Discrete Dynamics in Nature and Society

Dynamic Modeling and Quantitative Analysis in Complex Energy and Resource Market Systems

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Hindawi
Discrete Dynamics in Nature and Society
Volume 2023, Article ID 6695727, 10 pages
https://doi.org/10.1155/2023/6695727

Research Article

Swings in Crude Oil Valuations: Analyzing Their Bearing on China's Stock Market Returns amid the COVID-19 Pandemic Upheaval

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Received 4 December 2022; Revised 13 April 2023; Accepted 14 June 2023; Published 21 June 2023

Academic Editor: Anibal Coronel

The advent of the COVID-19 pandemic has markedly affected energy valuations and financial markets. As such, this article aims to scrutinize the dynamic interplay between stock market returns and crude oil prices, with a particular focus on China, factoring in the second-moment effect of volatility spillover. Employing an EGARCH process to model the leverage impact on returns' volatility, the analysis utilizes daily data spanning from January 30, 2020, to August 30, 2022, and incorporates causality-in-mean and variance assessments. Empirical findings indicate that the QDII-LOF benchmark, representing oil prices, exerts a substantial influence on stock market returns. Nevertheless, the complete sample reveals no discernible spillover effects attributable to oil price fluctuations. These insights imply that the Chinese government's actions should carefully weigh the ramifications of spillovers. Concurrently, investors are advised to attentively monitor the crude oil market when making portfolio allocation decisions.

1. Introduction

The exploration of the effects of crude oil price fluctuations on China's stock market returns during the COVID-19 pandemic is of paramount importance, as it provides valuable insights into the intricate dynamics between energy and financial markets in one of the world's largest economies. This line of inquiry is particularly crucial given China's status as a significant energy consumer and its role in shaping global oil demand patterns. Furthermore, understanding the interdependencies between crude oil prices and China's stock market returns during the pandemic enables policymakers, investors, and other stakeholders to make informed decisions in the face of unprecedented economic challenges and market volatility. The COVID-19 crisis, with its far-reaching consequences on energy demand, supply chains, and macroeconomic stability, has amplified the need for a comprehensive investigation of the oil-stock market nexus in the Chinese context. By delving into this critical research area, scholars contribute to a richer understanding of the complex interplay between energy and financial markets, ultimately facilitating the development of robust and adaptive strategies to navigate the evolving economic landscape. Amid the COVID-19 pandemic outbreak, China has experienced profound ramifications across numerous sectors, encompassing energy prices and stock markets. Energy, as the cornerstone of China's economic growth and financial market efficacy, plays a pivotal role in corporate production. Wang and Wu [1] noted that stock market stability could be jeopardized when uncertainty spawned significant energy price volatility. Chiarella et al. [2] elucidated that such volatility could impact firms' outputs and profits by altering production costs and subsequently causing stock price fluctuations. Conversely, energy prices could influence stock prices through mechanisms like speculative demand and investor expectation effects.

Traditionally, China has focused on stock market-associated financial risks. The innately elevated risk of the stock market renders it vulnerable to the destabilizing forces of both internal and external elements, including substantial price shifts. Concurrently, stock market volatility can permeate other markets, ultimately culminating in the accumulation or triggering of systemic financial perils. Consequently, during the COVID-19 pandemic, it is crucial to rigorously examine the volatility spillover nexus between China's energy and stock markets, elucidating the risk transmission mechanisms between them. This insight will aid governmental bodies in enhancing energy and stock market price stability measures while mitigating financial hazards.

This study aims to scrutinize the influence of crude oil price fluctuations on China's stock market returns amidst the COVID-19 pandemic, drawing from the comprehensive research context outlined earlier. Utilizing the exponential generalized auto-regressive conditional heteroskedasticity (EGARCH) model alongside causality-in-mean and variance tests for our empirical analysis, we employed daily data spanning from January 30, 2020, to August 30, 2022. The results, underpinned by the QDII-LOF benchmark, indicate a significant correlation between oil prices and China's stock market returns. However, when examining the entire sample, we observed no substantial spillover ramifications from oil prices. This research not only offers valuable insights for the Chinese government and investors regarding the pandemic's impact on energy prices and stock market performance but also enriches the existing academic discourse on the subject.

Moreover, this study presents two notable contributions to the existing Chinese literature on the subject. Firstly, by employing the exponential generalized auto-regressive conditional heteroscedasticity, causality-in-mean, and variance approaches, this work delves into the issue from a distinct analytical perspective, thus augmenting the current body of knowledge. This differs from previous Chinese research (Zhu et al. [3]; Li et al. [4]; Luo and Qin [5]; Fang and You [6]; Ding et al. [7]), which primarily utilized vector auto-regression, Granger causality, structural vector auto-regression, and other methodologies. Secondly, considering China's status as the world's largest energy importer and the COVID-19 pandemic's origin, selecting China as the sample for examining this issue offers a more representative and insightful approach. This not only complements existing literature (Bashir [8]; Katsampoxakis et al. [9]; Managi et al. [10]; Refai et al. [11]; Jareño et al. [12]) but also broadens the scope of the ongoing discourse on this subject.

This article unfolds in a meticulously structured manner, with each section serving a distinct purpose. Section 2 delves into a comprehensive review of relevant literature, setting the foundation for the analysis. Section 3 outlines the robust econometric methodology employed, ensuring the accuracy and reliability of the study's results. Section 4 presents the findings and engages in an insightful discussion, enhancing readers' understanding of the topic. Finally, Section 5 concludes the article by offering thought-provoking conclusions and valuable policy implications, paving the way for future research and policy development in this domain.

2. Literature Review

The objective of this section is to meticulously synthesize and examine prior investigations concerning the repercussions of crude oil shocks on stock market volatility, thereby establishing a robust, credible, and impartial theoretical basis for the present study. A unified agreement has yet to emerge within the diverse and extensive literature regarding the precise impact of crude oil shocks on stock market volatility.

The COVID-19 pandemic has generated a wealth of academic literature probing the influence of crude oil price shocks on stock market returns as researchers strive to unravel the intricate interconnections between energy and financial markets during this unprecedented global occurrence (Sharif et al. [13]; Alaoui Mdaghri et al. [14]; Abuzayed et al. [15]; Ren et al. [16]; Salisu et al. [17]; Ren et al. [18]). Foundational studies have explored the myriad pathways through which variations in the price of crude oil affect stock market returns, emphasizing factors such as cost, demand, and expectations as pivotal drivers of this nexus (Phoong et al. [19]; Wang et al. [20]; Duan et al. [21]; Managi et al. [10]; Naeem et al. [22]). The COVID-19 crisis has intensified these interactions, with the convergence of collapsing energy demand, disrupted supply chains, and pervasive economic downturns engendering unparalleled market dynamics (Martins and Cró [23]; G. Tuna and V. E. Tuna [24]; Liu et al. [25]).

Innovative methodologies have been harnessed to untangle the complex linkages between crude oil prices and stock market returns amid the pandemic. For instance, Bani-Khalaf and Taspinar [26], and Lúcio and Caiado [27] have detected negative correlations between crude oil price shocks and stock market returns, positing that the drastic decline in energy demand and the subsequent oil glut have exerted downward pressure on both markets. In contrast, Benlagha and El Omari [28], and Nham [29] have observed positive associations, arguing that the resurgence in oil prices following the initial collapse has invigorated stock market performance. These investigations have employed cutting-edge econometric techniques, such as vector error correction models (Wang et al. [30]; Ren et al. [31]; Fareed et al. [32]), dynamic conditional correlation models (DCC) (Zhou et al. [33]), and wavelet coherence analysis (Tiwari et al. [34]), to shed light on the multifaceted relationships between crude oil prices and stock market returns during the pandemic.

Throughout the COVID-19 pandemic, the interplay between crude oil price shocks and stock market returns has garnered significant scholarly interest. Pioneering studies by Zhang et al. [35] laid the groundwork by identifying an intensified interdependence between oil prices, stock markets, and exchange rates through dynamic conditional correlation and wavelet coherence models. This foundation spurred a plethora of subsequent inquiries. For example, Dutta et al. [36], Hung and Vo [37], and Salisu et al. [38] adopted wavelet analysis to scrutinize the oil-stock market relationship, while Salisu and Obiora [39], and Mezghani and Abbes [40] deployed network-based approaches to examine the spillover effects between the two variables. Furthermore, scholars such as Rowland et al. [41], Ding et al. [42], and Umar et al. [43] have utilized cross-sectional, copula, and Bayesian vector autoregression models, respectively, to showcase the negative correlation between oil prices and stock market performance during the pandemic.

As the body of literature on this topic continued to grow, researchers began incorporating more advanced methodologies and data samples. For example, Kilic et al. [44] and Apostolakis et al. [45] implemented time-varying parameter and mixed data sampling models, providing further evidence of the oil-stock market nexus. Additionally, Topcu et al. [46], Chien et al. [47], and Li et al. [48] employed Granger causality tests, panel vector autoregression, and structural vector autoregression approaches, respectively, to explore the impact of oil price shocks on stock market returns across different countries. Meanwhile, Mzoughi et al. [49], Liu et al. [50], and Abuzayed and Al-Fayoumi [51] utilized quantile regression, machine learning, and asymmetric nonlinear models to capture the heterogeneous responses of stock markets to oil price fluctuations. Cumulatively, this vast and diverse literature, which also includes notable contributions by Dogan and Inglesi-Lotz [52], Goodell and Goutte [53], and Liao et al. [54], emphasizes the critical role of oil price shocks in influencing stock market returns during the COVID-19 pandemic.

In essence, the prevailing literature suggests notable correlations between oil prices and stock market performance, as evidenced in numerous industrialized countries. This study aims to explore the presence of such relationships within the Chinese context. Specifically, the objective of this paper is to evaluate the influence of oil price shocks on China's stock market returns, spanning the period from January 30, 2020, to August 30, 2022. Employing the EGARCH model and causality tests in mean and variance for empirical analysis, our results substantiate the notion that oil prices, as represented by the QDII-LOF benchmark, have a significant impact on stock market returns. Contrarily, when examining the entire sample, we observe no discernible spillover effects attributable to oil price fluctuations. In conclusion, these novel findings may enrich the existing body of knowledge and offer fresh insights into the complex interplay between oil prices and stock market dynamics in the Chinese market.

3. Econometric Methodology

In this study, we employ the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model, a powerful approach pioneered by Nelson [55], to conduct rigorous empirical analyses. The EGARCH model is adept at capturing the leverage effect present in return volatility series, thereby providing a robust framework for examining the relationship between crude oil and stock market returns. To ensure the validity of our analysis, we first establish the stationarity of the identified stock market return series and crude oil return series, denoted by stock_t, respectively. Subsequently, we apply the EGARCH model to these two variables, as articulated in equations (1) and (3), thereby offering a comprehensive and incisive assessment of the intricate interplay between the two series.

