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Distributional Predictability and Quantile Connectedness of New Energy, Steam Coal, and High-Tech in China

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Abstract: From a novel quantile perspective, this paper employs nonparametric quantile causality and quantile connectedness to investigate distributional predictability and spillover effects among new energy, steam coal, and high-tech under normal and tail conditions. We first identify the quantile causality: there is a unidirectional causality between the quantile orders 0.1 and 0.4 from technology high-tech to new energy, indicating that the stock price of technology companies has a predictive power of the stock prices of new energy companies when the latter is relatively low. Next, in terms of quantile connectedness, while the risk shocks to the system do not propagate strongly around the median, there are strong spillover effects in both tails. Moreover, high-tech and new energy contribute most of the system's spillovers, and high-tech is the main net shock transmitter to all other variables. We further find that the strength of spillovers may depend on events such as China's stock market rout of 2015 and the COVID-19 pandemic.

Keywords: new energy; steam coal; high-tech; nonparametric causality in quantiles; quantile connectedness

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1. Introduction

The world is facing an energy transition in response to climate change, energy security, and environmental degradation, with substantial capital reallocated from the fossil fuel sector to the new energy sector [1,2]. To reach a carbon peak by 2030 and carbon neutrality by 2060, as proposed by China in September 2020, the transition of China's energy consumption structure to clean and low carbon is accelerating. In 2021, China's clean energy consumption accounted for 25.5 percent of total energy use and the proportion of coal consumption dropped to 56 percent. The cumulative installed capacity for clean energy power generation rose to 1.1 billion kilowatts, surpassing the installed capacity of coal power for the first time, with generation capacity of hydropower, wind, solar and biomass ranking top worldwide [3].

New energy is of great significance in achieving sustainable development, as the gradual withdrawal of traditional energy should be based on the safe and reliable replacement of new energy [4]. From the perspective of impact mechanisms, fossil energy and new energy are alternatives, and market volatility in the traditional fossil energy industry will significantly impact the development of the new energy industry, especially related to the investment and return of new energy in the capital market [5]. Additionally, new energy investments can be significantly boosted due to technological breakthroughs [6]. As a result, investors tend to view new energy stocks as having a similar risk profile to tech stocks [6–10]. Given that, we need to explore the linkage between fossil energy, new energy and high technology and the potential mechanism of their impact.

Our paper expands the literature in several ways. First of all, previous studies have mostly focused on the oil market. Considering China's energy consumption structure, great attention should be paid to the coal market, as coal has dominated the energy market for a long time [11–15], as shown in Figure 1. In compliance with the acceleration of China's energy transition, the supply and demand situation and price fluctuations of the coal market are essential determinants of the replacement effect of new energy on traditional energy. Accordingly, it impacts the stock price of new energy companies. On the other hand, some research has documented the significant relationship between the stock prices of new energy and technology companies in China's financial market. Investors should pay more attention to the volatility of technology stocks, which are one of the main contributors to the volatility dynamics of energy companies [16]. The Central Economic Work Conference proposed that it is necessary to tackle the critical problems of green and low-carbon technologies according to the actual national conditions of the coal-dominated energy structure and promote the optimal combination of coal and new energy in the process of China's energy transition. The core of the low-carbon economy is low-carbon energy technology, which is based on the efficient and clean utilization of traditional fossil energy and the replacement of new energy. Following the 21st conference of the parties (COP21)–Paris Climate Agreement of 2015 and China's clear carbon-neutral timetable in 2020, exploring the information flow among coal, new energy, and high-tech returns helps identify the correlation structure of risk contagion, and we bring coal, new energy, and high-tech into a unified framework.

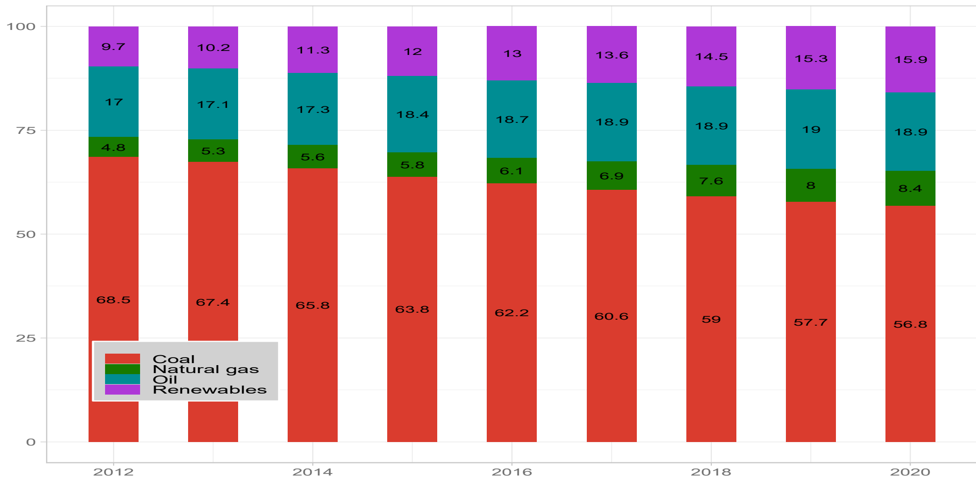


Figure 1. Energy consumption structure in China. (Source: National Bureau of Statistics).

