Linkages between Energy Prices and Energy Stocks in China: A Study Based on Wavelet Analysis

Tianyu Zhao
Henan Institute of Technology: Henan Institute of Science and Technology

Yongda He (hyda2008@126.com)
Shanxi University of Finance and Economics  https://orcid.org/0000-0002-3553-0920

Martin Bai
The University of Waikato

Shuai Shao
East China University of Science and Technology

Research Article

Keywords: Comprehensive energy price index, energy industry stock, Morlet wavelet, multi-resolution analysis

Posted Date: May 25th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2676028/v1

License: © This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License
Linkages between Energy Prices and Stock Markets in China:
A Study Based on Wavelet Analysis

Tianyu Zhao¹, Yongda He²,³,⁎, Martin Bai³, Shuai Shao⁴, #

1. School of Economics, Henan Institute of Technology, Xinxiang, 453003, China
2. School of Statistics, Shanxi University of Finance and Economics, Taiyuan 030006, China
3. School of Management, University of Waikato, Hamilton 0800, New Zealand
4. School of Business, East China University of Science and Technology, Shanghai, 200237, China

*Corresponding author
# The author is considered as equally contributing first author
Tel.: (+64) 22 657 7811, +86 351 7666902, 13703513896
E-mail addresses: yongdah@waikato.ac.nz; heyd@sxufe.edu.cn

Abstract: This study constructs a comprehensive energy price index and applies the Morlet continuous wavelet transform to investigate the relationship between energy prices and energy industry stock markets. It also tests the multi-scale linear and nonlinear causality using multi-resolution decomposition. The empirical findings indicate that: (1) energy prices and stock market volatilities demonstrate a stable negative correlation in the medium- and long-term frequency domain, and the fluctuation of energy stock prices precedes that of energy prices since 2018. (2) Energy prices and stock markets exhibit bidirectional causality. The short- and medium-term driving effects of energy stocks and energy prices are more pronounced than the overall change in stock markets over a period of 16 months. The linkage between energy prices and stock markets is primarily influenced by the stock market leading and driving energy price changes, indicating a common long-term trend. (3) In the long run, fluctuations in Chinese stock markets will lead to a reverse change in energy prices, providing policy management in the energy industry with an effective reference. However, the unstable short-term characteristics and lag of energy price changes suggest that the impact of energy prices on stock market investment has less reference value.

Key words: Comprehensive energy price index; energy industry stock; Morlet wavelet; multi-resolution analysis
1. Introduction

As an important industrial input factor and consumer product, energy is closely related to all aspects of modern economic life. The rapid economic development will inevitably lead to higher requirements for energy supply. From 2013 to 2019, energy production and consumption of China have increased year by year. In 2019, the national energy production increased by 5.1% year-over-year, and total consumption reached more than 4.8 billion tons of coal equivalent. At the same time, the external dependence of all kinds of energy, especially oil and gas resources, has reached new highs: after China had surpassed the United States (U.S.) as the world's largest oil importer in 2017, it surpassed Japan as the largest natural gas importer in 2018. In 2019, the net imports of crude oil and natural gas increased by 10% and 32% respectively, with external dependence exceeding 70% and 43% respectively. The Annual Development Report on World Energy (2020) points out that the global total demand for crude oil has decreased significantly due to many factors, such as the general slowdown of the global economy, the intensification of Sino-US trade frictions, and the normalization of COVID-19 pandemic control. Although the OPEC crude oil production reduction agreement has effectively prevented a cliff-like drop in oil prices, the downward trend of oil prices is still inevitable. In recent years, the market-oriented reform of China’s oil and gas sector led to further price liberalization and a highly shortened price adjustment period. The impact of frequent price fluctuations in the global energy market on domestic energy price fluctuations is thus expected to increase.

The interaction mechanism between energy prices and stock markets is mainly realized through the linkage with macroeconomic operations. A large number of existing theoretical articles and experience have shown that there is a very close relationship between energy prices, macroeconomic and stock markets. Any fluctuation of energy prices will inevitably affect the macroeconomic operations. From the perspective of supply, as a basic input factor in the production of most goods and services, a rise of energy prices increases production costs in corresponding industries, compresses the profit margin of enterprises, and therefore leads to a decline in output, which will lead to a reduction of industry scale or the shift to low energy intensive industries (Uri and Boyd, 1997; Erturk, 2011). From a demand perspective, rising energy prices lead to inflation and restrain consumption (John, 2009) and investment (Sweder, 1985). According to the stock pricing model, the stock price, as a discount of the future net profit of an enterprise, is affected by the expected cash flow and discount rate. The change in energy prices can affect both cash flow and discount rate (Huang et al., 2015). Energy prices’ changes affect the enterprises’ future cash flow by

---

① The relevant data has been retrieved from the data center of the National Bureau of Statistics of China.
② The Annual Development Report on World Energy (2020) jointly sponsored by the international energy security research center of the Graduate School of the Chinese Academy of Social Sciences and the Social Science Literature Press, was released in Beijing on December 11, 2020.
changing the cost, leading to stock prices’ fluctuations. The discount rate increases because a change of energy prices devalues the local currency of energy importing countries, which creates inflationary pressures. Moreover, rising factor prices also cause cost-based inflation, making it unprofitable to invest in stocks with lower yields.

The short-term and long-term effects of energy price shocks on the economy will be reflected in the stock market before the actual economy is affected. However, the degree of reaction of stocks is different for different industries (Oberndorfer, 2009). To a certain extent, the stock market reflects the pricing level and social expectations of energy resources. In turn, energy prices provide the action direction and decision-making basis for the supply and demand of funds in the stock market. As an "economic barometer", the stock markets reflect the comprehensive changes in the operation of the market economy and is affected by many factors including energy prices. Therefore, energy prices and the stock markets exhibit complex and diverse interactions in different regions, different periods and different industries. The studies of Wei et al. (2017), Zhang et al. (2019), Cevik et al. (2020) have strongly confirmed that the energy prices are important economic variables to explain the short-term and long-term fluctuations. In turn, the stock markets have an important guiding significance in energy price forecasting.

