\tau,s)$, their cross wavelet spectrum is defined as:

$$W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s) \tag{5}$$

where $W_y^*(\tau,s)$ is the complex conjugate of $W_y(\tau,s)$. The modulus of the cross wavelet spectrum $|W_{xy}(\tau,s)|$ reflects the covariance energy of the two series at the time-frequency point (τ,s).

To obtain a coherence measure between 0 and 1, the modulus of the cross wavelet spectrum needs to be smoothed and normalized. Wavelet coherence $R^2(\tau,s)$ is defined as the ratio of the squared modulus of the smoothed cross wavelet spectrum to the product of the respective smoothed wavelet power spectra:

$$R^2(\tau,s)=\frac{|S(s^{-1}W_{xy}(\tau,s))|^2}{S(s^{-1}|W_x(\tau,s)|^2)\cdot S(s^{-1}|W_y(\tau,s)|^2)} \tag{6}$$

where S denotes the smoothing operator in both time and scale dimensions. The closer $R^2(\tau,s)$ is to 1, the stronger the local correlation between the two series in the specific time-frequency region.

In addition, the phase difference of wavelet coherence $\phi_{xy}(\tau,s)=\arg(W_{xy}(\tau,s))$ provides information on the lead-lag relationship between the two series:

1. If $\phi_{xy}\in(0,\pi/2)$ or $(-\pi/2,0)$, the two series are positively correlated, and the arrow points to the right.
2. If $\phi_{xy}\in(\pi/2,\pi)$ or $(-\pi,-\pi/2)$, the two series are negatively correlated, and the arrow points to the left.
3. The specific angle of the phase difference can further judge which series leads and which lags.

3.2.3 Quantile Granger Causality Test

To reveal the possible nonlinear and multi-scale causal orientation between the crude oil market and the new energy stock market, this study combines the Maximum Overlap Discrete Wavelet Transform (MODWT) with the nonlinear Granger causality test to construct a multi-scale nonlinear causality test framework. This framework overcomes the limitations of traditional linear methods in single time scale and linear assumptions.

Step 1: Multi-scale Series Decomposition Based on MODWT

First, the original time series X_t and Y_t (representing the crude oil market and new energy stock market indices respectively) are decomposed by J-level MODWT. As a translation-invariant wavelet transform, MODWT is suitable for finite-length time series and can decompose them into components of different scales without losing sample size. The decomposition process is realized through a set of scale filters $h_{j,l}$ and wavelet filters $g_{j,l}$ (j=1,...,J):

$$\widetilde{W}_{j,t}=\sum_{l=0}^{L_j-1}\tilde{g}_{j,l}X_{t-l}\ \mathrm{mod}\ N,\tilde{V}_{J,t}=\sum_{l=0}^{L_J-1}\tilde{h}_{J,l}X_{t-l}\ \mathrm{mod}\ N \tag{7}$$

where $W_{j,t}$ is the j-th level wavelet coefficient (representing the detail component on scale $\tau_j=2^{j-1}$, i.e., fluctuations in a specific frequency band), $V_{J,t}$ is the J-th level scale coefficient (representing the approximate component on scale $\tau_J=2^J$, i.e., the long-term trend), L_j is the length of the j-th level filter, and N is the total sample size. Through inverse transform, the original series can be accurately reconstructed as the sum of each scale component:

$$X_t=\sum_{j=1}^{J}\widetilde{D}_{j,t}+\tilde{S}_{J,t} \tag{8}$$

where $D_{j,t}$ is the j-th scale detail component reconstructed from wavelet coefficients, and $S_{J,t}$ is the approximate component reconstructed from scale coefficients. The same operation is performed on Y_t to obtain the corresponding multi-scale decomposition series $D^Y_{j,t}$ and $S^Y_{J,t}$.