Secondly, the crucial characteristics of tail risk transmission may be concealed in the model using traditional conditional mean estimation [17]. Especially in recent years, COVID-19 has superimposed political crises, and uncertainty events have increased. Under extreme circumstances, market connections will be significantly strengthened [18]. In this context, we are interested in the causal relationship between the three in different quantiles. What is the magnitude and direction of the spillover effect between them? Is there a big difference between median and tail overflow? To address these still unexplored, we employ the nonparametric quantile causality test to measure the causal relationship at different quantiles and extend mean-based connectedness to upper and lower quantiles to define overflow networks under extreme conditions. We provide solid evidence for the predictability and extreme risk spillovers of coal, new energy, and high-tech under normal and tail conditions.

The rest of the article is structured as follows. We summarize the related literature in Section 2. Sections 3 and 4 outline the method and data and descriptive analysis. In Section 5, we introduce and discuss the empirical results, while the conclusion is reported in Section 6.

2. Literature Review

Recent related studies are summarized in Table 1. Numerous studies have explored the relationship between oil prices and clean energy [19–22]. Hamoudeh et al. [19] examined the causal relationship between oil price gains and volatility and five clean energy stock indices, showing that during and before the COVID-19 pandemic, only in normal market conditions will the oil return lead to the return of the renewable energy stock index. Clean energy stock returns cannot predict oil returns under any market conditions. Geng et al. [22] analyzed the dynamic impact of oil price changes on eight European clean energy companies' stock returns from a microscopic perspective. Another part of the literature not only focuses on oil but also examines the relationship between fossil fuels and clean energy [2,5,9,23,24]. Umar et al. [2] found a weaker volatility link between clean energy stocks and fossil fuel markets and contagion effects between energy markets during crises, such as the Global Financial Crisis, oil crisis, and the COVID-19 pandemic crisis. Sun et al. [9] believed that coal plays a dominant role in China's energy structure, and it is unreasonable to replace fossil fuels with oil. Using the Divisia price synthesis method to combine oil, coal, and natural gas into a comprehensive price index resulted in a similar conclusion: the price of fossil energy only accounts for a small part of the fluctuation of the share price of new energy companies. Wen et al. [23] have different views, arguing that the dynamics of spillovers between China's new energy and fossil fuel stock are significant but asymmetric. To identify asymmetry and extreme information spillovers, Xia et al. [5] constructed a positive and negative return network and value at risk (VaR) network. In the VaR connectedness network, oil and coal contribute the most to the change of China's renewable energy returns, and the contribution of fossil energy price change to renewable energy income has high volatility with time. In addition, due to the long-term dominance of coal in China's energy structure, Lin and Chen [11] explored the dynamic links and spillover effects between the carbon market, the coal market, and the new energy stock market to obtain the conclusions that the coal market and new energy stock market have high volatility persistence and a two-way spillover effect. Gu et al. [12] empirically studied the time-varying co-movement relationship between China's steam coal price and clean energy stock index at the sectoral level. It was considered that there is a significant bi-directional volatility spillover between the steam coal market and clean energy.

Cost reduction brought about by technological progress is the inherent driving force for the sustainable development of the new energy industry. Henriques and Sadorsky [25] developed one of the scarce studies that consider the impact of oil price movements and technology stock prices on alternative energy stock prices, and a large body of literature has expanded on this issue [6,7,26–29]. Specifically, Maghyereh et al. [30] and Zhang et al. [31] focused only on clean energy technology rather than high technology, and chose the FTSE ET50 index to represent the clean energy technology market instead of the Arca 100. Sadorsky [7] and Zhang and Du [8] considered new energy companies' share prices more correlated with tech stocks than oil prices. Managi and Okimoto [27] and Bondia et al. [28] considered possible structural transitions in the system, and Tiwari et al. [26] further considered tail dependencies under state transitions. Fahmy [29] argued that in the period post-Paris Agreement, for clean energy assets with strong nonlinear asymmetric persistence, technology stock prices are the best regime driver, while the influence of oil prices is entirely absent. Shahbaz et al. [32] showed that there is a causal relationship between the price change distribution centers of stocks, crude oil, and clean energy using nonparametric quantile causality. Under the bear market and bull market, the prediction ability between stock price and technology stock price is more vital. Qu et al. [33] showed that there is only a tiny amount of evidence to support the dramatic volatility spillover from oil to new energy sources, suggesting that crude oil should not be used as a bellwether for new energy volatility in China. China's high-tech sector and low-carbon notion are the main contributors to the volatility spillover of new energy.