Combing a large number of existing streams of literatures, scholars' discussions on the relationship between energy prices and stocks can be summarized into three main aspects: regional heterogeneity, heterogeneity of industry sectors, and periodical heterogeneity prices (Pham, 2019; Bohl et al., 2015; Wen et al., 2014). Furthermore, scholars also explored the predictability of stock prices and energy prices based on possible linkage features (Kim et al., 2019; Anupam, 2017; Zhang et al., 2020). First, considering the regional heterogeneity of the EU, BRICs, Southeast Asian economies, China, U.S., Japan and other major countries, the risk of energy price spillovers on the stock market mainly depends on the energy dependence degree, energy policies and corresponding risk management strategies (Jiang et al., 2020). Oil and electricity prices are the main drivers of clean energy stock revenue volatility in U.S. and the European Union (EU), with symmetrical impact characteristics. That means an increase or decrease in extreme energy prices have the same effect (Reboredo and Ugolini, 2018). However, Ramz et al. (2018), and Baris and Ugur (2019) who used the non-linear autoregressive distributed lag (NARDL) model found completely opposite. According to their results, the impact of oil prices on U.S. clean energy stocks is asymmetrical and has a non-linear transmission. In Asia, energy price shocks led to synchronous changes in Asian stock markets represented by China and Japan during the Global Financial Crisis (GFC) (Pham, 2019), while they had a negative impact in Pakistan (Arshad et al., 2016). In addition, the impact of energy demand shocks on energy prices and stock markets is also subject to significant regional differences (Ulusoy and Demiralay, 2017; Park and Park, 2014). Second, from a sub-sector
perspective, energy price shocks are also quite different in different sectors. Energy price shocks largely promote the herd behavior of financial investors, and there is evidence that rising oil prices cause greater damage to aviation, food and industry transportation sectors, while oil and gas exploration benefits during this period (Thorbecke, 2019). The impact on private enterprises’ stocks is greater, while the impact on state enterprises’ stocks is relatively small (Fan et al., 2019). There is a strong impact on the stock prices in the new energy vehicle sub industry in clean energy plate, and a smaller impact on the stock price fluctuation of other new energy (Lv et al., 2019). Third, research results based on economic cyclicality generally agree that the linkage between energy prices and the stock market has undergone a structural shift around the 2008 financial crisis (Managi and Okimoto, 2013; Tsai, 2015; Roman et al., 2018), and that the introduction of energy reform policies will also lead to structural mutation of energy stock prices (Ye et al., 2018). However, Christos et al. (2015) research on the Canadian stock markets showed that almost no stocks can be related to a particular commodity’s price at any certain market stage.

The authors of the aforementioned studies based their research on the classical vector autoregressive model (VAR) and successively optimized their research methods to multivariate VAR (MVAR), Markov-Switching (MS-VAR), multivariate GARCH (MGARCH), GARCH-in-meanVAR, EGARCH-copula, GARCH (including BEKK, DCC and CCC), quantile autoregressive distributed lag (QARDL), nonlinear autoregressive distributed lag (NARDL) model and other methods to analyze the linkage between energy price and stock market (Cong and Shen, 2013; Kyritsis and Serletis, 2017; Alsalman, 2016). At the same time, GMM estimation technique, directional spillover method, integrable non-autonomous Lotka-Volterra model, etc. have been introduced (Ahmad, 2017; Dominioni et al., 2019). We found that the above-mentioned multi-angle innovation models based on the traditional sequence analysis methods can easily draw empirical "final" conclusions about the relationship between the studied variables, but lack of sufficient grasp of more detailed information regarding the linkage impact. Furthermore, the traditional econometric model often requires many strict assumptions, including a linear structure of the model, the independence and normality of error variance, and the independence of explanatory variables. When some of the assumptions are not valid, the results may deviate greatly from reality.

Compared with the previous methods, wavelet analysis can effectively dispense with the specific assumptions made by traditional econometric models on volatility, covariance and structural mutations when studying financial time series, and expand the investigation of variables at a nonlinear level, enabling more comprehensive research progress. On the other hand, the wavelet transform process projects the one-dimensional sequence onto a time-frequency "two-dimensional plane". The multi-scale decomposition of the sample is more convenient for the extraction of certain basic features of the signal, so as to get more detailed time-frequency domain conclusions (Ramsey...
As oil is the most important energy resource for most countries and owns a strategic position in the global economy, most researchers tend to use the crude oil price fluctuation to represent the energy fluctuation of a country (region) when discussing the interaction between energy price and stock markets (Vasta and Basnet, 2020; Papapetrou, 2001). China is a large energy consumer. Its coal consumption overall accounts for more than 58% in light of its distinct resource endowment pattern. It is not applicable to simply use oil to represent the whole energy market (Cong and Shen, 2013; Sun et al., 2019; Xia et al., 2019). Rather, it is of great significance to investigate the comprehensive energy prices including coal and other major energy sources.

What impact will the fluctuation of China's energy prices have on the overall stock market and energy industry stock prices' changes? Conversely, how will stock market fluctuations affect energy market prices? To capture these possible effects, based on the construction of a comprehensive energy price index, this paper uses the wavelet method to expand the linkage analysis of China's energy prices, stock market, and energy stocks to the time-domain and frequency-domain, and tests the causality from the linear and nonlinear levels, so as to add comprehensive and detailed empirical conclusions to the relevant research in this region.

The structure of this paper is as follows: in the first part, the introduction, which includes a review of the research background on the linkage between energy prices and the stock markets, with an emphasis on the prevailing literature relating to the research direction and analysis tools. In the second part we provide a brief description of the mathematical expressions for the continuous wavelet transform, multi-scale decomposition principle and nonlinear Granger causality test in wavelet analysis. The third part entails our empirical analysis process and results, specifically based on construction of comprehensive energy price index with multiple indices. Furthermore, the linkage between energy prices and comprehensive stock prices, energy stock prices, and possible lead-lag structures are tested and discussed from the time-frequency domain perspective in this chapter. The fourth part is the conclusion and an outlook.

2. Models Selection and Specifications

2.1 Wavelet correlation theory

During the wavelet analysis, the window shape can automatically be adjusted according to the fluctuation characteristics of the signal. It has a higher (lower) time resolution and a lower (higher) frequency resolution when analyzing high (low) frequency part. Due to its "mathematical microscope" characteristic, this method is often used as a mathematical tool for time series analysis.

Let $\psi(t)$ be a square integrable function: $\psi(t) \in L^2(R)$. If its Fourier transform can satisfy the condition
\[ C_\psi \equiv \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \]  

(1)

\( \psi(t) \) can be defined as a wavelet function or generating function. Formula (1) is defined as the wavelet admissible condition.

2.1.1 Continuous wavelet

The continuous wavelet is a set of function sequences obtained by the expansion and translation of a single generating wavelet function. It is a real square integrable function and is given by the following formula:

\[ \psi_{a,t}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right), \quad a, \tau \in \mathbb{R}; a > 0 \]  

(2)

where \( a \) is the scale parameter, \( \tau \) being the translation parameter; \( a, \tau \) are continuously changing values, and \( \sqrt{a} \) is a standardized constant to ensure that the wavelet has unit variance. Since \( \psi(t) \) satisfies the admissible condition, the wavelet has an effective time-frequency location in both the time domain and the frequency domain.

**Continuous wavelet transform.** The inner product of the wavelet function \( \psi_{a,t}(t) \) and the signal to be analyzed is the continuous wavelet transform coefficient. The process means that a one-dimensional sequence \( x(t) \) is projected onto the two-dimensional plane of "time-frequency" to facilitate the extraction of following basic features:

\[ WT_s(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^*\left(\frac{t-\tau}{a}\right) dt, \quad a > 0 \]  

(3)

The corresponding frequency domain is expressed as:

\[ WT_s(a, \tau) = \frac{\sqrt{a}}{2\pi} \int_{-\infty}^{+\infty} X(\omega) \psi^* (a\omega) e^{j\omega \tau} d\omega \]  

(4)

When continuous wavelet transform is used to analyze the time evolution of frequency domain information of specific time series, the definition is further expressed as:

\[ W_s(s) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t}{s}\right) dt \]  

(5)

where * denotes complex conjugate and the scale factor \( s \) traverses the value to detect each frequency component in the sequence.