Step 2: Principle and Implementation of Quantile Granger Causality Test

After obtaining the component series on each scale j, the quantile Granger causality test is performed independently on each scale. The core idea of the test is: if the past information of series X can significantly improve the prediction accuracy of the current conditional quantile of series Y, then X is said to be the Granger cause of Y at the specific quantile τ.

For the component series $D_{j,t}^{X}$ and $D_{j,t}^{Y}$ on scale j, consider the following quantile autoregressive model:

$$Q_\tau(D_{j,t}^Y|\mathcal{L}_{t-1}) = \alpha(\tau) + \sum_{k=1}^{p} \beta_k(\tau) D_{j,t-k}^Y + \sum_{l=1}^{q} \gamma_l(\tau) D_{j,t-l}^X \tag{9}$$

where $Q_\tau(\cdot|L_{t-1})$ denotes the τ-th quantile ($\tau \in (0,1)$) conditional on the information set L_{t-1} (including past values of Y and X); p and q are the lag orders of Y and X respectively, which can be determined by information criteria; $\alpha(\tau)$, $\beta_k(\tau)$, $\gamma_l(\tau)$ are coefficients to be estimated depending on the quantile τ.

To test the null hypothesis $H_0{:}\gamma_1(\tau)=\gamma_2(\tau)=...=\gamma_q(\tau)=0$ that "D_j^X is not the Granger cause of D_j^Y at quantile τ", this study adopts the Quasi-Likelihood Ratio Test (QLR) or Wald test proposed by Koenker and Machado (1999). Taking the Wald test as an example, the statistic is constructed as:

$$W_\tau = \frac{\hat{\gamma}(\tau)'[\boldsymbol{\Omega}(\tau)]^{-1}\hat{\gamma}(\tau)}{\tau(1-\tau)} \sim \chi^2(q) \tag{10}$$

where $\hat{\gamma}(\tau)$ is the estimated coefficient vector $(\hat{\gamma}_1(\tau),...,\hat{\gamma}_q(\tau))'$, and $\hat{\Omega}(\tau)$ is a robust estimator of its covariance matrix. If W_τ is greater than the $\chi^2(q)$ critical value at a given significance level, the null hypothesis is rejected, indicating that there is a Granger causal relationship from X to Y at quantile τ.

Step 3: Constructing a Multi-scale Quantile Causality Network

By systematically performing the above tests on a set of representative quantiles (e.g., τ=[0.1,0.2,...,0.8,0.9], this study constructs a three-dimensional causality analysis network. It can simultaneously reveal the scale dimension heterogeneity, quantile dimension asymmetry, and directional dynamics of variables. Finally, this framework not only tests the existence of causality, but also finely quantifies the dependence of its strength and direction on market conditions and investment horizons.

4. Empirical Results and Analysis

4.1. Preprocessing Results and Descriptive Statistics

Table 2 shows the descriptive statistics of the logarithmic return series of each market. It can be seen that all six series have 1827 observations, covering the complete sample interval. In terms of mean value, each series ranges from 6.182 to 7.879, reflecting the differences in price levels of different assets during the sample period. In terms of fluctuation range, the standard deviations of photovoltaics and new energy lithium batteries rank among the top in all new energy sectors, indicating more intense price fluctuations in these two sectors. In contrast, the standard deviations of nuclear energy and hydropower are significantly smaller, showing higher stability of returns and relatively gentle fluctuations. The standard deviation of the crude oil market is 0.260, which is between those of various new energy sectors. The above characteristic differences initially indicate that there is significant heterogeneity in return volatility among different new energy sub-sectors, providing a preliminary basis for the subsequent sub-sector investigation of time-frequency correlation between crude oil and each sector.