For the stock market returns,

$$\text{stock}_t = \mu_{\text{stock},t} + \delta_t, \tag{1}$$

where $[\delta_t \mid \delta_{t-1}, \delta_{t-2}, \delta_{t-3}, \cdots, \text{stock}_{t-1}, \text{stock}_{t-2}, \text{stock}_{t-3}, \cdots] \in (0, h_{\text{stock},t})$; $\mu_{\text{stock},t}$ denotes the mean of stock_t; δ_t denotes the residuals.

$$h_{\text{stock},t} = \omega + \beta \log\left(h_{\text{stock},t-1} + \alpha \left| \frac{\delta_{t-1}}{\sqrt{h_{\text{stock},t}}} \right| + \gamma \frac{\delta_{t-1}}{\sqrt{h_{\text{stock},t-1}}} \right). \tag{2}$$

For the crude oil market returns,

$$\text{oil}_t = \mu_{\text{oil},t} + \varepsilon_t, \tag{3}$$

where $[\varepsilon_t \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}, \cdots, \text{oil}_{t-1}, \text{oil}_{t-2}, \text{oil}_{t-3}, \cdots] \in (0, h_{\text{oil},t})$; $\mu_{\text{oil},t}$ denotes the mean of stock_t; ε_t denotes the residuals.

$$h_{\text{oil},t} = \omega + \beta \log) h_{\text{oil},t-1} + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{\text{oil},t}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{\text{oil},t-1}}}. \tag{4}$$

Then, following He [56], it is assumed that A_t corresponds to the information set $A_t = (\text{stock}_t;\ b \geq 0)$. Similarly, it is assumed that B_t corresponds to the information set $B_t = (\text{oil}_t;\ \text{stock}_t;\ b \geq 0)$. As a result, oil_t is regarded as the cause of stock_t in variance unless the following equation holds:

$$E\left\{ \left(\text{stock}_t - \mu_{s,t+1}\right)^2 \middle| A_t \neq \left(\text{stock}_{t+1} - \mu_{s,t+1}\right)^2 \middle| B_t \right], \tag{5}$$

where the causality-in-variance concept was developed by Cheung and Ng [57], and it serves as the foundation for equation (5). Calculating both the squared standardized residuals, δ_t in equation (1) and ε_t in equation (2), is required when using the causality-in-variance technique:

$$\begin{aligned} \mu_t &= \frac{\left(\text{stock}_t - \mu_{\text{stock},t}\right)^2}{h_{\text{stock},t}} = \delta_t^2, \\ \nu_t &= \frac{\left(\text{oil}_t - \mu_{\text{oil},t}\right)^2}{h_{\text{oil},t}} = \varepsilon_t^2. \end{aligned} \tag{6}$$

In accordance with Hong [58], the following test statistics can be used in order to investigate any potential causal association over a specified lag (w):

$$Q = \frac{T \sum_{t=1}^{T-1} k^2 w^{-1} \widetilde{\rho_{\mu\nu}^2}(l) - C_{1T}(k)}{\sqrt{2 D_{1T}(k)}}, \tag{7}$$

where $\widetilde{\rho_{\mu\nu}^2}(b)$ denotes the sample cross-correlation on the period of lag (b). It is calculated as follows:

$$\widetilde{\rho^2_{\mu\nu}}(b) = \left[\widetilde{C_{\mu\mu}}(0)\widetilde{C_{\nu\nu}}(0)\right]^{-(1/2)}\widetilde{C_{\mu\nu}}(b). \tag{8}$$

The following are the results that the function of sample cross-covariance yields:

$$\widetilde{C_{\mu\nu}}(b) = \begin{cases} \frac{1}{T}\sum_{t=b+1}^{T}\widetilde{\mu_t}\widetilde{\nu_{t-b}}, b \geq 0, \\ \\ \frac{1}{T}\sum_{t=-b+1}^{T}\widetilde{\mu_{t+b}}\widetilde{\nu}_t, b < 0, \end{cases} \tag{9}$$

where $\widetilde{C_{\mu\mu}}(0) = 1/T\sum_{t=1}^{T}\widetilde{\mu}_t^2$; $\widetilde{C_{\nu\nu}}(0) = 1/T\sum_{t=1}^{T}\widetilde{\delta}_t^2$.

In equation (7), $k(l/W)$ denotes a weight function, and the Barlett kernel is used for this purpose.

$$k\left(\frac{l}{W}\right) = 1 - \left|\frac{l}{W} + 1\right|, \text{with } \frac{k}{(W+1)} \leq 1. \tag{10}$$

Otherwise,

$$\frac{k}{W} = 0. \tag{11}$$

Therefore,

$$\begin{aligned} C_{1T}(k) &= \sum_{l-1}^{T-1}\left(1 - \frac{|l|}{S}\right)k^2\left(\frac{l}{W}\right), \\ D_{1T}(k) &= \sum_{l-1}^{T-1}\left(1 - \frac{|l|}{T}\right)\left[1 - (|l|+1)k^4\left(\frac{l}{W}\right)\right.. \end{aligned} \tag{12}$$

Drawing upon the work of Hong [58], the Q-statistic, an essential component of the one-sided test, adheres to an asymptotic normal distribution. Consequently, employing the critical values corresponding to the right tail of the normal distribution is deemed appropriate. Our analysis proceeds with the calculation of the Q-statistic for equation (7), followed by a comparison of the derived Q-statistic value with the upper-tail critical value of the normal distribution at a suitable significance level. The null hypothesis of no causality is rejected if the estimated Q-statistic value surpasses the critical threshold. Notably, numerous studies have delved into the time-varying relationship between crude oil markets and stock market returns. For instance, Lu et al. [59] employ a causality-in-mean and variance test based on the time-varying principle, utilizing rolling subsamples to capture the evolving dynamics between these markets. The test statistic is defined as follows:

$$Q_{t\nu} = \frac{S\sum_{l=1}^{S-1}k^2(l/W)\widetilde{\rho^2_{\mu\nu}}(l,S) - C_{1S}(k)}{\sqrt{2D_{1s}(k)}}, \tag{13}$$

where $k(l/W)$ denotes the weight function, namely, the Barlett kernel.

$$\begin{aligned} C_{1S}(k) &= \sum_{l=1}^{S-1}\left(1 - \frac{|l|}{S}\right)k^2\left(\frac{l}{W}\right), \\ D_{1S}(k) &= \sum_{l=1}^{S-1}\left(1 - \frac{|l|}{S}\right)\left[1 - \frac{(|l|+1)}{S}\right]k^4\left(\frac{l}{W}\right). \end{aligned} \tag{14}$$

$Q_{t\nu}$ statistics belongs to the one-sided test. The critical values of the upper-tailed normal distribution are utilized. A rolling sample (S) is used to calculate the time-varying Hong test. According to Lu et al. [59], when the rolling sample size is too small, the test will provide biased findings. In contrast, when the rolling sample is too large, detecting changes in Granger causality would take a considerable amount of time. Regarding an adequate rolling window, Lu et al. [59] provide the following method for determining the optimal rolling sample (S):

$$S = \frac{2\left(z_{1-\alpha/2} + z_{1-\beta}\right)^2}{\left[\mu_0 - \mu_1/\sigma\right]^2}, \tag{15}$$

where z_{1-s} denotes the critical value of the significant level of N (0, 1); α denotes the type I error probability; β denotes Type II error probability; $\mu_0 - \mu_1/\sigma$ denotes the standardized difference between both mean values. In a manner analogous to equation (7), the Q-statistic will be computed. Then, at an appropriate level, the derived Q-statistic value is compared to the normal distribution's upper-tail critical value. The null hypothesis of no causality will be rejected if the estimated Q-statistic value exceeds the critical value.

4. Findings and Discussions

China emerged as the epicenter of the COVID-19 pandemic, reporting its first cases on January 23, 2020. To scrutinize the intricate relationship between oil prices and stock returns in this unprecedented context, we employ daily time series data from China spanning January 30, 2020, to August 30, 2022. By using a consistent trading day across all samples, we ensure a more accurate comparison of the number of trading days. The CSI 300 index serves as a representative proxy for China's stock market, while the DJ Global Oil & Gas (W1ENE) index embodies the global oil market. Furthermore, the QDII-LOF (162411) index reflects China's oil market. These indices were sourced from the reputable website investing.com. To facilitate model estimation, the return series is calculated by taking the first difference of the logarithm of the daily closing price series, thereby providing a solid foundation for our in-depth analysis.

4.1. Basic Description. Table 1 presents the outcomes of the essential descriptive statistical analyses conducted on each variable under investigation. This comprehensive examination of the data ensures a rigorous and insightful understanding of the underlying trends and patterns, thereby providing a solid foundation for subsequent analysis and interpretation.

Table 1 reveals several noteworthy observations about the return series under investigation. Firstly, the daily mean of the CSI return series is positive, while the W1ENE and QDII-LOF return series exhibit negative daily means throughout the study period. Among these, the CSI return boasts the highest mean, with the QDII-LOF return surpassing the W1ENE return in terms of the mean value. The W1ENE return's mean emerges as the lowest in the sample. Meanwhile, the CSI return series displays the highest volatility, as indicated by the standard deviation.

Intriguingly, all return series exhibit negative skewness and positive kurtosis, signifying the presence of leptokurtic distributions. Furthermore, the Jarque–Bera normality test confirms that none of the return series follow normal distributions at a 1% significance level. The Ljung–Box Q statistics indicate autocorrelation in both the return and squared return series. To assess the stationarity of all returns, three distinct unit root tests—augmented Dickey–Fuller, Phillips–Perron, and Kwiatkowski–Phillips–Schmidt–Shin—were employed. The results conclusively demonstrate that all return series are stationary at the 1% significance level, fulfilling a critical prerequisite for subsequent EGARCH model estimation.

Table 1: Results of basic descriptive statistics.

Variable & statistics	CSI	W1ENE	QDII-LOF
Mean	0.0004	−0.0014	−0.0012
Standard error	0.0076	0.018	0.014
Skewness	−1.114	−1.218	−0.098
Kurtosis	7.440	8.736	5.143
Jarque–Bera	122.335 (0.000)	192.562 (0.000)	22.959 (0.000)
Observation	119	119	119
ARCH (8)	17.392 (0.026)	19.472 (0.013)	17.612 (0.024)
Q (36)	24.867 (0.919)	50.155 (0.059)	40.574 (0.276)
Qs (36)	11.340 (1.000)	49.413 (0.067)	52.794 (0.035)
ADF	−11.889 (0.000)	−11.298 (0.000)	−11.299 (0.000)
PP	−11.764 (0.000)	−11.358 (0.000)	−8.647 (0.000)
KPSS	0.051***	0.089***	0.088***

Note: () stands for the p value; ARCH (8) stands for the LM conditional variance test; *** stands for the 1% significant level; Q (36) and Qs (36) represent the Ljung–Box serial correlation test, respectively.

4.2. (E)GARCH Model Estimation.

Table 1's insights enable us to ascertain the presence of ARCH effects in all return series, suggesting that the GARCH specification is aptly suited for each series. Consequently, the EGARCH model is employed for further empirical analyses. Model diagnostics indicate that the EGARCH (1, 1) represents an ideal fit for capturing the volatility inherent in each return series comprehensively. Additionally, the mean equation substantiates that the optimal lag length for autoregressive parameters, as determined by the Akaike information criterion, is one. The estimated outcomes are conveniently displayed in Table 2 for further examination and interpretation.

Table 2: Results of (E)GARCH model estimation.

Coefficient & variable	CSI	W1ENE	QDII-LOF
ω	−1.392 (0.094)	−1.112 (0.013)	−6.613 (0.012)
α	0.532 (0.004)	0.371 (0.046)	0.943 (0.000)
β	0.902 (0.000)	0.904 (0.000)	0.333 (0.025)
γ	−0.126 (0.018)	−0.235 (0.012)	−0.117 (0.048)
N	1.098 (0.000)	1.022 (0.000)	1.065 (0.000)
$\ln(L)$	−231.370	−247.927	−230.594
Q(36)	26.473 (0.651)	32.963 (0.324)	32.722 (0.335)
Qs(36)	28.046 (0.826)	22.773 (0.958)	21.025 (0.978)

Note: ( ) stands for the p value; Q(36) and Qs(36) stand for the Ljung–Box serial correlation test, respectively.

Table 2 provides a comprehensive summary of the GARCH model outcomes, illustrating that both α and β successfully pass the significance test at a 5% level. The value of α serves as a measure of the persistence of shocks, while β quantifies the endurance of volatility clustering. The γ value captures the negative leverage impact on conditional volatility, with all estimation coefficients deemed significant at the 5% level. These findings imply that negative news has a considerably more pronounced effect on volatility than positive news in both the oil markets (as assessed by W1ENE and QDII-LOF) and the stock market. The policy implications of these results are manifold. First and foremost, the prominence of negative news in driving market volatility underscores the importance of effective communication and transparency from policymakers and market participants. Accurate and timely information dissemination can mitigate the potential for negative news to trigger panic and exacerbate market fluctuations.

Regarding the generalized error distribution, the parameter ν shapes the distribution's form, with higher values corresponding to lighter tails and lower values to heavier tails. Table 2 reveals that the predicted stock return shape parameter is less than 2, suggesting a distribution characterized by fat tails. This finding indicates that extreme events and significant market movements occur more frequently than anticipated under normal distribution assumptions. Policymakers should, therefore, remain vigilant for such tail risks and implement appropriate measures to strengthen the resilience of financial markets against unexpected shocks.

Additionally, the Ljung–Box serial correlation test results point to an absence of autocorrelation between the variance and mean series. This observation implies that past returns and volatilities may not necessarily provide reliable predictions for future market behavior. Policymakers should be cautious about relying solely on historical data for forecasting and decision-making and instead adopt a more holistic approach incorporating various economic indicators, market sentiment, and global trends to assess market risks and devise effective policy responses. In summary, the GARCH model outcomes presented in Table 2 offer valuable insights into the drivers of volatility in oil and stock markets. Policymakers should consider these findings in formulating strategies to promote transparency, mitigate tail risks, and enhance market resilience in the face of uncertainties and potential shocks.

4.3. Causality-in-Mean and Variance. This subsection conducts the causality-in-mean test utilizing the standardized residuals derived from the EGARCH model, with the results meticulously presented in Table 3.