**Cross Wavelet Transform.** Cross wavelet power spectrum capture is the covariance contribution of sequences in time-frequency space. The cross wavelet transform of the time series \( x(t) \) and \( y(t) \) with continuous wavelet transform \( W_n^X(s) \) and \( W_n^Y(s) \) is defined as:

\[ W_n^{XY}(s) = W_n^X(s) W_n^{Y*}(s) \]  

(6)

where * denotes complex conjugate. The result is a representation of the interdependence between the series.

**Square wavelet coherence coefficient.** The concept of one-dimensional "square wavelet coherence coefficient" was proposed by Torrence and Webster (1999). It measures the local co-shift characteristics of two sequences in a specific time-frequency domain and is defined as:

\[ R_n^2(n) = \frac{\left| \left(s^{-1}W_n^{XY}(s)\right)\right|^2}{\left(s^{-1}\left|W_n^X(s)\right|^2\right)\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \]  

(7)
where $R^2(s)$ represents the degree of dependence between sequences. When the dependence between $x(t)$ and $y(t)$ is weak, it is close to 0 and when the dependence is strong, it is close to 1. Since the distribution of $R^2(s)$ is unknown, its statistical significance is obtained through Monte Carlo process simulation when performing spectral analysis.

**Wavelet coherent phase difference.** It is used to capture the negative or positive correlation of two time series in the time-frequency space and the lead-lag structure between them. Torrence and Webster (1999) defined the wavelet coherent phase difference as:

$$ \varphi_{xy}(s) = \tan^{-1}\left(\frac{\Im(s^{-1}(W^X_n(s)))}{\Re(s^{-1}W^X_n(s))}\right) $$

(8)

where $\Im$ and $\Re$ are the real part and the imaginary part of the smoothening power spectrum respectively. The phase relationship between the two-time series is as follows: when the arrow points to the right (left), the series changes in the same (opposite) direction, with positive (negative) correlation and when the arrow points down (up), the second (first) series will guide the first (second) series.

**Morlet wavelet.** The optimal wavelet base is mainly determined by the error of the wavelet analysis results. Each wavelet is divided into different application fields according to its own characteristic, which is used to represent all kinds of data features. In this paper, the Morlet wavelet is used for continuous wavelet transform, which is often used in the analysis of economic and financial data to study the amplitude and phase. It consists of Gaussian window Fourier transform including sine and cosine oscillations at the center frequency. The specific form is as follow:

$$ \psi(t) = \pi^{-\frac{1}{4}}e^{iw_{0}t} e^{-\frac{t^2}{2}} $$

(9)

where $\pi^{-\frac{1}{4}}$ is standardized parameter to ensure wavelet with unit variance. $e^{iw_{0}t}$ is the Gaussian envelope of a unit standard deviation. $e^{-\frac{t^2}{2}}$ is complex sine curve. The values of the parameter $w_0$ are set by themselves to realize local balance between time domain and frequency domain.

**2.1.2 Discrete wavelet**

In discrete wavelet analysis, the wavelet base is a set of standard orthogonal base which is obtained by a pair of specially constructed function $\phi$ and $\psi$ through binary stretching translation, in which $\phi$ and $\psi$ are defined as base function of the parent wavelet and generating wavelet respectively, and satisfy:

$$ \int \phi(t)dt = 1 $$

$$ \int \psi(t)dt = 0 $$

(10)

where the trend and low frequency information in the data series is obtained by the parent wavelet, while the detail and high frequency information is obtained by the generating wavelet. The complete wavelet base obtained by stretch translation transform is as follows:
In the formula, \( j = 1, \ldots, J \) represents the scale parameter and \( k = 1, \ldots, 2^j \) the displacement parameter. According to this, all functions in the \( L^2(\mathbb{R}) \) space can be extended to the set of the wavelet base, which is expressed as a linear combination of wavelet functions on a set of the wavelet base.

Discrete wavelet can be used to decompose the sequence \( y(t) \) into different time scales:

\[
y(t) = \sum_s s_{j,k} \phi_{j,k}(t) + \sum_k d_{j,k} \psi_{j,k}(t) + \sum_k d_{j-1,k} \psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k} \psi_{1,k}(t) \tag{12}
\]

where \( \phi(t) \) is defined as scale function, \( \psi(t) \) as wavelet function and \( s_{j,k}, d_{j,k}, \ldots, d_{1,k} \) as wavelet coefficient which measures the contribution of the corresponding wavelet function to the overall signal. Therefore, the time series can be expressed by \( J \)-level multi-resolution decomposition as:

\[
y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t) \tag{13}
\]

where the frequency component \( D_j \) corresponds to the short-term, medium-term and long-term changes explained by the shocks generated by the time scale \( 2^j \). \( S_j \) is the residual after \( D_{2^1}, \ldots, D_j \) is removed from the original sequence, and the value of \( J \) can be determined according to the need to set the multi-resolution level. \( D_j \) represents the series change of \( 2^j \) unit time scale.

**Maximum overlap discrete wavelet transform (MODWT)**. MODWT is an optimization method based on discrete wavelet transform proposed by Percival and Walden (2000). The relationship between wavelet filter \( \{h_j\} \) and scale filter \( \{g_j\} \) of MODWT and wavelet filter \( \{h_j\} \) and scale filter \( \{g_j\} \) of discrete wavelet transform is as follow:

\[
\tilde{h}_j = h_j / \sqrt{2} \tag{14}
\]

\[
\tilde{g}_j = g_j / \sqrt{2}
\]

For any time series of length \( N \), the wavelet coefficient and scale coefficient of MODWT are defined as:

\[
\tilde{W}_{j,t} = \sum_{l=0}^{L_j - 1} \tilde{h}_{j,l} x_{t-l \mod N} \tag{15}
\]

\[
\tilde{V}_{j,t} = \sum_{l=0}^{L_j - 1} \tilde{g}_{j,l} x_{t-l \mod N}
\]

where \( L_j \equiv (2^j - 1)(L - 1) + 1 \) is the width of wavelet filter \( \{h_{j,l}\} \) and scale filter \( \{g_{j,l}\} \). In this way, the time series can be decomposed into the high frequency part \( \tilde{W}_j \) and the low frequency part \( \tilde{V}_j \) by wavelet decomposition. We can obtain the multi-resolution decomposition process:

\[
\|x\|^2 = \|\tilde{W}_j\|^2 + \|\tilde{V}_j\|^2 = \sum_{j=1}^{J} \|\tilde{W}_{j}\|^2 + \|\tilde{V}_{j}\|^2 \tag{16}
\]

Similar to the discrete wavelet transform, its detail coefficient and approximate coefficient can be expressed as follow:
In formula (17), \( J_0 = J \).

Compared with the latter, it has following advantages: the length of series is not limited to an integer power of 2, its sampling characteristic increases the acquisition of low-frequency information in the process of multi-resolution decomposition, its translation invariance ensures that the wavelet coefficient do not change in the cyclic translation; and it produces a more progressive and effective wavelet variance estimation. Therefore, MODWT is usually used in the process of discrete wavelet transform.