Table 2. Descriptive Statistics of Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Crude Oil	1827	6.182	0.260	5.331	6.693
Photovoltaic	1827	7.879	0.422	7.081	8.681
Wind Power	1827	7.169	0.345	6.366	7.862
Nuclear Power	1827	7.769	0.105	7.521	8.032
Hydropower	1827	7.589	0.136	7.327	7.829
New Energy Lithium Battery	1827	7.823	0.461	6.922	8.699

To test the stationarity and distribution characteristics of each series, this study further conducts the ADF unit root test and Jarque-Bera normality test. Table 3 shows the test results. The ADF test results show that the ADF statistics of all series are highly significant, indicating that the null hypothesis of the existence of a unit root can be rejected at the 1% significance level. That is, all logarithmic return series are stationary processes, meeting the prerequisite requirements of subsequent time-frequency analysis for series stationarity. This result also indicates that each market does not show a random walk during the sample period, and price changes have a certain degree of mean reversion.

The JB normality test results show that the JB statistics of all series are large and the p-values are all less than 0.001, indicating that the null hypothesis of normal distribution can be rejected at the 1% level. This means that the return series of each market show significant "leptokurtosis and fat tail" characteristics, that is, the probability of extreme returns is higher than the theoretical expectation of normal distribution. This is consistent with the return distribution characteristics observed in empirical studies of other financial markets. Therefore, traditional linear models based on the normal distribution assumption may be difficult to fully capture the complex interaction between crude oil and new energy markets. Thus, it is necessary to adopt an analysis framework that can effectively characterize nonlinear correlation, which demonstrates the rationality of introducing multi-scale quantile Granger causality test in this paper.

Table 3. ADF Unit Root Test and Jarque-Bera Normality Test of Series

Variable	Level Value	First Difference	JB Statistic	JB Test p-value
Crude Oil	0.4683	<0.001	284.6	<0.001
Photovoltaic	0.9364	<0.001	119.3	<0.001
Wind Power	0.917	<0.001	74.14	<0.001
Nuclear Power	0.0672	<0.001	50.67	<0.001
Hydropower	0.0228	<0.001	110.6	<0.001
New Energy Lithium Battery	0.849	<0.001	78.68	<0.001

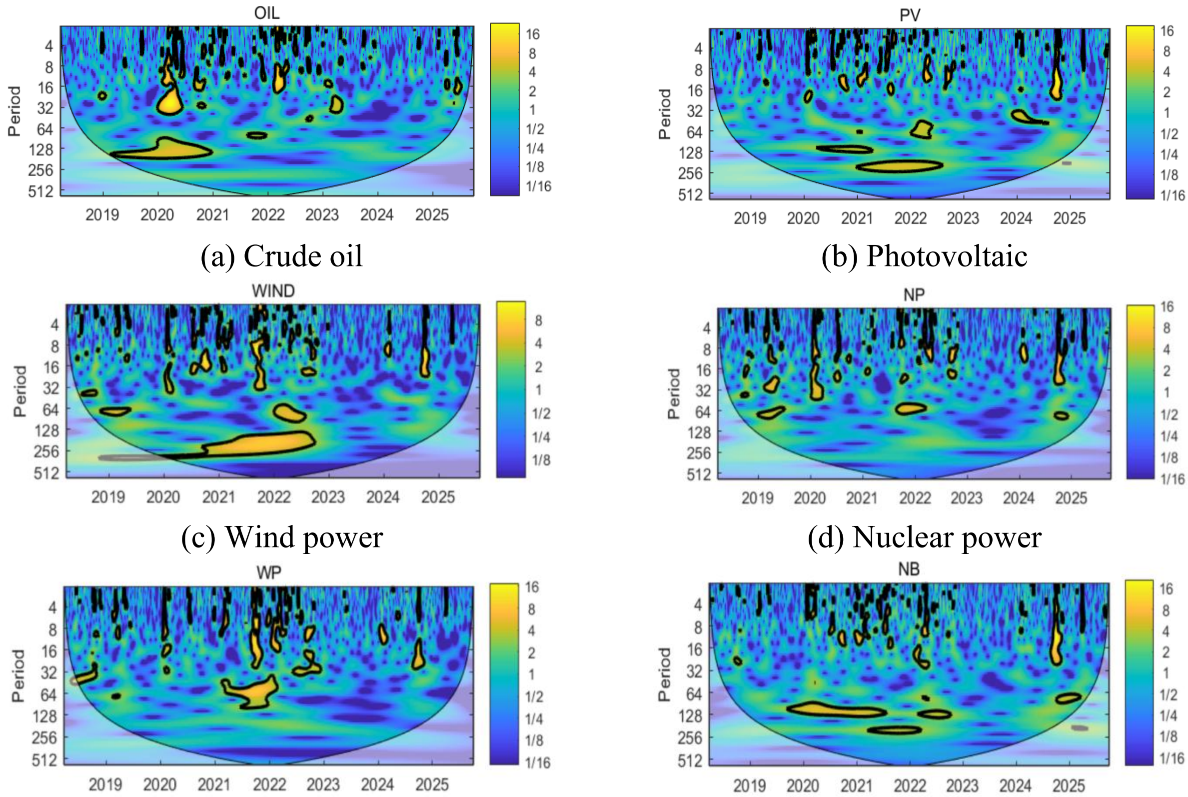
4.2. Time-Frequency Correlation Analysis