Table 3 reveals a conspicuous absence of a causal connection between QDII-LOF and W1ENE; however, it distinctly identifies a causality between QDII-LOF and CSI across all lag periods. This observation highlights the impact of QDII-LOF oil price fluctuations on China's stock markets. Given China's significant consumption of QDII-LOF-type oil, the existence of such a causal relationship is reasonably anticipated. Consequently, understanding this relationship bears crucial policy implications. To assess the volatility spillover effects between the oil market and the stock market, the causality-in-variance test employs squared standardized residuals. These detailed results, presented in Table 4, offer valuable insights for policymakers. As China's economy continues to depend on oil imports, the interdependence between oil prices and stock market performance necessitates vigilant monitoring and proactive policy responses to safeguard the stability of financial markets and the broader economy. Policymakers should be cognizant of the potential risks associated with oil price volatility and consider formulating strategies to minimize its impact on stock market returns. This might involve diversifying the energy portfolio to reduce reliance on oil imports, increasing investment in renewable energy sources, and encouraging industries to adopt energy-efficient technologies. Additionally, promoting financial market resilience by enhancing risk management capabilities and strengthening regulatory oversight could mitigate the adverse effects of oil price fluctuations on stock market performance. In summary, the observed causal relationship between QDII-LOF oil prices and China's stock markets, as evidenced by Table 3, underscores the importance of comprehensive policy interventions to manage the ramifications of oil price volatility. By heeding the results of the causality-in-variance test displayed in Table 4, policymakers can better navigate the intricate dynamics between the oil market and the stock market, ultimately fostering greater economic stability and growth.

Table 3: Results of the causality-in-mean test.

Causality direction	Lag1	Lag2	Lag3	Lag4
CSI $\longrightarrow$ W1ENE	0.012	0.267	0.097	0.064
W1ENE $\longrightarrow$ CSI	0.245	0.146	0.598	0.194
CSI $\longrightarrow$ QDII-LOF	1.297	1.149	0.175	2.260
QDII-LOF $\longrightarrow$ CSI	5.242^{**}	8.838^{***}	4.799^{**}	8.160^{***}

Note: $\longrightarrow$ stands for the causality direction; ** stands for 5% significant level; *** stands for 1% significant level.

Table 4: Results of causality-in-variance test.

Causality direction	Lag1	Lag2	Lag3	Lag4
CSI $\longrightarrow$ W1ENE	0.172	2.717	1.352	0.104
W1ENE $\longrightarrow$ CSI	0.226	0.248	0.0569	0.194
CSI $\longrightarrow$ QDII-LOF	0.883	0.409	0.830	1.117
QDII-LOF $\longrightarrow$ CSI	1.512	1.108	0.118	0.067

Note: $\longrightarrow$ stands for the causality direction.

As per the insights provided in Table 4, the volatility spillover effect between the stock market and the oil market remains indiscernible. This observation is attributed to the null hypothesis of no causality failing to pass the conventional significance test for all variables. The absence of clear volatility spillover effects between these markets has noteworthy policy implications. The lack of a discernible volatility spillover effect suggests that shocks in one market may not necessarily trigger immediate or significant repercussions in the other market. Consequently, policymakers should exercise caution in interpreting the relationship between the stock market and the oil market, as the implications may not be as straightforward as initially anticipated. This finding highlights the importance of adopting a multifaceted approach when formulating policies to manage market risks. Policymakers should consider both the direct and indirect channels through which oil price fluctuations may impact the stock market, and vice versa. In doing so, they can develop targeted interventions to address sector-specific vulnerabilities and bolster the resilience of the financial markets. Moreover, it is crucial for policymakers to monitor macroeconomic indicators and global economic trends, as these factors may influence the dynamics between the oil market and the stock market. This vigilance can facilitate the early identification of potential risks and enable timely policy responses to mitigate adverse effects on the economy. In conclusion, the inability to identify a clear volatility spillover effect between the stock market and the oil market, as indicated in Table 4, underlines the need for a nuanced understanding of the relationship between these markets.

4.4. Discussion. Annually, China experiences fluctuations in oil imports; however, since the advent of reform and opening-up policies, both oil consumption and imports have consistently grown. According to data from the China Energy Administration, China's oil consumption reached 737 million tons in 2020, with domestic production accounting for 195 million tons. Consequently, imported crude oil constituted a staggering 73% of China's total consumption. Given China's significant reliance on imported energy, particularly crude oil, several factors contribute to energy price fluctuations. Primarily, global energy price volatility, especially crude oil prices, must be considered. These prices are determined by supply and demand variables in the international market. Similar to other commodities, sophisticated auction markets and derivatives exist to manage risk and facilitate speculation. Therefore, supply and demand are not the sole contributors to oil price fluctuations. The heightened sensitivity of oil prices to demand and supply shifts, along with the growing utilization of oil as a financial asset, warrants further exploration. The increased demand and supply sensitivity may hinge on the potential for lower price elasticity, resulting in heightened oil price volatility. Escalating global uncertainties could contribute to declining price elasticity. Additionally, the expanding use of oil as a financial asset may precipitate oil price oscillations. The growing employment of oil for financial investments, hedging, and speculation could heighten oil prices' sensitivity to investor sentiment and financial market information flows. However, no definitive evidence has established a link between oil's role as a financial instrument and global oil price shifts, leaving the inquiry unresolved (Alquist and Kilian [60], Kaufmann and Ullman [61], and Liu et al. [62]). Notably, Van Robays [63] and Lin and Bai [64] posited that local oil price volatility could alter economic outlooks and, consequently, oil demand, generating a secondary feedback effect. Lastly, fluctuations in the value of the Chinese lira, which amplify the impact of global oil price shifts on the domestic economy, affect the cost of domestically produced petroleum products in China. Secondly, although our empirical investigation is limited to the relationship between global oil price shifts and China's stock market performance, we can postulate that China's retail energy prices have also experienced significant increases. This can be attributed, in part, to the dependence on energy product consumption taxes and the automotive sector's special consumption tax, both of which influence energy demand. These factors not only induce retail energy price volatility but also generate regulatory uncertainty and energy price instability.

Our study's findings reveal that global oil price volatility influences China's stock market returns, and in certain subperiods of the sample, these fluctuations have notable spillover effects on volatility. These results bear significant regulatory implications. It can be inferred that government actions, particularly frequent tax rate adjustments, contribute to retail energy price fluctuations both directly and indirectly through policy influence and uncertainty generation. This is attributable to China's substantial taxation on gasoline and the high special consumption tax imposed on the automobile industry and other products. In light of these findings, it is evident that the Chinese government levies a heavy tax on gasoline. If such governmental efforts exacerbate energy price volatility, they could negatively impact risk management strategies employed by consumers and businesses. Additionally, the Chinese government may alleviate some of the concerns by implementing policies that facilitate the adoption of more stable alternative energy sources. These measures could potentially contribute to pollution reduction in major urban areas. However, it is essential to recognize that alternative energy sources may entail high costs, necessitating substantial direct expenditures and investments in infrastructure. Furthermore, relying on strategic oil reserves serves as another viable approach to mitigating the impacts of significant global oil price fluctuations and guarding against potential supply disruptions. The Chinese government can also explore the potential of alternative renewable energy sources, such as solar, wind, and other forms of sustainable energy, to promote greater energy stability and resilience.

The relationship between oil prices and stock market performance encompasses multiple dimensions. Steady oil prices contribute to the stabilization of production costs and consistent cash flow, bolstering profit and dividend forecasts. This, in turn, may result in higher retained earnings, increased investments, enhanced output, and employment, as well as elevated stock values and overall economic growth. Furthermore, consumers stand to reap additional benefits. Investors need to be cognizant of global oil price trends and the potential spillover effects in China when determining their portfolio allocation. When oil prices exert both first- and second-moment impacts, the returns from incorporating oil commodities into a portfolio are constrained in relation to both the oil price and traditional portfolio income. Concerning the latter, diversifying investment portfolios across various asset classes, including oil and other financial instruments, can offer valuable benefits for investors. These policy discussions are particularly relevant for countries akin to China in terms of dependence on energy imports and geographic or natural advantages. By addressing these considerations, investors and policymakers can better navigate the complexities arising from the interplay between oil prices and stock market performance, ultimately fostering a more resilient and prosperous economic landscape.

5. Conclusions

This research examines the dynamic relationship between stock market returns and oil price fluctuations in China during the COVID-19 pandemic, with particular attention to volatility spillovers. Utilizing causality-in-mean and variance tests on daily data from January 30, 2020, to August 30, 2022, the empirical analysis delves into this complex interaction. The results indicate that oil prices, as represented by the QDII-LOF benchmark, significantly influence stock market returns. However, when examining the entire sample, no discernible spillover effects stemming from oil prices are observed. These findings echo the conclusions of Cevik et al. [65], whose study on Turkey provided analogous results, thereby reinforcing the outcomes of this investigation.

Drawing from the empirical findings, several policy recommendations emerge. Firstly, policymakers and regulators should closely monitor the relationship between oil prices and stock market returns in order to proactively address potential risks and challenges arising from the dynamic interaction during periods of economic uncertainty. Secondly, encouraging investment in alternative and renewable energy sources could help mitigate the impact of oil price fluctuations on stock market returns, promoting economic stability and fostering sustainable growth. Thirdly, maintaining and promoting financial market stability should be a priority for policymakers, as this would help insulate stock markets from the adverse effects of global oil price movements during crises such as the COVID-19 pandemic. Fourthly, promoting greater awareness among investors about the relationship between oil prices and stock market returns could enable them to make more informed decisions when allocating their portfolios, potentially minimizing the impact of oil price fluctuations on their investments. Fifthly, policymakers should consider reviewing and adjusting fiscal policies related to oil taxation and consumption, as this could reduce the impact of oil price fluctuations on stock market returns and contribute to a more stable financial environment. Lastly, strengthening international cooperation among countries that are heavily reliant on oil imports could facilitate the sharing of best practices and the development of joint policy strategies to manage the economic consequences of oil price fluctuations and their spillover effects on stock markets.

This investigation presents two significant contributions to the existing Chinese scholarship on the topic. Firstly, by adopting the exponential generalized auto-regressive conditional heteroscedasticity, causality-in-mean, and variance methodologies, the study offers a unique analytical lens, thereby enriching the prevailing literature. This departs from prior Chinese studies that largely relied on vector autoregression, Granger causality, structural vector autoregression, and other techniques. Secondly, given China's position as the world's leading energy importer and the origin of the COVID-19 pandemic, using China as a case study provides a more illustrative and meaningful examination of the issue. This not only supplements existing literature but also expands the boundaries of the continuing dialogue surrounding this matter.

This study, while offering valuable insights, also presents certain limitations that can guide future research in promising directions. Firstly, the research exclusively examines the connection between energy price fluctuations and the performance of the Chinese stock market. Future scholars may build upon these findings to investigate similar relationships in other nations, particularly those that are net importers of oil and energy resources. Secondly, although escalating energy prices pose serious concerns for countries dependent on these resources, this paper solely focuses on the impact of such changes on stock market performance. Indeed, energy price volatility may have far-reaching consequences for various economies. Future research can delve deeper into these aspects. Thirdly, instead of concentrating solely on the COVID-19 pandemic, future researchers should consider exploring the broader implications of market volatility on the stability of energy supply, a critical factor for the growth of the global economy. Fourthly, future investigations could reevaluate these assertions employing advanced methodologies, such as machine learning and neural networks, potentially yielding more fascinating conclusions. Lastly, within the scope of this study, we utilize variable substitution as a means for conducting robustness tests. Scholars in the future are encouraged to explore more advanced and fitting methodologies for re-evaluating robustness tests, potentially yielding enhanced reliability in the outcomes.

Data Availability

The data presented in this study are available from the authors upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the Universities' Humanities and Social Science General Research Project of Henan Province (2023-ZZJH-018), Research Start-Up Foundation of Henan Finance University (2021BS009), and General Project of the National Social Science Foundation in 2022 (22BJY202).

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Hindawi
Discrete Dynamics in Nature and Society
Volume 2023, Article ID 5126128, 15 pages
https://doi.org/10.1155/2023/5126128

Research Article

The Spillover Effect among CET Market, Coal Market, and New Energy Market for Dual-Carbon Target: New Evidence from China

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Received 23 September 2022; Revised 2 January 2023; Accepted 23 March 2023; Published 19 April 2023

Academic Editor: Jean Vasile Andrei

The spillover effect of the energy markets and the CET plays an important role in guiding the realization of two-carbon target; using the network spillover methodology of Diebold, Yilmaz, Jozef Barunı´k, and Toma´sKrehlı´k, we examine both the static and dynamic connectedness of CO_2 emissions trading (CET) market, steam coal market, new energy, and traditional energy market in China from early Dec 2013 to the end of July 2021. At last, we verified the stability of the model and obtained the following findings: (1) the total spillover effect index is 13.91% between those markets, and it is mainly focused on short term. Moreover, the dynamic spillover effect is time-varying, and it is greatly influenced by the domestic and international environment; (2) the connectedness of the CET market with other energy markets is neutral, the development of new energy market is strong, it is the main transmitter to other markets, especially to the traditional energy market except for the steam coal market, and the coal market is an effect transmitter. These results provide a theoretical reference for investors and policy makers who are concerned with the return connectedness among the CET market, new energy market, and steam coal market in China.