### 2.2 Nonlinear Granger causality test

The disadvantage of linear causality test is that it cannot detect potential nonlinear dynamic structure. This paper uses the nonlinear Granger causality test method proposed by Hiemstra and Jones (1994) and adjusted by Diks and Panchenko (2006) to reduce the risk of rejecting too much to the null hypothesis in nonlinear causality test.

Let \( X_{lt} = (X_{l-t-1}, \ldots, X_l) \) and \( Y_{lt} = (Y_{l-t-1}, \ldots, Y_l) \) be lag vectors of two time series, in which \( (l_x, l_y) \geq 1 \). Then the null hypothesis is that \( X_{lt} \) does not contain any information about \( Y_{lt} \) and the null hypothesis is expressed as:

\[
H_0: (X_{lt}, Y_{lt}) \sim (Y_{lt})
\]  

(18)

Let \( W_t \) be \( W_t = (X_{i-l}, Y_{i-l}, Z_t) \), in which \( Z_t = Y_{lt} \). Since the distribution of \( W_t \) is invariant under the null hypothesis, the subscript can be removed \( (l_x = l_y = 1) \), then \( W = (X, Y, Z) \). Under the null hypothesis, \( Z \) and \( X \) are independent of each other, and the distribution of \( Z \) is the same under \( (X, Y) = (x, y) \) and \( Y = y \). If \( f_{X,Y,Z}(x, y, z) \) is used to denote the joint probability density, we get following:

\[
\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y, z)}{f_Y(y)}
\]  

(19)

Correspondingly, the null hypothesis of nonlinear causality can be represented as:

\[
H_0: \{X_t\} \text{ is not the Granger causation of } \{Y_t\}, \text{ which means:}
\]

\[
q_x = E[f_{X,Y,Z}(x, y, z)f_Y(y) - f_{X,Y}(x, y)f_{Y,Z}(y, z)] = 0
\]  

(20)

The estimator of local probability density \( f_W(W_t) \) is as follows:

\[
\hat{f}_W(W_t) = (2\varepsilon)^{-dW} n^{-1} \sum_{j=1}^{n} I_{ij}^W
\]  

(21)

Where \( \varepsilon \) is bandwidth parameter. when \( \|W_i - W_j\| \leq \varepsilon \), the value of indicative function \( I_{ij}^W = I(\|W_i - W_j\| \leq \varepsilon) \) is 1; in other cases, the value is 0. he construction statistics \( T_n \) is as follow:

\[
T_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i (\hat{f}_{X,Y,Z}(x_i, y_i, z_i)f_Y(y_i) - \hat{f}_{X,Y}(x_i, y_i)\hat{f}_{Y,Z}(y_i, z_i))
\]  

(22)
The standardized form is as follow:

\[
\sqrt{n} \frac{\left( T_n \left( \hat{\varphi} \right) - \theta \right)}{S_n} \xrightarrow{d} N(0,1)
\]  

Where, \( S_n \) is the asymptotic variance estimate of \( \sigma^2 \).

3. Empirical Results and Analysis

3.1 Construction of China’s comprehensive energy price index

3.1.1 Indicators selection

The energy price index comprehensively reflects the changes of various regional energy prices. Until now, China’s energy consumption is dominated by conventional fossil energy. in 2019, coal, oil and natural gas accounted for more than 85% (with coal accounts for 57%, oil accounts for 19.3%, and natural gas accounts for 8.1%) while other non-fossil energy sources accounted only for 14.9%. China is a major energy consumer and energy importing country: already being the world’s largest coal importer, its import volume has further increased in recent years with Australia and Indonesia ranking first and second most important import sources respectively. Oil and natural gas consumption is also heavily dependent on imports and the import volume continued to increase from 2015 to 2019, repeatedly reaching new highs. In 2019, the import volume of oil and natural gas increased by 9.5% and 6.9% year-on-year respectively. Despite the influence of the COVID-19 pandemic, the import volume in the first three quarters of 2020 still increased by 12.1% and 3.22% year-on-year respectively.

Due to the import dependence of China, energy consumption changes in the domestic energy price are highly affected by international changes. Considering the main components of energy in China’s consumer market, we incorporated domestic energy product price indicators and key foreign energy price indicators to jointly construct the CEPI.

Comprehensively considering the timeliness of data and the rationality of variable selection, this paper selects monthly data reflecting a total of 12 price variables of crude oil, coal, natural gas, power generation and electricity at home and abroad with sample interval from January 2007 to October 2020 (Table 1). The data has been retrieved from the National Bureau of Statistics, the Wind database and the official website of the U.S. Energy Information Administration (EIA). The export prices of Australian steam coal and Indonesian steam coal have been recorded by the General Administration of Customs during transportation to China.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Indicator description</th>
<th>Indicator type</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>Ex-factory price index of industrial products in China's coal mining and washing industry</td>
<td>Coal price</td>
</tr>
<tr>
<td>QHD</td>
<td>China's Qinhuangdao Datong premium mixed liquidation price</td>
<td></td>
</tr>
<tr>
<td>AC</td>
<td>Monthly average export price of Australian steam coal</td>
<td></td>
</tr>
<tr>
<td>YC</td>
<td>Monthly average export price of Indonesian steam coal</td>
<td></td>
</tr>
<tr>
<td>OI</td>
<td>Ex-factory price index of industrial products of China's oil and gas</td>
<td>Crude oil price</td>
</tr>
</tbody>
</table>
3.1.2 Data preprocessing and index construction

In order to eliminate the influence of exchange rate and price inflation fluctuations, the monthly average exchange rate of RMB against USD has been used to convert the price series (DQ, WTI, Brent, Henry, AC, YC) from USD into RMB. Then using the production price index PPI, all nominal price series have been deflated to obtain the real series of each indicator. Furthermore, the PPIRM, CI, OI, EI, GI year-on-year series are fixed based on the year of 2006 in order to facilitate analysis and comparison.

For standardizing the indicators, we have used the H-P filtering method adopted by scholars such as Goodhart and Hofmann (2001) for calculating the sample gap value based on the X-12 seasonal adjustment method. The sample trend value has been obtained with a parameter value which has been set as 14,400 according to the needs of monthly data filtering. The indicator gap value then equals the original sample value minus the sample trend value. Finally, the various indicators have been standardized using the variable name plus the suffix “gap” represents each variable’s gap value corresponding to the original index. The unit root test results show that all indicators are stationary series and can be constructed.