4.2.1 Continuous Wavelet Analysis

Using the Morlet wavelet function, this study implements continuous wavelet transform on the daily return series of Brent crude oil futures closing prices and each new energy stock index, and calculates the corresponding wavelet phases synchronously. This process aims to obtain the dynamic characteristics of the two markets in the time-frequency dimension and empirical evidence of their mutual correlation. Figure 1 shows the time-frequency distribution results of the return series of crude oil and each new energy stock index after continuous wavelet transform. In the figure, the horizontal axis represents time, and the vertical axis represents frequency and corresponds to different time periods. The area circled by the black contour is the significant area at the 5% level. The color gradient of the image changes from light to dark, representing the change of the wavelet power spectrum value at the corresponding time-frequency local position. The darker the color, the stronger the volatility energy at that position.

From the wavelet power spectrum of the crude oil return series (Figure 1-a), the significant high-energy areas are mainly concentrated in the low-frequency band, indicating that the price fluctuations of the crude oil market are mainly driven by long-term factors. In contrast, the energy in the medium- and high-frequency bands is relatively weak, indicating that short-term shocks are not significant. This confirms that the crude oil market is much more sensitive to long-term variables such as geopolitics and macroeconomic policies than to short-term noise. The wavelet power spectra of each new energy stock index show differentiated characteristics. The photovoltaic (Figure 1-b) and new energy battery (Figure 1-f) indices show extensive significant energy areas in the medium- and high-frequency bands, indicating that their price fluctuations have both short-term event response and medium-term trend change characteristics. The significant energy of the nuclear energy (Figure 1-d) and hydropower (Figure 1-e) indices is mostly distributed in the medium-frequency range, reflecting that their fluctuations are mainly affected by medium-term factors such as industrial policies and project construction cycles. The significant energy of the wind power index (Figure 1-c) is relatively concentrated in the low-frequency area, indicating that its trend is more dominated by slow variables such as long-term climate conditions and macro planning.

From the perspective of time-domain evolution, from early 2020 to 2021, each market generally showed energy accumulation in the higher frequency bands, which is consistent with the severe short-term shocks caused by the outbreak of the COVID-19 pandemic and subsequent policy responses. After 2021, the energy of most new energy indices in the medium- and low-frequency bands increased, which may correspond to the gradual emergence of medium- and long-term factors such as post-pandemic economic recovery and continuous efforts in energy transition policies. In addition, the color of the low-frequency area of some indices deepened in the later period of the sample, suggesting a possible structural shift, which needs to be further explained in combination with subsequent coherence and causality analysis.