1. Introduction

At present, global climate change has become one of the greatest challenges and threats to human development. In the process of economic development, the carbon dioxide emission caused by energy consumption, especially fossil energy consumption, is the main cause of global climate change [1, 2]. Thus, over the past decade, global initiatives are being taken to reduce the use of traditional energy to clean energy for emission reduction [3]. Nevertheless, China is facing great pressure in the energy structure transformation. Statistically, steam coal accounts for 56% of China's total energy consumption, oil accounts for 18.7%, and clean energy sources such as natural gas, hydropower, wind power, nuclear power, and solar power generation account for 25.3% in 2021. Although Chinese government regards new energy development as an important strategic development direction, coal will still be the main source of energy in China in the future [4]. Furthermore, the international community is increasingly attaching great importance to the sustainable development of energy [5], climate, and the environment which urge carbon emissions to become the most urgent environmental problem in China. So, in the next five years, China is further deepening energy price reform, especially the price of coal and other fossil energy, which has become an important measure to control the total energy consumption and improve energy efficiency [4].

On the other hand, in order to reduce carbon emissions, countries internalize the externalities of carbon emissions by establishing a carbon emission trading (CET) system. Since the Kyoto Protocol and the Paris Agreement were signed, Europe has set up the EU Emissions Trading System (EU ETS), which has effectively reduced the intensity of carbon emissions [6]. Since 2013, China has established eight pilot carbon emission trading markets in Beijing, Shanghai, Wuhan, Guangzhou, and so on. By October 2022, the cumulative trading volume of the 8 pilot projects was close to 196 million tons and the cumulative turnover of the 8 provinces and cities exceeded 8.58 billion yuan. However, the grandfather rules focused on the historical emissions lead to overallocation and low carbon prices. The carbon emission price is much lower than 100 CNY/ton. Therefore, it is of great practical significance to study the correlation mechanism and spillover dynamics between the CET market and a specific energy market to establish a perfect and sustainable CET market [4].

Over the past few decades, because of its cleanliness, new energy has received the favor of various countries. China has taken the development of new energy industry as a national strategy to be vigorously implemented. The new energy industry is of great significance for China to realize the transformation of the energy utilization mode and the development of green economy for the dual-carbon goal [7].

The vigorous development of the new energy industry will also attract the attention of investors in the capital market. Investors are generally optimistic about the development direction of new energy companies which reflected in the investment in the stocks of new energy companies. Therefore, it has great significance for financial investors and policymakers to acquaintance the new energy company stock price influence factors.

Above all, because the carbon emission rights have both commodity and financial attributes in the financial markets, the CET market has both resource allocation and financial functions. Due to the link of economic fundamentals, there are some connections between "carbon-finance-energy" markets by means of information transfer [8]. The financialization of the energy markets can reflect the fundamental links between energy markets through financialization means so as to better deepen the energy price reform and realize the transformation of green energy utilization. This may be why the Chinese central bank has repeatedly proposed to financialize the energy market and develop carbon finance to realize carbon control and emission reduction in a market-oriented way. With increased globalization and carbon financialization, the correlation between carbon emission market and energy market is also strengthening. This paper studies the connectivity spillover relationship among the CET market, coal market, new energy market, and the traditional energy market in China; the research results can show the total spillover effect between the CET market and the given energy markets which can further show the important role of the CET market in the task of emission reduction. On the other hand, the spillover effect of each financial market can become an important investment channel for the diversification of profits and risks, and it can provide certain reference information for investors to make investment decisions and hedge financial risks.

2. Literature Reviews

The connectivity and the spillover effect between the CET market and the energy market have attracted the attention of many scholars. Numerous scholars have confirmed the relationship between the CET market and the energy market [4, 7]. The existing literature about the connectivity between CET and energy markets has conducted studies on different aspects [9, 10]. Different energy markets have been selected for the study, such as fossil fuel [11] and crude oil [12, 13]; scholar Yang Lu also studied the spillover effects between the CET market and the cryptocurrency market [14]. A variety of research methods have been involved, such as wavelet coherency [7], multiscale entropy [15], structural equation modelling [16], quantile-on-quantile approach [17], multiscale analysis [6], and DCC-MVGARCH model [10]; it is worth mentioning that electricity as an important part of energy is of great significance to the energy transformation and utilization and carbon emission reduction. In the existing literature [18], we studied the role of peak-valley electricity price and trait factors in the information spillover mechanism between the European electricity market and the carbon market, and the result proved the dominant role of the electricity market [19]. We studied the value of renewable energy generation for emission reduction and power supply [8]. We also studied the interaction among Guangdong power, fossil fuel, and carbon market price and confirmed the long-term cointegration relationship among them.

On the other hand, the methods of DY index and BK index have been widely used to measure the connectivity among specific objects [20]. After studying the related literature, these two methods have been applied in various fields up to now, such as these methods can not only be used to measure the total connectivity among all objects [21], but it can also survey the pairwise connectivity [22] between each two objects of the system which may contain multiple objects and the net spillover effect of each object [23]; they can not only be used to measure the objects' connectivity based on the time dimension [24, 25] but also on different frequencies [26]; just because of the unique capabilities of the DY and BK methods, this method system has been widely used by scholars [27, 28].

In summary, there were massive studies about the connectivity between CET and energy markets, while there are few about the research among CET, steam coal, and new energy markets [4]. In the few existing literature studies on CET, coal market, and new energy markets, we have the following research gaps. Firstly, most of the research is about the bidirectional causality between the CET market and the single energy market, but there is lack of simultaneous studies on the interaction between multiple markets. Secondly, the research studies on the correlation among the CET market, coal market, new energy market, and traditional energy market lack directional spillover and net spillover of impact identification and mutual influence of the complex networks of all markets. Thirdly, the relationship among the CET market, coal market, and the new energy market should be measured from both static and dynamic aspects, and whether the relationship between the CET market and the given energy markets has time-varying nature is worth exploring.

In order to fill the gap in the existing literature, this paper studies the connectivity and spillover effect among CET, steam coal, new energy, and traditional energy markets in China based on the method of Diebold and Yilmaz [29]. The reason we elect this method is that it is independent of element sorting [12]. The aim of research is to explore the connectivity, especially the directional spillover effects and net spillover effects between the various markets of the research framework. Firstly, the paper analyses the characteristics and the regular development of each market from the perspective of time sequence, and then we constructed the DY and BK indices to reveal the connectedness among the CET market, coal market, new energy market, and traditional energy market in the time and frequency domain. Finally, we study the directional spillover index and the net spillover index from a time-varying perspective.

Thus, the contributions to the existing literature are from the following aspects: first, the study from the perspective of connectivity to research the total spillover effect, net spillover effect, and the pairwise spillover effect among the CET market, coal market, new energy market, and traditional energy market, this holistic research approach simplifies the process of understanding the role of direct and indirect effects between multiple markets. Second, the study surveys the spillover effect between CET and energy markets from the perspective of static and dynamic spillover effects, as well as from the perspective of time dimension and the frequency dimension, all of this further broaden the scope of research on the given markets. Thirdly, we identified the net information recipients and net information contributors in the CET market, coal market, new energy market, and traditional energy market in the current Chinese context.

The rest of this article is organized as follows: Section 3 illustrates various descriptions and data collection as well as constructs the methodology of the DY and BK indexes. The preliminary analysis and the empirical results of the series of CET prices, new energy market prices, traditional energy prices, and coal prices are demonstrated in Section 4. In Section 5, we analyzed the empirical findings of the static and dynamic spillover effects. Finally, the conclusion, the policy implication, and the further work are summarized in Section 6.

3. Data and Methodology

3.1. Data. This paper investigates the connectedness of the CET market, new energy market, steam coal market, and traditional energy market in China.

Considering that Beijing Carbon Exchange has been running smoothly and efficiently compared to other CET markets since its inception, this study selects the CET price in the Beijing Carbon Exchange as the proxy of the CET market price. Moreover, the Chinese stock market has become quite efficient through a series of institutional and regulatory reforms after China's accession to the WTO; thus, the market data (e.g. prices) of the listed companies can effectively reflect the relevant information of the company and the market expectation for future performance. The development of the new energy industry can be effectively measured by its corresponding stock price movement; this paper selects the CSI New Energy Index (CSINE), which is composed of 80 companies listed on the Shanghai Stock Exchange Composite and Shenzhen Stock Exchange Composite. The paper selects the CSI All Share Energy Index and the steam coal price as the proxies of the traditional energy market. Furthermore, according to the national data, traditional energy consumption accounts for 75% of total energy consumption in China, so this paper uses the CSI All Share Energy Index (ASEI) as the proxy of the traditional energy market. In particular, the paper investigates the connectedness and spillover between the steam coal market and three other markets. Since the futures price is a better representation than the spot price, this paper selects the stem coal futures price named COAL instead of the steam coal spot price as the representation of the steam coal market. Finally, the stability of the connection model is tested using CSI energy, namely, CSIEN.

The CET data were obtained from the China Beijing Green Exchange (https://www.cbeex.com), and the steam coal future contract price was obtained from Zhengzhou Commodity Exchange (ZCE). The CSI All Share Energy Index (the ticker symbol is 000986) and CSI New Energy Index (the ticker symbol is 399808) were obtained from the database provided by Wind Information Co., Ltd. (WIND). Because CET market trading is not continuous every workday, instead of utilizing daily data, we use weekly average data. The ASEI and CSINE indices use the weekly closing prices, and the CET price and the coal futures price use the weekly average of trades. The data sampling period ranges from early December 2013 to the end of June 2021, and a total of 353 observations are available. The beginning point and data size depend on the availability of data on the Beijing CET market.

3.2. Methodology. In this research, we explore the overall connectivity, the directional spillover index, and the net spillover index among CET, steam coal, new energy, and the traditional energy. Firstly, we established VAR (vector auto regression model) with indices of the markets we considered, and then we apply the measurement approaches for the connectedness among different markets set up by Diebold and Yilmaz [29], namely, the DY index, and Barunik and Křehlík [30], namely, the BK index. Those indexes were calculated on the basis of the generalized variance decomposition (GVD) of the covariance-stationary VAR (p) model, which is expressed by the following equation:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t. \tag{1}$$

In equation (1), parameter y_t is an $N \times 1$ vector that represents the endogenous variables, Φ_i is the autoregressive coefficient matrices with dimension $N \times N$, i is the lags of the model, and ε_t is the model's random error that is independent and identically distributed.

Moreover, the basic idea of the DY approach is using the generalized variance decomposition technique. The following DY approach can obtain the contribution of the change of each variable to the other variables. Here, we describe this contribution as the spillover index, and the spillover index from market j to market i is denoted by $\theta_{ij}(H)$. This is the proportion of the H-step prediction error variance of variable y_i explained by variable y_j. Therefore, the value of $\theta_{ij}(H)$ is from 0 to 1. Furthermore, as H increases, $\theta_{ij}(H)$ gradually tends to decrease until it stabilizes.

The significance of generalized variance decomposition is that the analysis result will not be influenced by the sequence of variables in the VAR model, so we can obtain robust analysis results. The formula of $\theta_{ij}(H)$ is defined as the following equation:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j^2\right)}{\sum_{h=0}^{H}\left(e_i' A_h \sum A_h' e_i^2\right)}, \tag{2}$$

where Σ is the $N \times N$ variance matrix of the errors ε in the VAR (p) model, σ_{jj} is the standard deviation of the error ε shown in the jth diagonal element of Σ, and e_i is an $N \times 1$ selection vector with one as its ith element and zero otherwise.

Because the sum of the composition of the own and cross-variable variance is not unity, we normalized each variance composition using the row sum, and the normalized formula is given as follows in the equation:

$$\widetilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)}. \tag{3}$$

In equation (3), $\sum_{j=1}^{N}\widetilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}(H) = N$ are involuntary. $\widetilde{\theta}_{ij}(H)$ shows the pairwise directional connectedness from j to i visually at horizon H.