In this paper, we use the iterative master-factor method to solve the common factors. According to the principle that the characteristic root is greater than 1, three common factors have been obtained. The KMO and Bartlett test values are 0.839 and 2551.915 respectively, which explains the total variance of more than 82% and let us include that the common factor solution is reasonable and effective. Table 2 shows the factor loading results of each index on Fac1, Fac2, and Fac3 after factor rotation. It can be seen that Fac1 has a relatively large load on many domestic and foreign crude oil prices and foreign natural gas indicators. Therefore, Fac1 can be taken as the common factor of domestic and foreign crude oil prices. Similarly, Fac2 can be seen as the common factor of domestic and foreign coal prices, and Fac3 as the common factor of natural gas prices.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Indicator name</th>
<th>Load on Fac1</th>
<th>Load on Fac2</th>
<th>Load on Fac3</th>
</tr>
</thead>
<tbody>
<tr>
<td>the factor of domestic and foreign crude oil price</td>
<td>PPIRM_gap</td>
<td>0.769</td>
<td>0.531</td>
<td>0.236</td>
</tr>
<tr>
<td>the factor of</td>
<td>OI_gap</td>
<td>0.918</td>
<td>0.260</td>
<td>0.162</td>
</tr>
<tr>
<td></td>
<td>DQ_gap</td>
<td>0.958</td>
<td>0.120</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>WTI_gap</td>
<td>0.957</td>
<td>0.024</td>
<td>-0.056</td>
</tr>
<tr>
<td></td>
<td>BRENT_gap</td>
<td>0.968</td>
<td>0.040</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>HENRY_gap</td>
<td>0.726</td>
<td>0.273</td>
<td>-0.232</td>
</tr>
<tr>
<td>the factor of</td>
<td>CI_gap</td>
<td>0.289</td>
<td>0.870</td>
<td>0.241</td>
</tr>
</tbody>
</table>
domestic and foreign coal price
QHD_gap  0.392  0.764  -0.097
AC_gap   0.071  0.791  -0.012
YC_gap   -0.069 0.835  0.266
the factor of natural gas price
El_gap   -0.241  0.183  0.827
Gl_gap   0.491  0.083  0.699

Finally, referring to the research of Hai and Lin (2013) and others, we can get the comprehensive energy price index (Fig.1) by taking the variance contribution rate after factor rotation as weight. As visible in Fig.1, China’s energy prices’ fluctuation since 2007 can be separated into three periods: 2007 to early 2009 was a period with high fluctuations, domestic energy prices rose at first and then fell deep. From 2009 to the end of 2015, the energy price index rose at first and then fell deep again. During this period, the rise and fall of the price index crossed and fluctuations have been relatively small. Since the 13th Five-Year Plan period, energy prices have basically stabilized. In the beginning of 2020, energy prices have fallen sharply under the impact of the epidemic, but with the resumption of work and production they have begun to pick up as well.

![CEPI trend](image)

3.2 The linkage between comprehensive energy price index and stock market fluctuations

The monthly return series of the Shanghai 180 index (sz180, code 000010. SH), and the Shanghai and Shenzhen 300 index (HS300, code 399300. SZ) are used to characterize the market movements of China’s stock market, and the monthly return series of the Shanghai 180 energy index (sz180e, code h50001. SH), and the Shanghai and Shenzhen 300 energy index (hs500e, code 000908. CSI) and China Securities 500 energy index are used to represent the stock market of China's energy industry. All these indexes are further used to study the interaction between the CEPI and the stock market.

According to Heisenberg’s uncertainty principle, an increase of the decomposition scale means that the coefficient error increases at a higher boundary level. However, if the number of scales is too low, the decomposition effect may be unsatisfactory and the information extraction may be insufficient. This article uses Morlet wavelet to do a 7-scale continuous wavelet transformation on the CEPI and return series of the stock indices to obtain the empirical results of variable fluctuation
characteristics and the linkage relationship between the CEPI and stock indices.

![Wavelet Power Spectra](image)

**Notes:**
1. The line contour region representation is statistically significant at a 5% confidence level, which has been estimated by Monte Carlo simulation using a phase randomized substitution series. The blue to red coloring indicates the weak to strong wavelet power spectrum in the time-frequency domain which is corresponding to the intensity of the CEPI and stock index fluctuation.

In the wavelet analysis power spectrum shown in Fig.2, the horizontal axis represents time and the vertical axis frequency (the frequency level has been converted to a time unit (month)).

According to the time interval length of frequency, the frequency domain is divided into high, medium, and low frequency, corresponding to short, medium, and long-term shocks. For the convenience of analysis, the short-term frequency domain is specified as 1-8 months, the medium-term is 8-32 months, and the long-term frequency domain consists of more than 32 months.

It can be observed from Fig.2 that in following periods appeared more severe fluctuations of the CEPI in the time-frequency domain: 2007-2011 (medium-term (16-32 months) fluctuations), 2008-2009 (medium-term (~8 months) fluctuations), 2016-2018 (medium-term (~16 months) fluctuations), and from 2007 to present (long-term (32-64 months) fluctuations). The fluctuations...
in the time-frequency domain of general stock indices have been higher in following periods: 2007-2011 and 2014-2016 (medium-term (16-32 months) fluctuations), 2007-2010, 2014-2016 and in 2018 (short-term (2-8 months) fluctuations), and in 2012, 2013 and 2020 (very short-term (2-4 months) fluctuations). Fluctuations of stock indices reflecting the domestic energy industry have been high in: 2007-2010 (short and medium-term fluctuations (2-32 months), 2012-2014 (short-term fluctuations (2-4 months), 2015 and 2016 (short-term fluctuations (2-8 months), and 2018 and 2019 (short-term fluctuations (~4 months).

Generally speaking, the CEPI index shows much mid-long-term volatility but less short-term volatility. Energy market prices have strong stability in the short-term but adjust in the long-term. The stock market on the other hand is mainly characterized by short-term volatility, especially, the 2-4 months periodical short-term volatility is very significant. The volatility of the energy industry stock market is similar to the overall stock market’s and only shows a few differences in medium-term fluctuation (e.g., no 16-32 months- fluctuations from 2014-2016 but 2-8 months- fluctuations in 2018 and 2019). Even during the global epidemic in 2020, China's domestic energy prices maintain its long-term adjustment, while the overall stock markets and the energy industry stock markets show moderate short-term volatility characteristics in the frequency band of 2-4 months. The fluctuations being moderate, shows that the sudden outbreak did not cause drastic changes of the domestic energy prices or stock market fluctuations.
CEPI-ZZ500E

Notes:
1. The line contour region representation is statistically significant at a 5% confidence level, which has been estimated by Monte Carlo simulation using a phase randomized substitution series. 2. The blue to red coloring indicates the weak to strong wavelet power spectrum in the time-frequency domain, which is corresponding to the correlation degree between the indicators. 3. The direction of the arrow indicates the phase relationship between the two-time series: when the arrow points to the right (left), the series changes in the same (opposite) direction, and thus a positively (negatively) correlated; when the arrow points down (up), a change of the stock index (CEPI) leads to a change of the CEPI (stock index).

![Wavelet coherence and phase of the wavelet power spectrum of CEPI and stock index](image)

The time-frequency-domain linkage between the CEPI and the stock market prices fluctuations shown in Fig.3 is measured by the wavelet coherence coefficient and of phase difference of the cross-wavelet transform. The wavelet coherence coefficient measures the local correlation in the time-frequency domain, and the wavelet phase difference measures the lead-lag structure.