(a) Crude oil (b) Photovoltaic

(c) Wind power (d) Nuclear power

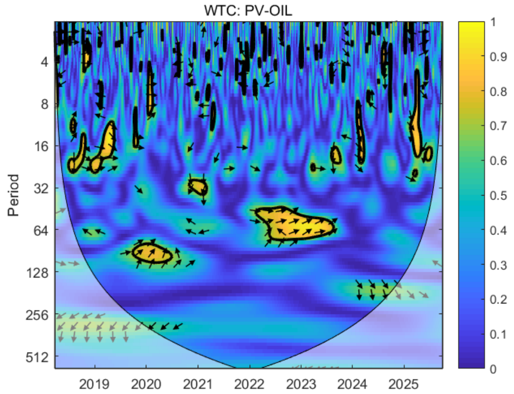
(e) Hydropower (f) New energy lithium battery

Figure 1. Continuous Wavelet Transform of Crude Oil and New Energy Stock Market Indices

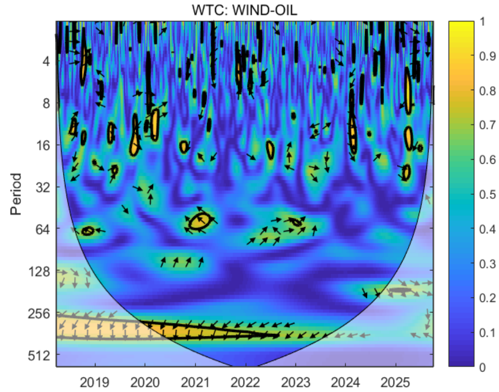
4.2.2 Wavelet Coherence Analysis

Wavelet coherence analysis is used to characterize the local correlation strength and phase relationship between the crude oil market and the new energy stock market in the time-frequency domain, so as to reveal the dynamic correlation pattern and lead-lag structure between the two across different time scales. Figure 2 shows the wavelet coherence maps between Brent crude oil and the five sub-sector indices of photovoltaics, wind power, nuclear power, hydropower, and new energy lithium batteries. The color depth indicates the coherence strength, the arrow direction indicates the phase relationship, and the significant areas are tested by Monte Carlo simulation at the 5% significance level.

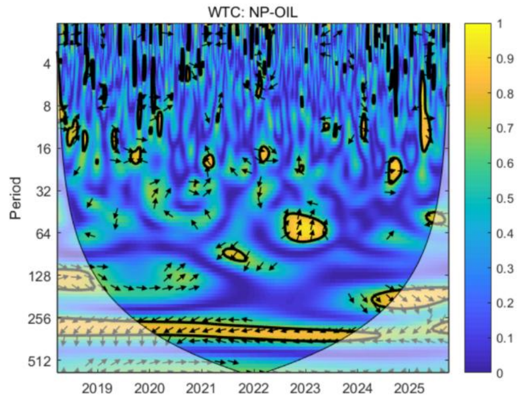
Overall, the correlation between crude oil and each new energy sector shows obvious scale dependence and time-varying characteristics. In the higher frequency bands, the coherence is generally weak and unstable, indicating that the two markets are driven by their own specific factors in the short term, and the linkage is not significant. In the medium- and low-frequency bands of the medium- and long-term cycles, several sustained and significant coherence areas appear, indicating that there is a structural correlation between the two in the medium and long term.