In order to better analyze the connectedness relationship between variables, Debold and Yilmaz constructed a series of network spillover indices on the basis of a generalized variance decomposition matrix, and the details are as follows:

$$\begin{aligned} C(H) &= 100 \times \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}(H)}{\sum_{i.j=1}^{N}\widetilde{\theta}_{ij}(H)}, \\ &= \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}(H)}{N}. \end{aligned} \tag{4}$$

We name $C(H)$ the total spillover index of the system, and it represents the total connectedness between each market we consider. In this study, it can measure the spillover effect of the CET market, new energy market, traditional market, and coal market.

We denoted the pairwise directional spillover index from market j to market i in the system as $C_{i\leftarrow j}^{H}$, so $C_{i\leftarrow j}^{H} = \widetilde{\theta}_{ij}(H)$, and $C_{i\leftarrow j}^{H}$ is generally not equal to $C_{j\leftarrow i}^{H}$. Thus, we further define the net-pairwise directional index from market j to market i as the deviation value between $C_{i\leftarrow j}^{H}$ and $C_{j\leftarrow i}^{H}$ denoted as C_{ij}^{H}, $C_{ij}^{H} = C_{i\longrightarrow j}^{H} - C_{i\leftarrow j}^{H}$ and $C_{ij}^{H} = -C_{ji}^{H}$.

Therefore, it is natural that the total directional connectedness from all other markets to market i is denoted as $C_{i\leftarrow *}(H)$, and the calculation formula is given as follows in the equation:

$$\begin{aligned} C_{i\leftarrow *}(H) &= \frac{\sum_{j=1,j\neq i}^{N}\widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N}\widetilde{\theta}_{ij}(H)} \times 100, \\ &= \frac{\sum_{j=1,j\neq i}^{N}\widetilde{\theta}_{ij}(H)}{N} \times 100. \end{aligned} \tag{5}$$

The total directional connectedness to all other markets from market j is denoted by $C_{*\leftarrow j}(H)$, and the calculation formula is given as follows in the equation:

$$\begin{aligned} C_{*\leftarrow j}(H) &= \frac{\sum_{i=1,i\neq j}^{N}\theta_{ij}(H)}{\sum_{ij=1}^{N}\theta_{ij}(H)} \times 100, \\ &= \frac{\sum_{i=1,i\neq j}^{N}\theta_{ij}(H)}{N} \times 100. \end{aligned} \tag{6}$$

Here, we focus on the net spillover effect of market i, which is denoted as C_i^H. This index measures the net spillover from market i to all other markets.

4. Preliminary Statistical Analysis

The change details of the coal futures price, the CET price, the CSI new energy index, and the ASEI during the period of early December 2013 to the end of July 2021 are presented in Figure 1. The figure shows that there are different trend details in the four markets starting in early December 2013.

It can be clearly noticed that the coal price continued to fall from the end of 2013 to the end of 2015, and then the coal price rapidly returned to normal levels in half a year. Furthermore, the coal price rapidly increased after June 2020, which can be attributed to increased demand. According to our investigation, the demand for electricity is rising across the country as the economic recovery accelerates and heat persists in the postpandemic era period, and 70% of China's power plants are coal-fired, which has pushed coal prices soaring in turn. The CET price fluctuated after June 2018 and fluctuated more in September 2019. The results can be attributed to President Xi setting the goal of peak carbon use and carbon neutrality in the Seventy-fifth Session of the United Nations General Assembly. For the last three years, the CET price has fluctuated considerably. In the energy market, China has paid great attention to develop the new energy industry in recent years, which has led to a flood of money into the new energy sector. Moreover, it can be seen that the CSINE index has been rapidly increasing since early 2020, and the traditional energy market has been declining with shocks since the end of 2015, which may be some of the results of the transition from traditional energy to new energy.

Because the return price has better statistical characteristics, the study treats the original data with formula $R_t = \ln(P_t/P_{t-1})$ to serve as the return index of the variable before the preliminary statistical analysis.

P_t represents the weekly data of the CET price, coal futures price, new energy index, and traditional energy firms stock price. Therefore, in the following descriptive statistical analysis and empirical analysis, the paper will adopt the return series of the four markets for analysis.

Figure 2 shows the dynamic evolution of the CET market returns, new energy market returns, coal market returns, and traditional energy market returns. We clearly obtain the fluctuation of each return series. The coal price and the CET price have more similar volatilities. However, in the early days, the CET market fluctuated earlier than the coal market.

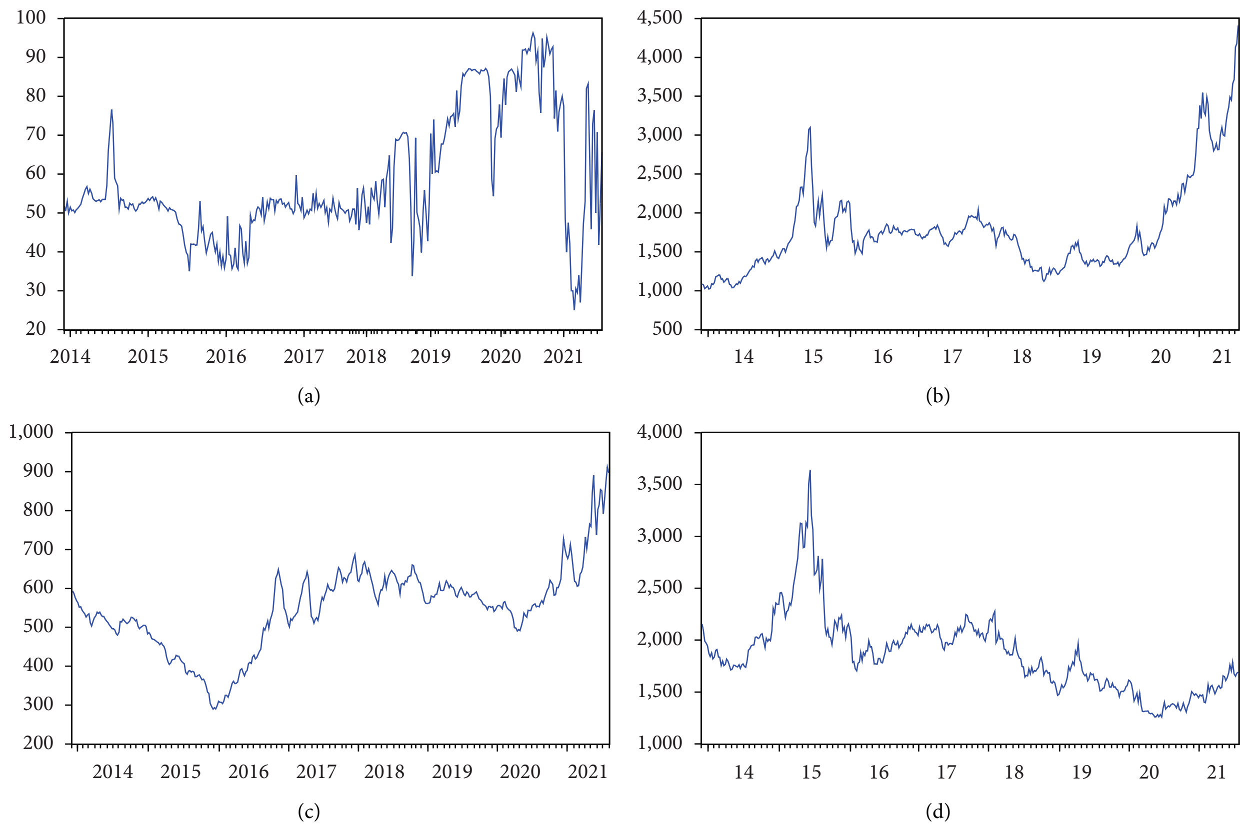

Figure 1: The price movement of the CET market, new energy market, coal market, and the traditional energy stock market. (a) The price movement of the CET market. (b) The price movement of the new energy firms stock market. (c) The coal future price movement of the coal market. (d) The price movement of the traditional energy firms stock market.

For example, the CET market is middle in 2017, while the coal market is in the middle early in 2018. However, in the subsequent volatility, the two series' movements are almost synchronous. This suggests that markets are sufficiently flexible and efficient to reflect market information. We can also find that the volatility of the new energy market is similar to the volatility of the traditional energy market. As shown in Figure 2, the CSINE market and the traditional energy market fluctuate more in the period of July 2015 to April 2016, and the traditional energy market tends to be stable. Furthermore, new energy has higher volatility than the traditional energy market because increasingly more fields have paid attention to the new energy field in recent years. Moreover, new energy is an inevitable choice to realize green economy development.

Table 1 shows the descriptive statistics of the variables' weekly returns. It is evident that the mean returns of the four markets are all near zero. Furthermore, the standard deviation of the CET return price is the largest, while the standard deviation of the coal market is the smallest, which shows that the CET market has the largest volatility and the coal market has the lowest volatility. The skewness shows that the skewness of the coal futures return price is similar to a normal distribution, while the other three markets' return prices are negatively skewed. Furthermore, the kurtosis coefficients of the four markets are greater than zero, which means that they are all leptokurtic. Moreover, the J-B test is a normality test based on the skewness and kurtosis, and the results show that the test results are all significant at 1% significance level, which indicates that the four return series do not all obey the normal distribution.

The stationarity of the four return series can be checked by the augmented Dickey–Fuller (ADF) test. It is clear that the T statistics of the above four variables are all less than the corresponding critical values from Table 1. Therefore, the null hypothesis is rejected at the 1% level, indicating that there is no unit root in the return series of the CET price, coal futures price, new energy index, and traditional energy firm stock, which are stationary series. The KPSS test also obtained the same conclusion, and this further confirms the suitability of using the VAR model for analysis.

Figure 3 depicts a visual Pearson's correlation matrix for the four markets' various return series. We note that the color which changes from blue to red indicates the strength of the correlation which changes from negative to positive. First, it is found that there is a significantly strong and positive correlation (0.63) between the traditional energy market and the new energy market. As expected, the correlation ship between the coal market and the traditional energy market is positive (0.22). Because coal is a major part of the traditional energy market, there is an inherent connection between them. Judging from the current data, there

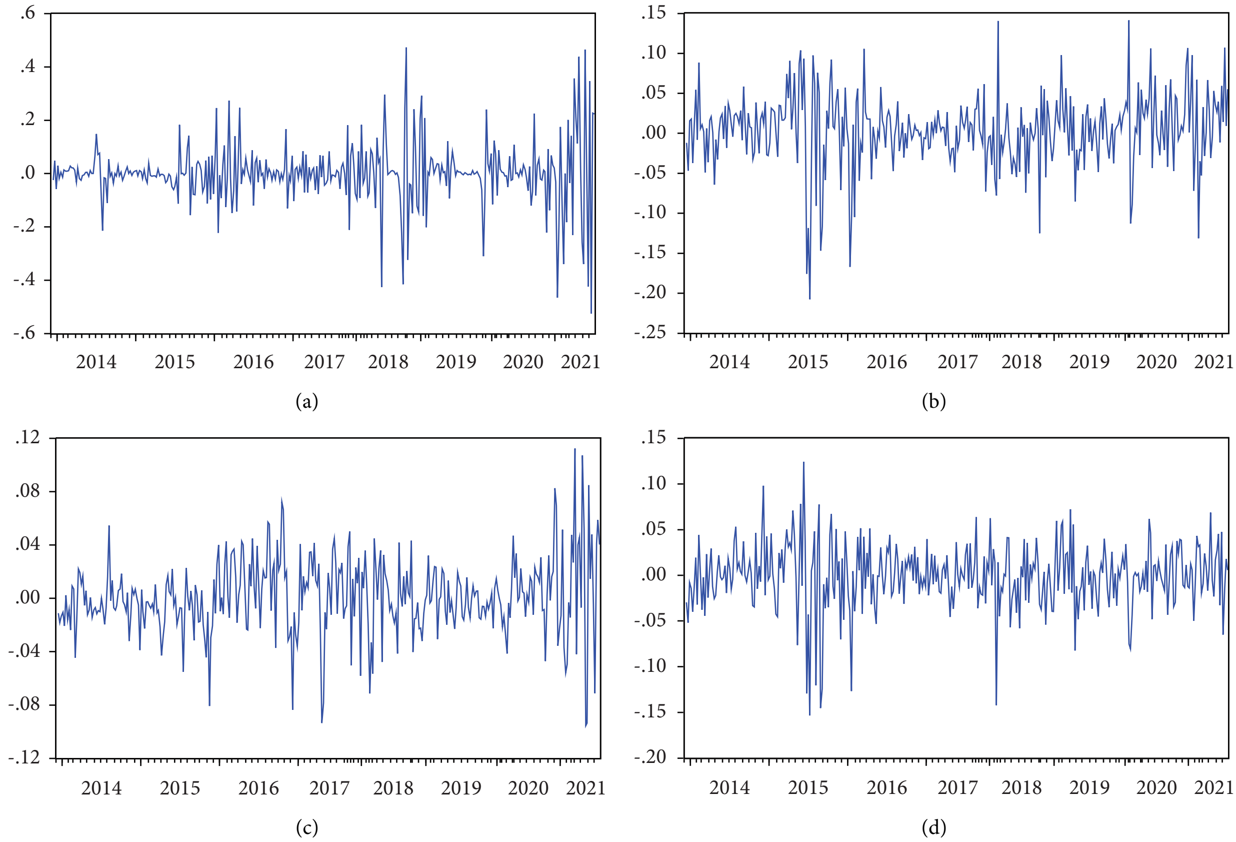

FIGURE 2: Dynamics of sample returns price of the four markets during the periods of the first week of December, 2013, and the last week of July, 2021. (a) Dynamics of the CET returns. (b) Dynamics of the CSINE returns. (c) Dynamics of the COAL returns. (d) Dynamics of the ASEI returns.