As can been seen from the results in Fig.3, there has been a strong negative correlation between the fluctuations of the CEPI and SZ180’s, and HS300’s in the time-frequency domain in following periods: 2007 to 2011 (between the medium-term volatilities (16-32 months)), in 2014 and 2015 (between the medium term volatilities (16 months)), each without lead-lag structure; in 2008 (between the short-term volatilities (2-4 and 8 months)), 2011 ((between the short-term volatilities (4-8 months)), and 2019 ((between the short-term volatilities (<2 months)) . Furthermore, there could have been found positive short-term correlation between the 4 months volatilities in 2014 and between the 2 months volatilities in the end of 2017, and a lead-lag structure of "CEPI-SZ180". In addition, the spectrum analysis results of “CEPI-SZ180” show that there is a strong negative correlation between the medium-term volatilities (16 months) from 2017 to the present with lead-lag structure of "SZ180-CEPI" from 2017 to 2018. Following negative correlations between the CEPI and the energy industry stock market could have been found: strong negative correlation between mid-term (16-32 months) volatilities from 2007 to 2011 with lead-lag structure of "energy stock index-CEPI" in the 16-month frequency band from 2009, strong negative correlation between short-term (2-4 months) volatilities in 2008, short-term (4 months) volatilities in 2011 and short-term (8-16 months) volatilities in 2015 with lead-lag structure of "energy stock index-CEPI" in the short-term frequency band in 2011. Furthermore, there could have been found a strong positive correlation between the short-term (8-16 months) volatilities from 2012 to the beginning of 2013 and from 2018 to 2019 (between short-term (8-months) volatilities), each with lead-lag
structure of the "CEPI-Energy Stock Index".

According to the results of the phase difference calculations (Fig.4), there is no obvious lead-lag relationship between 2012 and 2017. However, in the two periods from 2007 to 2011 and from 2018 to now, the fluctuation of energy stocks is higher than the one of the energy prices.

In overall, we could find a negative correlation between the CEPI and stock markets in the medium- and long-term frequency domain, while there is a periodic alternation between negative and positive correlation in the short-term frequency domain. From 2007 to 2011, the short-term (2-8 months) volatilities mainly showed negative correlation. Since 2014, the short-term correlation turned positive.

### 3.3 Granger causality test results

In order to retain the information integrity as much as possible and reduce the marginal effect caused by wavelet decomposition, the asymmetric Daubechies wavelet filter \((La_8)\) with a length of \(L = 8\) has been employed to perform the maximum overlapping discrete wavelet transform.

---

\(\dagger\) According to the research conclusion of Gencay et al. (2002), Daubechies wavelet filter can improve the stationarity of wavelet coefficients after discrete wavelet transform.
When conducting price changes and stock market fluctuations. For MODWT, the indicator series are divided into 7 scales, the short-term scales include scale D1, D2, and D3, which respectively represent the series’ fluctuations under the short-term scales of $2^1=2$ months, $2^2=4$ months, and $2^3=8$ months. Similarly, the medium-term scales include scale D4 and D5, which respectively represents the series fluctuations on the $2^4=16$ and $2^5=32$ months scales. The long-term scales include scale D6 and D7, which represent the series fluctuations on the $2^6=64$ and $2^7=128$ months scales. S7 represents the remaining long-term trend of the original series excluding scale D1 to D7. In order to ensure the stability and reliability of the test results, the bandwidth parameters are according to the empirical experience of the literature and the sample simulation test\cite{41,42} set as $\varepsilon=1.5\sigma$ when conducting the nonlinear Granger test.

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Number of lag periods</th>
<th>Granger causation of stock fluctuation are not CEPI fluctuations</th>
<th>Granger causation of CEPI fluctuations are not stock fluctuations</th>
<th>Test result</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEPI &amp; SZ180</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original series</td>
<td>5</td>
<td>3.114, 0.010**</td>
<td>5.392, 0.000***</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>D1</td>
<td>3</td>
<td>3.634, 0.014**</td>
<td>0.675, 0.569</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>D2</td>
<td>3</td>
<td>1.454, 0.229</td>
<td>1.523, 0.210</td>
<td>×</td>
</tr>
<tr>
<td>D3</td>
<td>3</td>
<td>0.114, 0.951</td>
<td>6.157, 0.000***</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>D4</td>
<td>3</td>
<td>3.554, 0.015**</td>
<td>2.883, 0.037***</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>D5</td>
<td>3</td>
<td>0.650, 0.583</td>
<td>0.332, 0.802</td>
<td>×</td>
</tr>
<tr>
<td>D6</td>
<td>3</td>
<td>1.842, 0.141</td>
<td>2.262, 0.289</td>
<td>×</td>
</tr>
<tr>
<td>D7</td>
<td>3</td>
<td>11.567, 0.000***</td>
<td>0.011, 0.998</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>S7</td>
<td>3</td>
<td>10.932, 0.000***</td>
<td>8.227, 0.000***</td>
<td>CEPI→SZ180</td>
</tr>
<tr>
<td>CEPI &amp; HS300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original series</td>
<td>5</td>
<td>2.906, 0.015**</td>
<td>5.975, 0.000***</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>D1</td>
<td>3</td>
<td>3.421, 0.018**</td>
<td>1.017, 0.386</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>D2</td>
<td>3</td>
<td>1.617, 0.187</td>
<td>1.864, 0.137</td>
<td>×</td>
</tr>
<tr>
<td>D3</td>
<td>3</td>
<td>0.090, 0.965</td>
<td>7.189, 0.000***</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>D4</td>
<td>3</td>
<td>3.619, 0.014**</td>
<td>3.067, 0.029**</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>D5</td>
<td>3</td>
<td>0.584, 0.626</td>
<td>0.460, 0.710</td>
<td>×</td>
</tr>
<tr>
<td>D6</td>
<td>3</td>
<td>1.907, 0.130</td>
<td>1.208, 0.308</td>
<td>×</td>
</tr>
<tr>
<td>D7</td>
<td>3</td>
<td>11.802, 0.000***</td>
<td>0.189, 0.903</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>S7</td>
<td>3</td>
<td>10.998, 0.000***</td>
<td>9.493, 0.000***</td>
<td>CEPI→HS300</td>
</tr>
<tr>
<td>CEPI &amp; SZ180E</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original series</td>
<td>2</td>
<td>3.397, 0.006***</td>
<td>4.672, 0.000***</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>D1</td>
<td>3</td>
<td>3.537, 0.016**</td>
<td>1.042, 0.375</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>D2</td>
<td>3</td>
<td>1.400, 0.244</td>
<td>0.663, 0.575</td>
<td>×</td>
</tr>
<tr>
<td>D3</td>
<td>3</td>
<td>1.733, 0.162</td>
<td>10.648, 0.000***</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>D4</td>
<td>3</td>
<td>4.318, 0.005***</td>
<td>1.548, 0.204</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>D5</td>
<td>3</td>
<td>1.307, 0.273</td>
<td>0.408, 0.746</td>
<td>×</td>
</tr>
<tr>
<td>D6</td>
<td>3</td>
<td>2.226, 0.087</td>
<td>1.572, 0.198</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>D7</td>
<td>3</td>
<td>12.318, 0.000***</td>
<td>4.896, 0.002**</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>S7</td>
<td>3</td>
<td>11.045, 0.000***</td>
<td>22.710, 0.000***</td>
<td>CEPI→SZ180E</td>
</tr>
<tr>
<td>CEPI &amp; HS300E</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original series</td>
<td>2</td>
<td>3.113, 0.047**</td>
<td>5.386, 0.005***</td>
<td>CEPI→HS300E</td>
</tr>
<tr>
<td>D1</td>
<td>3</td>
<td>2.674, 0.049*</td>
<td>0.791, 0.500</td>
<td>CEPI→HS300E</td>
</tr>
</tbody>
</table>
The lag order is determined according to the Akaike information criterion. Notes: 1. The lag order is determined according to the Akaike information criterion. 2. "**" "***" symbolizes a rejection of the original hypothesis at the confidence level of 10%, 5% and 1% respectively. 3. "×" means that there is no Granger causality between them.