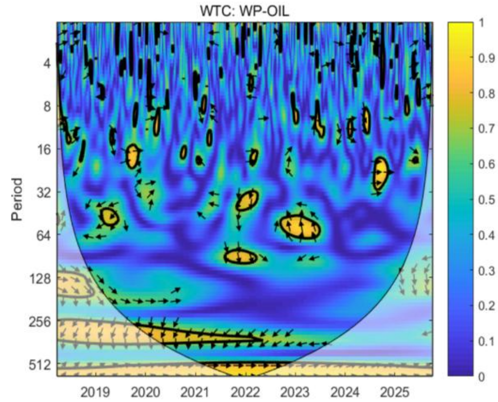
(a) Photovoltaic-oil



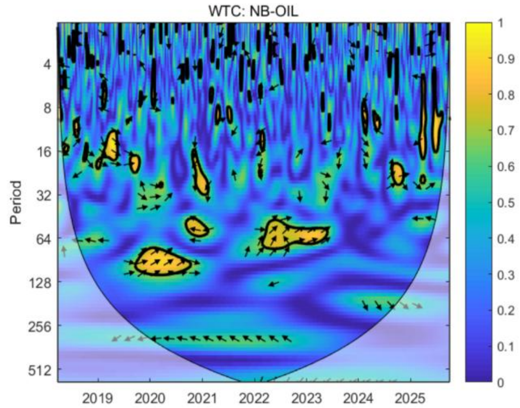
(b) Wind power-oil;



(c) Nuclear power-oil



(d) Hydropower-oil



(e) New energy lithium battery-oil

Figure 2. Wavelet Coherence Between Crude Oil and New Energy Stock Market Indices

Specifically, photovoltaics and crude oil (Figure 2-a) show significant positive coherence in the medium-frequency band from 2019 to 2021, and most arrows point to the upper right. This indicates that crude oil price changes led the photovoltaic sector during this period, which may reflect that oil prices affect the investment sentiment of the photovoltaic industry through cost transmission or substitution expectations. The coherence between the wind power sector and crude oil (Figure 2-b) increased in the medium- and low-frequency bands after 2021, and the phase arrows mostly point to the lower left, suggesting a negative correlation. The wind power trend shows a certain lagged reverse adjustment relative to crude oil, which may be related to wind-solar complementary policies and power grid accommodation mechanisms. The coherence areas between nuclear power, hydropower and crude oil (Figure 2-c, Figure 2-d) are mainly concentrated in the low-frequency band, and the coherence is weak, reflecting that these two sectors, which are strongly constrained by policies and natural conditions, have a relatively weak long-term correlation with the crude oil market. The new energy lithium battery sector (Figure 2-e) shows intermittent coherence areas with crude oil on multiple scales, especially significant positive coherence in the medium- and high-frequency bands from 2020 to 2022. The phase relationship shows that the two fluctuate almost synchronously, which may be related to the high sensitivity of the electric vehicle industry to oil prices and the interaction of the industrial chain.

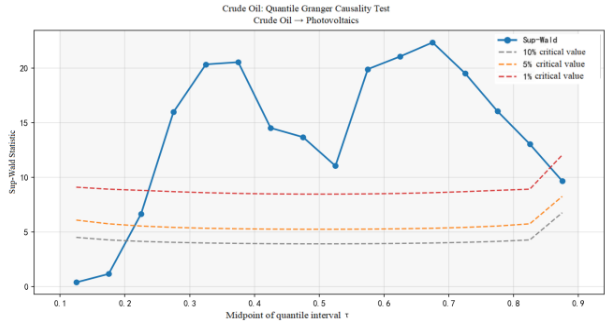
In summary, the correlation between crude oil and the new energy stock market is not uniformly distributed, but depends on the time scale and sub-sectors. In the medium- and long-term scales, the substitution effect and macro linkage are more obvious, and there is a leading relationship from crude oil to some new energy sectors, which provides an important frequency-domain basis for the subsequent multi-scale causality test.