TABLE 1: The descriptive statistics of the return series.

Variables	Min.	Mean	Max.	Std. dev.	Skewness	Kurtosis	J-Bera	ADF (1%: −3.98)	KPSS
CET	−0.5258	0.0007	0.4731	0.0459	−0.7909	7.9573	363.45	−17.4487***	0.0236
CSINE	−0.2077	0.0040	0.1415	0.0454	−0.6860	5.8925	150.32	−11.7935***	0.3272
COAL	−0.0955	0.0012	0.1123	0.0285	0.01457	4.9498	55.769	−12.0409***	0.2197
ASEI	−0.1533	−0.0004	0.1244	0.0359	−0.7524	5.9760	163.11	−12.6731***	0.0519

is a weak negative correlation between the new energy market and the traditional energy market, and there is a weak correlation between the CET market and the new energy market.

5. Empirical Results and Discussion

Our initial result of the significant correlation ship among the CET market, traditional energy market, coal market, and new energy market offers some preliminary indication of the network connectedness and spillover effects among the markets we consider. In this section, we will utilize the decomposition of the prediction error variance based on the VAR model to construct the DY and BK indices. The network connectivity and spillover effects between each energy market and the CET market are analyzed from both the static and dynamic directions, filling the gap in the existing literature in the related fields. This method can not only measure the direct effect between the variables but can also measure the directional parameters, which enables the more detailed description of the interaction relationship between the market pairs in the system.

5.1. The Full-Sample Volatility of Spillover Analysis of Return Series. We use the return series connectedness network to Chinese environmental and energy to study their spillover connectedness in a static environment. Following Jiang et al. [7] and Lin and Chen [4] who examined the systemic spillover of China's CET market, coal market, and new energy market using the multivariate wavelet method, VAR(1)-BEKK-AGARCH(1, 1) and VAR(1)-DCC-GARCH(1, 1) models were used. Firstly, the VAR $(p = 2)$ model was constructed based on the weekly data of China's coal futures price, CO_2 emissions trading price, traditional

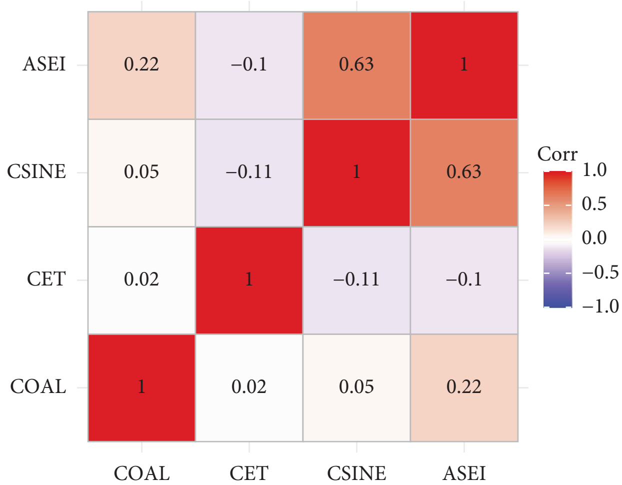

Figure 3: Visualization of the correlation matrix.

energy market, and new energy index for which the model lag order $p = 2$ was selected after comparing the model results with the model's Bayes–Schwarz Information Criterion (BIC). Then, we use the methods proposed by Diebold and Yılmaz in the time domain and the method of BK in the frequency domain to reflect the mutual influence and spillover effects within the four markets and construct the return spillover network based on the estimation of 100-step-ahead error variance prediction, and the results are shown in Table 2.

Table 2 is the net connectedness table for each market during the entire period from early December 2013 to the end of July 2021. The predictive horizon H is 100 weeks, which is sufficiently high so that it will not change with the additional period, and the VAR lag order p is 2 weeks.

In Panel A, the (i, j) th element in the $4 * 4$ (from x_i to x_j) matrix shows the estimated contribution to the forecast error variance of variable i coming from market j, which represents the 100-week-ahead forecast error variance of market i due to the shock from market j. "FROM (j)" and "TO (i)" represent the from-connectedness of market j and the to-connectedness of market i, respectively, e.g., in the line direction, steam coal return series' forecast error variance was explained 98.65% by itself, while there was 1.29% explained by ASEI which presented traditional energy, and there was 1.29% forecast error variance which was explained by other markets. There was 55.42% forecast error variance of the shock of ASEI market which was explained by itself, and the shock of CSINE market explained 37.74% forecast error variance of the ASEI market. There is a total of 44.57% of the forecast error variance which was caused by other market shocks. This shows that the fluctuation of the energy market has a great impact on the traditional energy market. This can be interpreted as follows: new energy is an alternative product of traditional energy sources. With the intensification of the global warming, the use of new energy materials and products is becoming more and more popular, so the use of traditional energy-related products decreases accordingly. This impact effect will also be reflected in the corresponding stock market data. From the column direction, we can see the shock of every market contribute rate to the variance error decomposition in other markets, such as there is 5.42% forecast error variance of the ASEI explained by the steam coal market. There are similar interpretations to other data in the Panel A. As can be seen from Panel A, the degree of mutual influence between every two markets is inconsistent. In general, the more stable the market, the less it is affected by other markets and the smaller the value of "From" in Panel A [26, 31].

Table 2 shows that the total spillover index is 13.91%, which means that 13.91% of the variation in the system is due to the interaction between variables. It is obvious that for the CET market, the spillover effect from the coal market is much greater than that from the CSINE and ASEI markets. As for the traditional energy market, the spillover effect from CSINE, which reaches 37.74%, is much greater than those for other market indices. Overall, the CSINE, which represents the new energy market, has the largest spillover effect (9.54%), and this is mainly because the new energy market has a high spillover effect on the traditional energy market. Panel B shows the pairwise directional connectedness among the four markets, including the net-pairwise connectedness and the conclusion. We find that the traditional energy market is a recipient market, and the largest transmitter is the new energy market in the system. As expected, this is because these two markets have considerable substitution effects on each other. Furthermore, the CET market in China is neutral, and the spillover effect between the CET market and other markets is nonsignificant.

5.2. Analysis of the Static Return Spillover Effect Based on the BK Index. The abovementioned analysis in a static environment used the method of the DY index, and this method can examine the connectedness at a specific time. In order to study the time and frequency dynamics between the CET market and the energy markets in China, we next focus on the method proposed by Baruník and Křehlík [30] to measure the spillover effects of the return series of the CET market and the energy markets in China.

Table 3 shows the empirical findings of the return series spillover between the CET market and the energy market based on the BK index at different time frequencies. As shown in Table 3, there are three different time-frequency ranges, namely, Panel A, Panel B, and Panel C. Panel A is the table of the overflow index in the short-term (1–5 weeks) frequency band, Panel B is the table of the overflow index in the medium-term (5–20 weeks) frequency band, and Panel C is the table of the long-term (longer than 20 weeks) frequency band.

Regarding the results in Table 3, we focus on the "FROM_ABS" statistics. The total spillover index is 10.57% in the short term, and following the time-frequency band growth, the total spillover index dropped rapidly to 2.44% in the medium term and 0.90% in the long term. Therefore, the spillover effect has time-varying characteristics in the

TABLE 2: Total spillover indices and net-pairwise indices among variety markets.

	From (j)					
To (i)	COAL	CET	CSINE	ASEI	From-others	FROM
Panel A: total spillover index within various markets						
COAL	98.68	0.02	0.01	1.29	1.32	0.33
CET	5.32	94.25	0.39	0.04	5.75	1.44
CSINE	0.58	1.72	96.01	1.69	3.99	1.00
ASEI	5.42	1.41	37.74	55.42	44.57	11.14
To-others	11.32	3.15	38.14	3.02		
TO	2.83	0.79	9.54	0.75		**13.91**
Panel B: net-pairwise spillover index within various markets						
COAL	0	−1.33	−0.14	−1.03		
CET	1.33	0	−0.33	−0.34		
CSINE	0.145	0.33	0	−9.01		
ASEI	1.03	0.34	9.01	0		
Net	2.5	−0.65	8.54	−10.34		
Conclusion	Net-transmitter	Neutral	Net-transmitter	Net-recipient		

TABLE 3: The dynamic analysis of the static return spillover effect based on the BK index.

	COAL	CET	CSINE	ASEI	FROM_ABS	FROM_WTH
Panel A: corresponds to 1 week to 5 weeks						
COAL	70.32	0.01	0.01	0.91	0.23	0.29
CET	4.48	82.03	0.33	0.02	1.21	1.54
CSINE	0.25	1.52	73.51	1.33	0.77	0.98
ASEI	4.21	1.03	28.18	46.57	8.36	10.62
TO_ABS	2.24	0.64	7.13	0.56	10.57	
TO_WTH	2.84	0.82	9.06	0.72		13.43
Panel B: corresponds to 5 to 20 weeks						
COAL	20.65	0.01	0.00	0.28	0.07	0.45
CET	0.62	9.06	0.05	0.01	0.17	1.09
CSINE	0.24	0.15	16.49	0.27	0.16	1.05
ASEI	0.88	0.28	7.00	6.56	2.04	13.05
TO_ABS	0.43	0.11	1.76	0.14	2.44	
TO_WTH	2.77	0.70	11.28	0.89		15.63
Panel C: corresponds to 20 to inf weeks						
COAL	7.71	0.00	0.00	0.01	0.03	0.46
CET	0.22	3.16	0.02	0.00	0.06	1.06
CSINE	0.10	0.05	6.00	0.09	0.06	1.07
ASEI	0.33	0.10	2.57	2.29	0.75	13.16
TO_ABS	0.16	0.04	0.65	0.05	0.90	
TO_WTH	2.84	0.67	11.35	0.89		15.76

system, and the spillover effect between those markets mainly focuses on the short-term horizon.

Specifically, Panels A, B, and C show that the steam coal market is the largest spillover communicator for the CET market, while the spillover effect for the CET market to the energy market is nonsignificant. Furthermore, the new energy market is the largest spillover communicator for the traditional energy market in the short term, medium term, and long term.

5.3. Time-Varying Spillover Indices Analysis with Rolling-Window Analysis. Full sample analysis is insufficient to reveal the time variability of return series overflow; therefore, we measure the time variability of return series overflow using the dynamic spillover index which is named the DY index, and we use a rolling-sample estimation method to estimate the VAR model with the rolling window width W = 100 weeks which is approximately two years, the predictive horizon H is 100 weeks, and the VAR lag order p is 2 weeks.

5.3.1. Dynamic Total Spillover Effect Analysis among the Four Major Markets of China. The total spillover index of the return series in China's four energy markets is shown in Figure 4. On average, the total spillover index of the four energy markets in China is 19.16%. From the analysis data, we know that this level is mainly determined by the connectedness between the traditional energy market and the new energy market. The total connectedness curve shows that the total volatility fluctuates greatly in the case of a rolling window of 100 weeks and varies from 12.68% to 24.43% because the sample periods span seven years and great changes occurred in China's energy sector during this period. Starting in early December 2013, tremendous changes occurred in China's economy, and China's GDP increased from 9169.77 billion dollars in 2013 to 15711.53 billion dollars in 2020. China's GDP growth rate remained at approximately 6%, except for being 1% in 2020, which was due to the impact of COVID-19 in that year. However, China's economic development has shifted from a stage of rapid economic growth to a stage of high-quality development. With the growing awareness of high-quality development in China, the Chinese government has paid more attention and invested more in the energy sector and made increasingly more efforts to improve the energy environment, all of which inevitably had greater impacts on the energy environment market. Figure 4 shows that there are three obvious circles in this period.