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Number of lag periods</th>
<th>Original hypothesis</th>
<th>Granger causation of stock is not CEPI</th>
<th>Granger causation of CEPI is not stock</th>
<th>Test result</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Tₜ</td>
<td>P</td>
<td>Tₜ</td>
<td></td>
</tr>
<tr>
<td>CEPI &amp; SZ180</td>
<td>Original series</td>
<td>5</td>
<td>1.328</td>
<td>0.092*</td>
<td>1.203</td>
</tr>
<tr>
<td></td>
<td>D₁</td>
<td>3</td>
<td>-0.539</td>
<td>0.705</td>
<td>0.294</td>
</tr>
<tr>
<td></td>
<td>D₂</td>
<td>3</td>
<td>0.268</td>
<td>0.394</td>
<td>0.433</td>
</tr>
<tr>
<td></td>
<td>D₃</td>
<td>3</td>
<td>0.077</td>
<td>0.469</td>
<td>0.893</td>
</tr>
<tr>
<td></td>
<td>D₄</td>
<td>3</td>
<td>1.937</td>
<td>0.026**</td>
<td>1.088</td>
</tr>
<tr>
<td></td>
<td>D₅</td>
<td>3</td>
<td>-0.257</td>
<td>0.601</td>
<td>1.805</td>
</tr>
<tr>
<td></td>
<td>D₆</td>
<td>3</td>
<td>1.550</td>
<td>0.060*</td>
<td>-0.698</td>
</tr>
<tr>
<td></td>
<td>D₇</td>
<td>3</td>
<td>1.251</td>
<td>0.105</td>
<td>0.305</td>
</tr>
<tr>
<td></td>
<td>S₇</td>
<td>3</td>
<td>2.107</td>
<td>0.017**</td>
<td>-</td>
</tr>
<tr>
<td>CEPI &amp; HS300</td>
<td>Original series</td>
<td>5</td>
<td>1.508</td>
<td>0.065*</td>
<td>1.352</td>
</tr>
<tr>
<td></td>
<td>D₁</td>
<td>3</td>
<td>-0.668</td>
<td>0.748</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>D₂</td>
<td>3</td>
<td>-0.211</td>
<td>0.583</td>
<td>0.536</td>
</tr>
<tr>
<td></td>
<td>D₃</td>
<td>3</td>
<td>0.486</td>
<td>0.313</td>
<td>1.107</td>
</tr>
<tr>
<td></td>
<td>D₄</td>
<td>3</td>
<td>1.987</td>
<td>0.023**</td>
<td>1.421</td>
</tr>
<tr>
<td></td>
<td>D₅</td>
<td>3</td>
<td>-0.369</td>
<td>0.643</td>
<td>2.024</td>
</tr>
<tr>
<td></td>
<td>D₆</td>
<td>3</td>
<td>1.758</td>
<td>0.039**</td>
<td>-0.564</td>
</tr>
<tr>
<td></td>
<td>D₇</td>
<td>3</td>
<td>1.226</td>
<td>0.110</td>
<td>0.305</td>
</tr>
<tr>
<td></td>
<td>S₇</td>
<td>3</td>
<td>2.068</td>
<td>0.019**</td>
<td>-</td>
</tr>
<tr>
<td>CEPI &amp; SZ180E</td>
<td>Original series</td>
<td>2</td>
<td>1.668</td>
<td>0.047**</td>
<td>1.316</td>
</tr>
<tr>
<td></td>
<td>D₁</td>
<td>3</td>
<td>-0.128</td>
<td>0.550</td>
<td>-0.089</td>
</tr>
<tr>
<td></td>
<td>D₂</td>
<td>3</td>
<td>-0.145</td>
<td>0.557</td>
<td>-0.050</td>
</tr>
<tr>
<td></td>
<td>D₃</td>
<td>3</td>
<td>0.380</td>
<td>0.351</td>
<td>1.409</td>
</tr>
<tr>
<td></td>
<td>D₄</td>
<td>3</td>
<td>1.263</td>
<td>0.103</td>
<td>1.083</td>
</tr>
<tr>
<td></td>
<td>D₅</td>
<td>3</td>
<td>0.718</td>
<td>0.236</td>
<td>1.879</td>
</tr>
<tr>
<td></td>
<td>D₆</td>
<td>3</td>
<td>0.688</td>
<td>0.245</td>
<td>1.016</td>
</tr>
<tr>
<td></td>
<td>D₇</td>
<td>3</td>
<td>1.323</td>
<td>0.092*</td>
<td>1.229</td>
</tr>
<tr>
<td></td>
<td>S₇</td>
<td>3</td>
<td>2.222</td>
<td>0.013*</td>
<td>-</td>
</tr>
</tbody>
</table>
According to the linear test results (Table 3), the analysis based on the original indicator series shows that there is linear Granger causality between the fluctuations of CEPI, comprehensive stock indices, and energy industry stock indices. The multi-resolution analysis reveals that there is bidirectional causality on the long-term D7 + S7 scale. Regarding fluctuations on the short-term D1 and long-term D7 scales, the comprehensive stock market volatilities are the linear Granger causes of CEPI fluctuations, while on the short-term D1 and medium-term D4 scales, the fluctuations of the energy stock markets are the linear Granger causes of CEPI fluctuations. In addition, fluctuations of the CEPI in the medium-term D3 frequency domain cause short-term fluctuations in the stock markets.

As a complement to the linear results, the nonlinear test of the CEPI and stock indices fluctuation linkages highlights the one-way impact stock markets have on the energy market. At the original sequence level, fluctuations in comprehensive and energy industry stock markets are the nonlinear Granger causes of energy price fluctuations. The multi-resolution analysis reflects this one-way effect in the medium- and long-term (D4 + D6 + S7) volatility trend level, and in the short- and long-term volatility trend level (D3 + D4 + S7). On the medium-term (D5) scale and the medium and long term (D5 + D6 + D7) scale, the CEPI’s fluctuation causes the fluctuations in the overall stock markets and energy industry stock markets.