4.3. Multi-scale Nonlinear Granger Causality Test

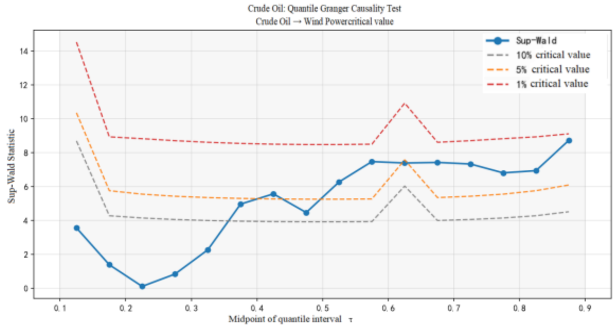
To reveal the nonlinear causal relationship between the crude oil market and new energy sub-sectors under different time scales and market conditions, this study further conducts a multi-scale quantile Granger causality test. First, each variable is decomposed into three typical time scales: short term (2–4 days), medium term (8–16 days), and long term (32–64 days) through the maximum overlap discrete wavelet transform. Then, nine representative quantiles from 0.1 to 0.9 are selected on each scale to systematically test the nonlinear causal effect of crude oil returns on each new energy sector return. Figure 3 shows the test results of crude oil on the five sectors of photovoltaics, wind power, nuclear power, hydropower, and new energy lithium batteries. The color depth indicates the size of the test statistic, and the asterisk mark indicates that causality exists significantly at the 5% level.

It can be seen from the results in Figure 3 that the causal effect of crude oil on each new energy sector shows significant scale heterogeneity. The causality of the photovoltaic sector (Figure 3-a) is mainly concentrated in the medium- and long-term scales, and is continuously significant at quantiles above 0.5. This indicates that crude oil has a stable predictive ability for the medium- and long-term trend of photovoltaics in a stable or rising market state. The causal effect of the wind power sector (Figure 3-b) presents a pattern of coexistence of short-term and long-term, and the causality is particularly significant at extreme quantiles. This indicates that the impact of crude oil on wind power is more prominent under extreme market sentiment. The causal structure of the nuclear power and hydropower sectors (Figure 3-c, Figure 3-d) is relatively sparse. Significant causality only appears at the long-term scale and extreme quantiles, and the strength is generally lower than that of photovoltaics and wind power. This reflects that these two sectors are strongly constrained by policies and natural conditions, and their marketization degree is relatively low. In contrast, the new energy lithium battery sector (Figure 3-e) shows the most abundant causal structure, with significant causality on short-, medium-, and long-term scales, covering the full quantile range. This reflects that the lithium battery industry, as the core link of electric vehicles and energy storage systems, has multiple transmission mechanisms with crude oil prices.

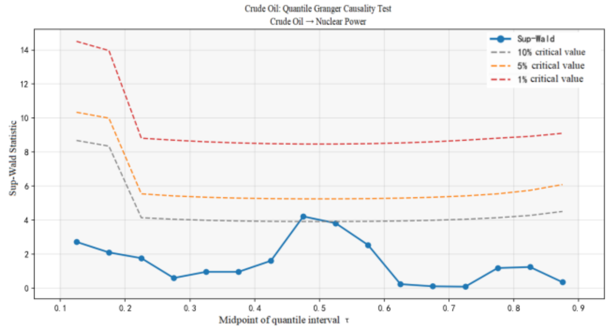
Thus, the causal effect of crude oil on the new energy sector has significant economic significance. Photovoltaics and lithium batteries are driven by changes in oil price expectations in the medium- and long-term rising markets, reflecting the substitution effect and cost transmission mechanism. That is, higher oil prices strengthen the economic efficiency of new energy, thereby stimulating investment and capacity expansion. Wind power is sensitive to oil price fluctuations under short-term extreme market sentiment, which stems from its high subsidy dependence and policy uncertainty, making it vulnerable to sudden changes in risk appetite. Nuclear power and hydropower are rigidly constrained by natural endowments and administrative pricing, so the market transmission channels are not smooth, resulting in a sparse causal structure in this study.