The first circle, which maintained relatively high connectivity, started at the beginning of 2016 and ended in mid-2017. In this period, the Chinese government submitted to the United Nations "Strengthening Action on Climate Change—China's Nationally Determined Contributions," which proposed that China's $C0_2$ emissions would peak in approximately 2030 and strive to reach the peak as soon as possible. The structural adjustment of China's coal industry began in early 2016. At this point, the price of products in the energy industry will fluctuate sharply, and the risk will spill over to other energy markets so that the volatility between the markets will rise rapidly. Furthermore, various new energy cars have gradually entered the public eye, and major car companies have entered the new energy field.

The second circle began in mid-2017 and ended in Q4 2019, and China's energy consumption structure changed rapidly in this period. The total returns connectedness shape decreased from the highest value of 24.43% in mid-2017 to the lowest value of 15.61% in mid-2018, jumped up to a temporary high point and then quickly fell back to the normal level. This small bump lasted only 2 months, and then the curve slowly rose to the end of the cycle at the end of 2019. The reason for the fluctuation at the end of 2018 can be ascribed to the influence of crude oil price fluctuations. As the impact of factors such as the resumption of U.S. sanctions on Iranian oil exports continued to decline into early 2019, the significant uncertainty in the energy market during this period resulted in a sharp increase of the spillover index among the domestic energy markets.

The third circle began in Q1 2020 and ended in mid-2021. In this period, the total spillover index fluctuated greatly, while the average level was relatively low. This phenomenon is due to the influence of COVID-19 on energy consumption sectors and the economy at the beginning of 2020. Due to COVID-19, the national economy almost halted and all energy consumption suddenly dropped until the end of June 2020 when the COVID-19 epidemic improved. China's economic development gradually recovered, and the spillover effect of major energy markets increased sharply. This suggests that the impact of extreme events can make markets more interconnected, and the four energy markets have higher connectedness with each other over all of 2020.

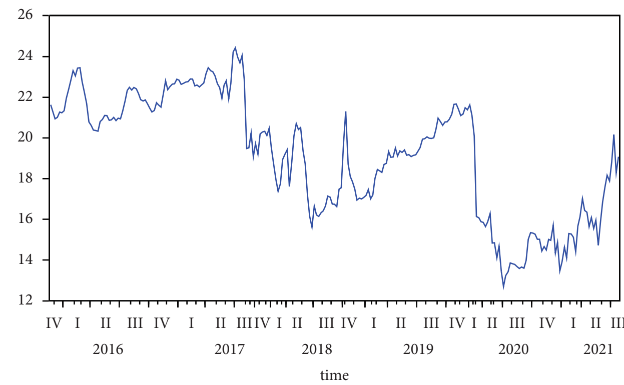

Figure 4: Dynamic total connectedness for China's four major markets in energy.

5.3.2. Total Directional Connectedness over Time. In this section, we assess the dynamic total directional connectedness including the from-connectedness, to-connectedness, and net connectedness for the four energy markets in China. Figures 5–7 show each energy market's dynamic to-connectedness, from-connectedness, and net connectedness, respectively.

Figure 5 shows the dynamic from-connectedness of the CET market and energy markets. Generally, the from-connectedness varies substantially across time and markets. It is obviously that the from-connectedness strength of the CET market is lower than those of the other three markets. From 2015 to 2017, the CET market had a higher from-connectedness and a lower to-connectedness. Figure 6 shows that from 2018 to 2020, the from-connectedness is lower, while the to-connectedness is higher. Notably, at the beginning of 2020, the from-connectedness hit rock bottom. This can be explained by the impacts of COVID-19 on economy, and in turn, it affects the four major energy markets. Then, the from-connectedness increased. In this system, the traditional energy market has the largest form-connectedness and the from-connectedness curve of the coal markets shows a large change during the entire period.

Figure 6 shows the dynamics of the to-connectedness for the CET market and three energy markets. We know that the connectedness of the CET market is also lower. Furthermore, the to-connectedness of the coal market and the new energy market is higher compared to their from-connectedness, and the traditional energy market is lower. Overall, the risk spillover between the CET market and the energy market fluctuates greatly, which indicates that the overall spillover of the energy-carbon system presents significant time-varying characteristics during the period of investigation.

Figure 7 shows the dynamics of the net connectedness for the CET market and the energy market in China. In the three circles, the CET market is a net receiver, net transmitter, and net receiver, respectively, and the steam coal market is always a net receiver, which may be because steam coal is the major energy source in the energy industry. The traditional energy market is always a net receiver, which indicates that traditional energy except for steam coal, such

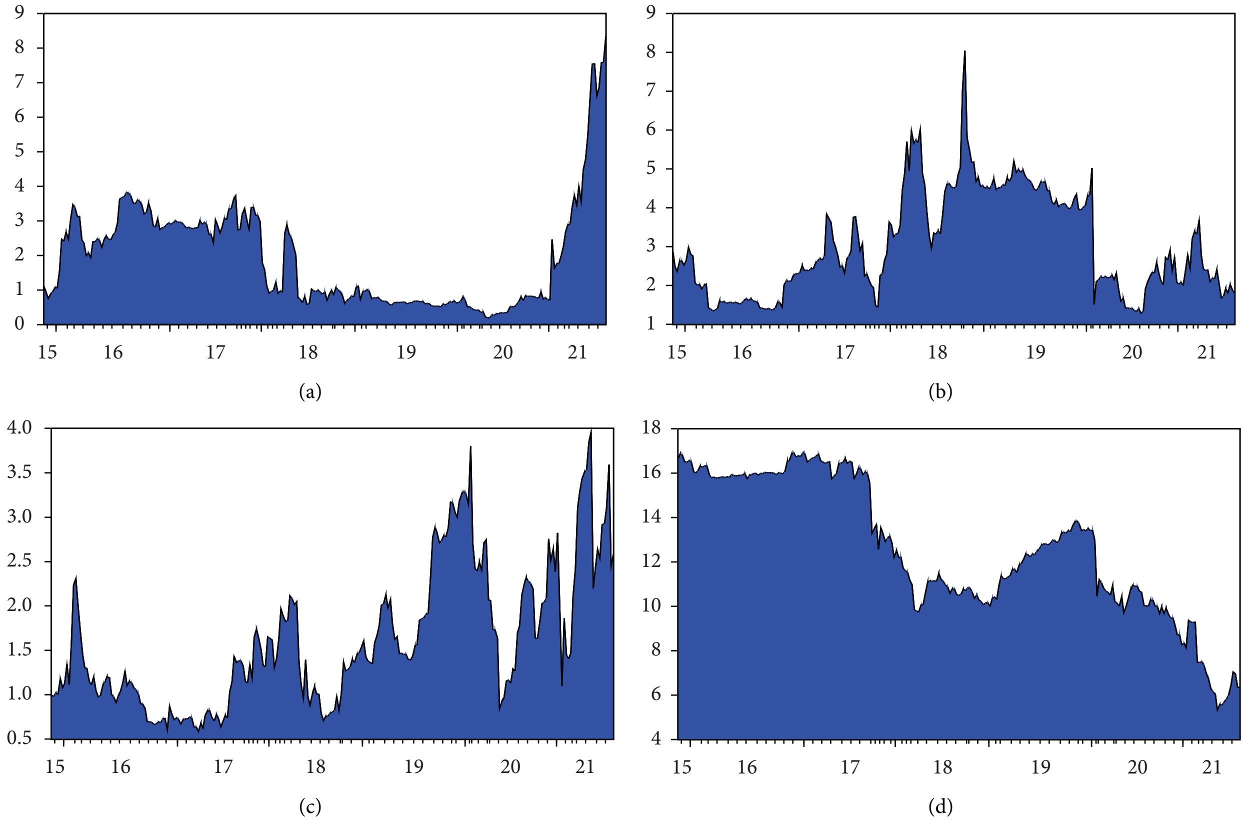

Figure 5: Dynamic from-connectedness of the CET market, new energy market, coal market, and the traditional energy market in China. The results based on the rolling window width W at 100 weeks, the predictive horizon H at 100 weeks, and the VAR lag order p at 2 weeks. We note that the scales of y-axis for subfigures are different. (a) CET (CET market). (b) CSINE (new energy market). (c) COAL (steam coal market). (d) ASEI (traditional energy market).

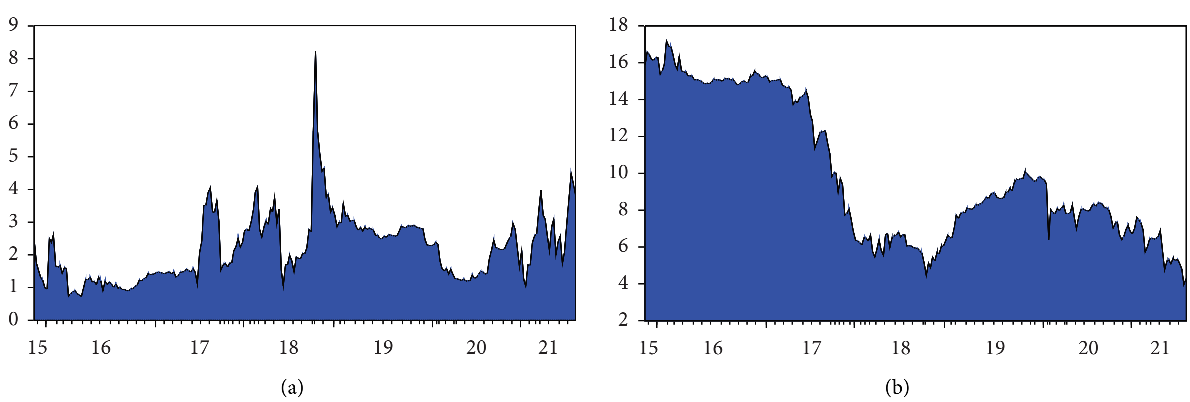

Figure 6: Continued.

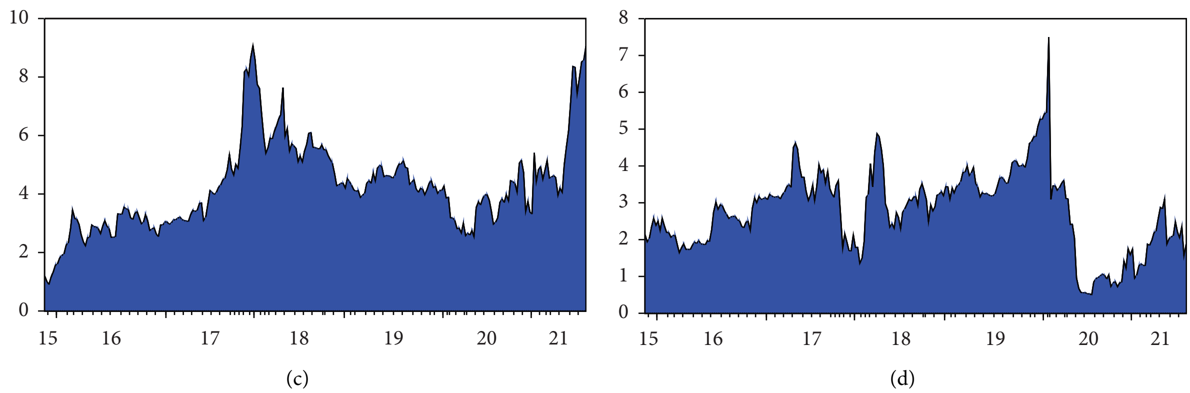

FIGURE 6: Dynamic to-connectedness for the CET market, the new energy market, the coal market, and traditional energy market in China. The rolling window width W is 100 weeks, the predictive horizon H is 100 weeks, and VAR lag order p is 2 weeks. We note that the scales of y-axis for subfigures are different. (a) CET (CET market). (b) CSINE (new energy market). (c) COAL (steam coal market). (d) ASEI (traditional energy market).