In overall, we have found a close causal relationship between the CEPI’s fluctuations and the stock market changes, and can manifest that stock markets’ fluctuations mainly influence the energy price fluctuations. This causal relationship between the two is furthermore more prominent at a level of long-term trend changes in the low frequency domain. We have found that fluctuations in China’s energy price and stock market prices influence and interact with each other. Price fluctuations in the

| Original series | 2 | 1.547 | 0.060* | 0.169 | 0.432 | CEPI—HS300E |
| D1 | 3 | 0.634 | 0.015** | -0.097 | 0.538 | CEPI—HS300E |
| D2 | 3 | 1.456 | 0.262 | 0.075 | 0.469 | × |
| D3 | 3 | -0.620 | 0.072* | 0.738 | 0.229 | CEPI—HS300E |
| D4 | 3 | 1.488 | 0.732 | 0.266 | 0.394 | × |
| D5 | 3 | 0.431 | 0.068* | 1.536 | 0.062* | CEPI—HS300E |
| D6 | 3 | 1.118 | 0.333 | 1.847 | 0.032* | CEPI—HS300E |
| D7 | 3 | 1.261 | 0.131 | 1.494 | 0.067* | CEPI—HS300E |
| S7 | 3 | 2.153 | 0.103 | - | - | × |

| Original series | 2 | 1.641 | 0.050* | 0.254 | 0.399 | CEPI—ZZ500E |
| D1 | 3 | 0.382 | 0.351 | -0.608 | 0.728 | × |
| D2 | 3 | 0.819 | 0.206 | -0.023 | 0.509 | × |
| D3 | 3 | -0.707 | 0.760 | 0.829 | 0.203 | × |
| D4 | 3 | 1.427 | 0.076* | -0.631 | 0.736 | CEPI—ZZ500E |
| D5 | 3 | 1.075 | 0.140 | 1.739 | 0.040* | CEPI—ZZ500E |
| D6 | 3 | -0.885 | 0.812 | 2.227 | 0.012* | CEPI—ZZ500E |
| D7 | 3 | 1.175 | 0.119 | 1.718 | 0.042* | CEPI—ZZ500E |
| S7 | 3 | 2.131 | 0.016** | - | - | × |
energy market will trigger a response of the corresponding stock prices on the stock market. At the same time, when the price of energy stocks changes due to factors such as macro policy, energy industry and company decision-making adjustment, all kinds of energy prices in the real economy will also react. However, it should be noted that this interactive relationship between Chinese stock market prices and energy prices is not short-term sensitive but responds more in the medium and long term.

4. Conclusion and Policy Implications

Based on the wavelet multi-resolution analysis method, this paper discussed the time-frequency domain linkage between fluctuations in China's energy prices, stock markets, energy stocks. The conclusions are as follows:

According to the results of the Morlet cross wavelet transform, the correlation between fluctuations in energy and stock market prices shows obvious scale differences. In the medium and long-term frequency domain, there is a relatively stable negative correlation, but in the high frequency domain, the relationship between the two appears alternately in positive and negative directions, and there is no stable correlation direction. The fluctuations of the CEPI showed a significant medium- and long-term (16-64 months) trend, but low fluctuation intensity in the short term. The stock markets showed their most significant volatility intensity in short-term periods within 4 months, and the COVID-19 pandemic has no structural impact on the energy prices and stock market. The fluctuation cycle difference causes the stock market to respond to information faster than the energy trading market in the short term. Therefore, in actual analysis, it is impossible to obtain favorable information about short-term investment in the stock market with the help of energy price trend.

According to the wavelet phase difference analysis, there is no obvious lead-lag relationship between energy prices and the overall stock market during the inspection period, but there are obvious phase characteristics between energy prices and the energy sector stock: between 2008 and 2012, the lead-lag structures of "energy stock - energy price", "energy price - energy stock", and "energy stock - energy price" are presented respectively, which means that the price fluctuation in the energy market is lagging behind the energy stocks at this stage.

With reference to the linear and nonlinear tests of causality, the causality between energy price and stock markets differs in different frequency-domain scales. In the low-frequency domain, energy prices and stock prices are mutually influenced. In the medium and high frequency domain, we could only find a one-way impact of stock markets on energy prices. To be more specific: in the short-term frequency domain of less than 2 months and medium-term frequency domain of 16 months, the fluctuation of energy industry stock leads to the fluctuation of energy prices, but the fluctuation of energy price in the frequency domain of 8 months leads to short-term fluctuation of
stock markets. However, the short- and medium-term (<16 months) mutual impact of energy stock and energy prices is more significant. The long-term trend linkage is dominated by the stock market leading and driving energy price changes.

Based on the summarized findings above, it can be concluded that the comprehensive Chinese stock, especially energy stock, directly affect the reverse changes in the trading price of the energy market, and that there is a time lag between the stock market changes and energy price changes, which has a certain reference significance for the prediction of energy prices and for relevant policy decisions of the energy industry. Furthermore, unlike Cong’s (2013) research on Chinese data which indicated that energy prices can be taken as an explanation for stock market fluctuations, energy price changes have not been a significant cause of stock market fluctuations between 2007 and 2020 according to our study.

**Funding:** This paper was supported by the Major Projects of National Social Science Fund of China (20ZDA069); the National Natural Science Fund of China (71573088); the Key Projects of National Social Science Fund of China (15AZD002, 17AZD009); Henan Provincial Soft Science Program (232400411167).

**Data availability:** If readers have any inquiries about data and its processing or methodology, please do not hesitate to contact us by corresponding email.

**Declarations**

**Ethical approval** We certify that the manuscript titled “Linkages between Energy Prices and Stock Markets in China: A Study Based on Wavelet Analysis” (Hereinafter referred to as ‘the Paper’) has been entirely our original work except otherwise indicated, and it does not infringe the copyright of any third party. The submission of the Paper to Environmental Science and Pollution Research implies that the Paper has not been published previously (except in the form of an abstract or as a part of a published lecture or academic thesis), that it is not under consideration for publication elsewhere, that its publication is approved by all authors, and that, if accepted, will not be published elsewhere in the same form, in English or any other language, without the written consent of the Publisher.

Copyrights for articles published in Environmental Science and Pollution Research are retained by the author(s), with first publication rights granted to Environmental Science and Pollution Research.

**Consent to participate** We affirm that all authors have participated in the research work and are fully aware of ethical responsibilities.

**Consent to publish** We affirm that all authors have agreed for submission of the paper to ESPR and are fully aware of ethical responsibilities.

**Competing interests** The authors declare no competing interests.

**Authors Contributions**
Tianyu Zhao: Methodology, Investigation, Data curation, Writing-original draft.

Yongda He: Methodology, Investigation, Data curation, Writing-review & editing, Software.

Martin Bai: Conceptualization, Funding acquisition, Project administration, Writing-review & editing.

Shuai Shao: Conceptualization, Methodology, Investigation, Writing-original draft, Funding acquisition.

Availability of data and materials

If readers have any inquiries about data and its processing or methodology, please do not hesitate to contact us by corresponding email.

References


Pham L. Do all clean energy stocks respond homogeneously to oil price? [J]. Energy Economics, 2019, 81(Jun.):355-379.