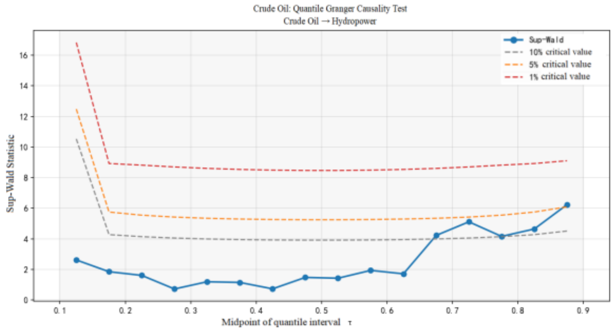
(a) Crude oil → Photovoltaic



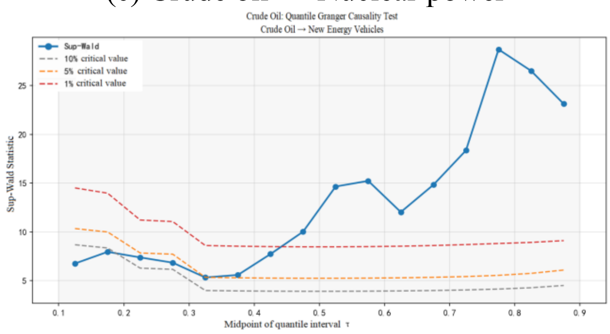
(b) Crude oil → Wind power



(c) Crude oil → Nuclear power



(d) Crude oil → Hydropower



(e) Crude oil → New energy lithium battery

Figure 3. Results of Multi-scale Nonlinear Granger Causality Test Between Crude Oil and New Energy Stock Market

5. Conclusions and Recommendations

This paper mainly uses a time-frequency analysis framework composed of continuous wavelet transform, wavelet coherence, and multi-scale quantile Granger causality test to systematically investigate the dynamic correlation structure between Brent crude oil futures and China's five major new energy sub-sectors from March 2018 to September 2025. The empirical results show that the interaction between crude oil and the new energy stock market presents a significant dynamic correlation relationship. The main conclusions are as follows. First, they have differentiated distribution characteristics. The volatility energy of crude oil is concentrated in the low-frequency area, indicating that its price changes are mainly driven by long-term structural factors such as macroeconomics and geopolitics. New energy sectors generally also show significant energy accumulation in the medium- and high-frequency bands, reflecting their high sensitivity to short-term market sentiment and policy news. Second, the correlation shows obvious time-frequency dual heterogeneity. Wavelet coherence analysis shows that crude oil and new energy sectors have a structural correlation in the medium- and long-term scales, while the coherence is weak and unstable in the short-term scale. Third, the causal effect has significant scale dependence and quantile asymmetry. Multi-scale quantile Granger causality tests show that the causal effect of crude oil on different new energy sectors differs significantly in both time scale and market state dimensions.

Based on the above conclusions, the following recommendations are put forward. At the policy level, the traditional "one-size-fits-all" intervention idea for new energy sectors should be abandoned. For photovoltaic and lithium battery industries, which are closely related to crude oil and have significant medium- and long-term causality, a dynamic monitoring mechanism for oil price expectations should be established. In the stage of sustained high oil prices, the regulation of key raw material reserves and price guidance should be appropriately strengthened. For nuclear power and hydropower sectors with low marketization and sparse causal structure, the long-term stability of electricity price policies and project approval should be maintained to avoid frequent adjustments due to short-term oil price fluctuations. In addition, oil price expectation variables should be incorporated into the design of carbon markets and green power trading systems. A dynamic benchmark price mechanism in green power trading should be explored, and the supply of carbon allowances should be appropriately adjusted according to the medium-term trend of crude oil prices to improve the efficiency of price signal coordination between traditional and new energy markets. At the investment and risk management level, short-term traders should recognize that the correlation between crude oil and most new energy sectors is not significant on the 2–4-day scale, and strategy formulation should focus on the technical signals of each sector itself. Medium- and long-term allocators can focus on the predictive ability of crude oil trend changes on photovoltaic and lithium battery sectors, especially in the stable or rising market stage. For extreme market environments, risk managers need to be alert to tail risk spillovers from sharp oil price fluctuations to wind power assets through sentiment channels. It is recommended to include the crude oil volatility index as an early warning variable in the hedging strategy of wind power assets.

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