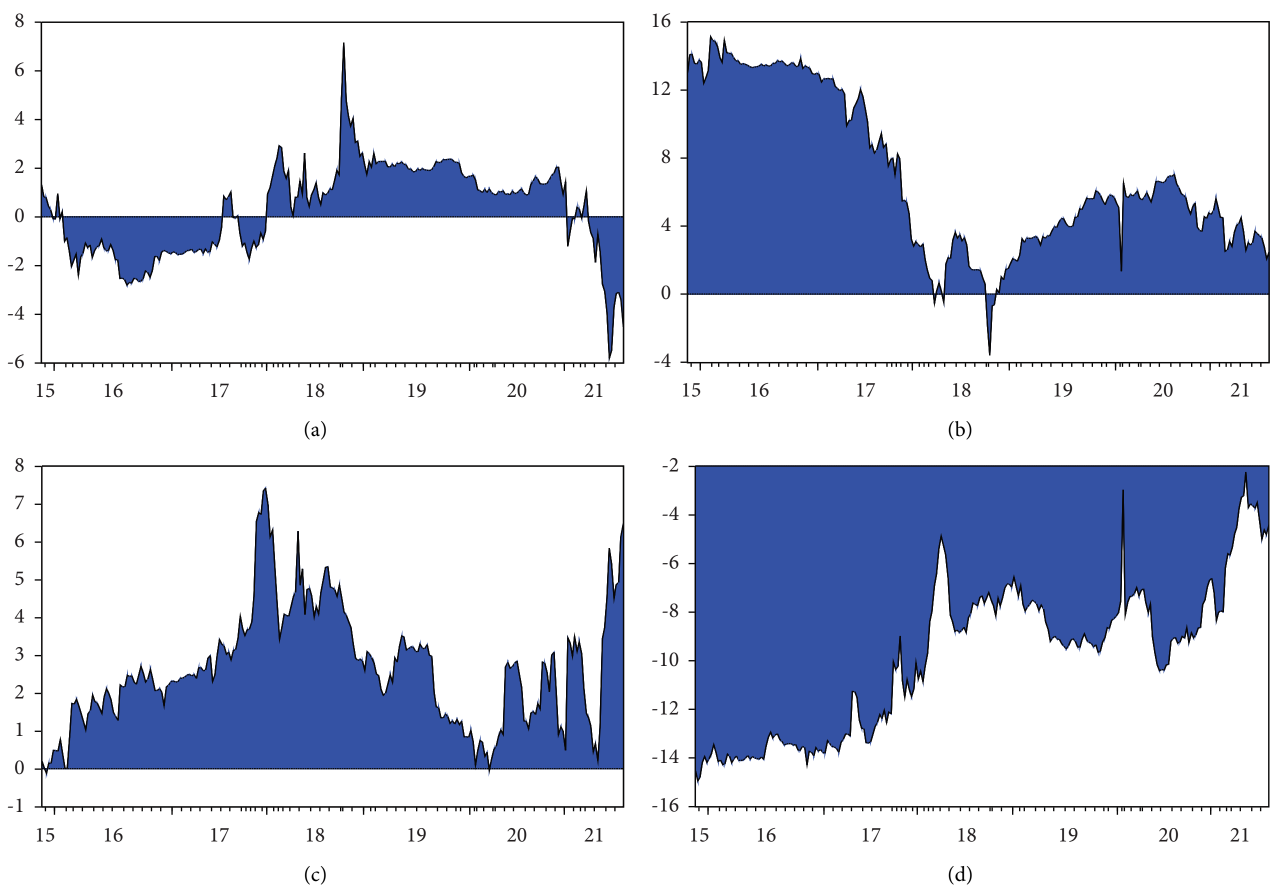

FIGURE 7: Dynamic net connectedness for the CET market, the new energy market, coal market, and the traditional energy market in China (the rolling window width W is 100, the predictive horizon H is 100, and the VAR lag order p is 2). We note that the scales of y-axis for subfigures are different. (a) CET (CET market). (b) CSINE (the new energy market). (c) COAL (steam coal market). (d) ASEI (the traditional energy market).

as oil and gas, is a net receiver of spillovers. The new energy market is mainly a net transmitter of volatility connectedness or shocks. The new energy industry is one of China's emerging strategic industries, and it has a very strong momentum. In order to cope with the global warming trend, new energy must be future energy.

In order to demonstrate the role of the CET market in the financial market, this paper conducted a network analysis of

Table 4: Total spillover connectivity between the major CET markets.

	SZA	SHEA	HBEA	GDEA	BEA	FROM
SZA	67.31	18.13	8.16	1.87	4.52	6.54
SHEA	14.53	66.39	0.87	0.43	17.77	6.72
HBEA	18.12	14.67	60.29	2.14	4.78	7.94
GDEA	19.34	20.06	18.33	36.87	5.41	12.63
BEA	5.9	13.95	1.46	1.44	77.24	4.55
TO	11.58	13.36	5.77	1.18	6.5	38.38

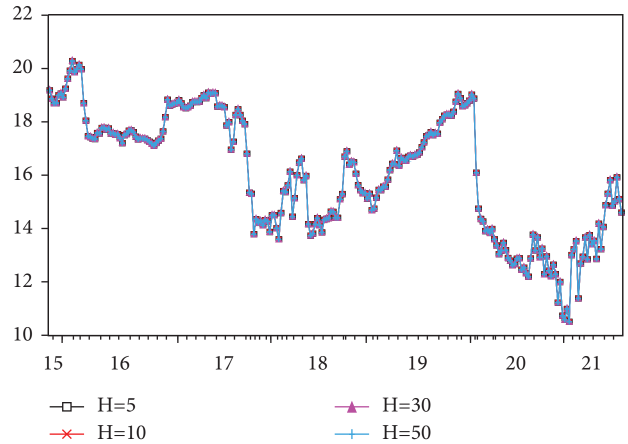

Figure 8: Total spillover index chart of the VAR model in different H steps.

the connectivity between CET markets in Beijing, Shanghai, Shenzhen, Guangdong, and Hubei exchanges. The data are selected for the weekly closing price from June 2014 to July 2021. The analysis results are shown in Table 4.

As we can see, there are 38.38 percent total variance influences from other trading markets in the system, which can demonstrate that the CET market in China can influence each other. The Beijing CET market has been most affected by other markets, while the Shanghai CET market has the biggest impact on other markets. In the given five CET markets, the Guangdong CET market price is most affected by the CET market price in Shanghai. The connectivity between the major CET markets in China shows that the carbon rights as a financial asset can effectively affect the carbon emission price.

Our findings are important for investors who have bought equities such as energy company. For example, when an investor owns a portfolio containing traditional energy shares and new energy shares, the close relationship between traditional shares and new energy shares reduces the diversified return strategy, and the investor needs to make appropriate adjustments to the trading strategy based on this time-varying information. Moreover, our findings about the relationship among the CET market, coal market, new energy market, and the traditional energy market play an important role in China's scientific and technological development and environmental improvement. For example, through the fluctuation of the CET price, enterprises can be enforced to increase technological innovation to reduce carbon emissions.

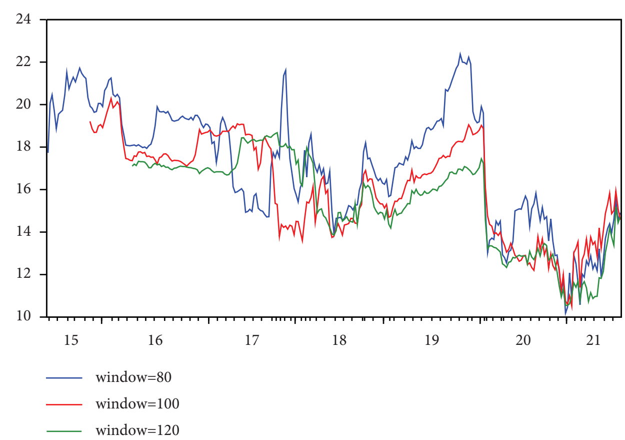

Figure 9: The dynamic total return spillover index based on different rolling windows.

5.4. Robustness Tests. In order to test the robustness of the aforementioned results, we use a variety of methods to test the return series spillovers among the CET market, coal market, new energy market, and the traditional energy market in China as the robustness test about eliminating the model assumptions' condition was mentioned by Raquel M. Gaspar. In the application of the connectedness network proposed by Diebold and Yilmaz, there are three main parameters, such as the predictive horizon H for variance decomposition, the rolling window width W for the dynamic analysis, and the lag order p of the VAR model. In this section, we will test the robustness of the abovementioned

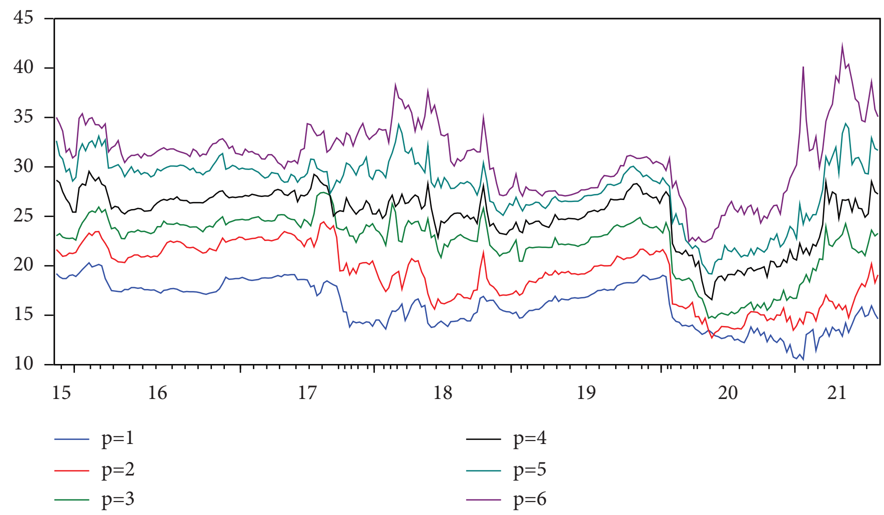

FIGURE 10: Dynamic total return spillover index with different VAR lags.

results with different values of the three parameters and variable substitution method to test the model.

The results of the robustness test by the transformation parameters are shown in Figures 8–10, respectively. It is obviously reflected that the trend of the curves is consistent with the original results in different steps, different rolling windows, and different VAR lags' order.

In addition, we use the index of the CSI Energy Index to replace the ASEI as the representative of the traditional energy market and then recalculate the spillover index and net-pairwise spillover index. The results show that the total spillover is 12.57 which is not far away from 13.91, and the net-pairwise of each market is in line with the original results. All of the abovementioned methods demonstrate the reliability of the original results.

6. Conclusion and the Policy Implication

With the intensification of the marketization process, the relationship among the CET, coal market, new energy market, and traditional market has been confirmed by many scholars. In this paper, we describe the static and dynamic influence relationship between the CET market and the new energy market, steam coal market, and the traditional market by constructing the VAR model. We first use the method of DY indices to study the network connectivity of the four markets in the temporal dimension, and then we use the method of BK to study the connectivity of CET, new energy, steam coal, and traditional in the frequency dimension; then, we study the dynamic connectivity among the four markets through a rolling window approach. At last, we test the result robust. The conclusions and enlightenment are as follows:

(1) From the static perspective, the results confirm the spillover effect among the CET, new energy, steam coal, and traditional energy with the total spillover effect index being 11.39% and the effect is mainly in the short term; (2) in all the markets, it is neutral that the spillover relationship among the CET, coal market, new energy market, and traditional energy market, while the steam coal spillover to CET is the highest with the spillover effect index being 1.33, and obviously, with the development of the CET market, the effect between them will be increased. New energy and the steam coal energy are net transmitters, while the traditional energy is a net receiver. (3) From the dynamic perspective, the spillover effect among the given markets has a time-varying characteristic, and the spillover index shows periodic changes, and it is affected by the international and domestic environment. Additionally, the results of the pairwise net directional spillover effects show that the new energy price returns play a dominant role in the total connectedness, followed by coal futures price returns. Furthermore, the traditional energy market plays the main net receiver role. Because traditional energy includes oil and gas without steam coal, we infer that the main net receiver is the oil and gas market in China.

The result indicates that the steam coal as the major energy source of the Chinese industry has a strong spillover effect, while new energy sources have strong development momentum under the background of the Chinese goal of carbon peak and carbon neutrality, and the new energy industry has been accepted by all sectors as an important way to achieve the dual-carbon goal in China. At the present stage, the aforementioned results also provide theoretical basis and support further research studies on cross-market and cross-regional information transmission and risk transmission mechanisms in the future, and it also provides a perspective to understand the connectivity and the spillover effect between the CET and the relevant energy market. The results can provide certain reference significance for marketing managers and formulate corresponding policy guidance for the policy markets, as well as for the investors. They can develop appropriate portfolios and hedge funds based on the connectivity results. In the future research, other commodity markets and a more broad range of data can be added to the research framework or we can use other methods to analyse the connectivity for the larger object.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Fengwei Gao contributed to the conceptualization, writing reviews, editing, and reading the manuscript. Yimin Wu was responsible for the methodology, writing the review, and editing. Ding Chen was responsible for software. Mengyao Hu was responsible for validation. All the authors have read and agreed to the published version of the manuscript.

Acknowledgments

This research was funded by the key research project of the Suzhou University (grant: 2020yzd15 and 2022yzd14); Anhui Quality Engineering Project (grant: szxy2020xxkc04); Key Research Projects of Humanities and Social Sciences in Anhui Province (grant#: SK2021A0695).

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