Table 1. Summary of literature among new energy, steam coal, and high-tech.

Author(s)	Period	Variables	Modeling	The Main Results
Umar et al., 2022 [2]	Jan 1, 2004 to Dec 31, 2020 (Daily)	Clean energy, oil, natural gas, gas oil, and fuel oil	Baruník and Krehlík	Weak volatility connections among clean energy stocks and fossil fuel markets, contagion effects between the energy markets increase in the crisis periods.
Xia et al., 2019 [5]	Apr 2008 to Jul 2019 (Daily)	Renewable energy, oil, natural gas, electricity, coal, and carbon	VaR network	The electricity market behaves as the major contributor to the changes of renewable energy returns in the return connectedness network, while oil and coal contribute most to the changes of renewable energy returns in the VaR connectedness network.
Nasreen et al., 2020 [6]	Dec 2000 to Jun 2017	Clean energy, technology, and crude oil	Wavelet coherency, Baruník and Krehlík, DCC	Returns of technology stocks appear to be the main source of volatility transmission.
Sadorsky, 2012 [7]	Jan 2001 to Dec 2010 (daily)	Clean energy, technology, and crude oil	Multivariate GARCH	The stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices.
Zhang and Du, 2017 [8]	Jul 2011 to Dec 2015	New energy, technology, and coal and oil index	TVP-SV-VAR	New energy correlate more highly with high technology stock than with coal and oil stock prices.
Sun et al., 2019 [9]	Jul 2010 to Dec 2016 (monthly)	Technology, carbon futures, China's new energy, and Divisia index (oil, coal and natural gas)	VAR, Divisia price synthesis	Compared with Divisia fossil energy price index, the dynamic relationship between technology index and new energy stock prices is more significant.
Lin and Chen, 2019 [11]	Nov 2013 to Jul 2017 (daily)	Beijing carbon emission allowance, new energy, and coal	DCC, BEKK	The coal market and the new energy market have higher volatility persistence and bi-directional spillover effects.
Gu et al., 2020 [12]	Jan 2008 to Feb 2019	Coal, stock, environmental protection, and five clean energy sectors	VAR-DCC-GARCH	Significant bi-directional volatility spillover between the steam coal market and the clean energy stocks.
Janda et al., 2022 [16]	May 2012, to Jul 2021 (Daily)	Oil, Chinese and U.S. clean energy and technology	CCC, DCC and ADCC	China technology is the best asset to hedge Chinese clean energy stocks.
Hammoudeh et al., 2021 [19]	Oct 2010 to Sep 2020 (Daily)	Oil, and renewable energy (five sub-sectors)	Nonparametric causality	Oil returns cause the renewable returns during normal market conditions. Renewable energy sectoral stock returns have no predictive power of oil returns.
Geng et al., 2021 [22]	Sep 2009 to Jun 2019 (weekly)	Oil, and eight European clean energy companies	DCC, Asymmetric Connectedness	Information interdependence for crude oil returns and clean energy companies' returns remains at a relatively high level, bad news on information connectedness is greater than that of good news.
Wen et al., 2014 [23]	Aug 2006 to Sep 2012	China's new energy, and coal and oil index	Asymmetric BEKK	The dynamics of new energy/fossil fuel stock spillover are found to be significant and asymmetric.

Table 1. *Cont.*

Author(s)	Period	Variables	Modeling	The Main Results
Tiwari et al., 2021 [26]	Dec 2000 to Jun 2017 (daily)	Clean energy, technology, and crude oil	Dependence-switching copula	Asymmetric dependence structure under the positive correlation regimes, while a symmetric dependence under negative correlation regimes.
Managi and Okimoto, 2013 [27]	Jan 2001 to Feb 2010 (weekly)	Clean energy, technology, crude oil, and interest rate	Markov-switching VAR	There was a structural change in late 2007, a positive relationship between oil prices and clean energy prices after structural breaks.
Bondia et al., 2016 [28]	Jan 2003 to Jun 2015 (weekly)	Clean energy, technology, crude oil, and interest rate	Threshold cointegration tests	The stock prices of alternative energy companies are impacted by technology stock prices, oil prices and interest rates in the short run, there is no causality running towards prices of alternative energy stock prices in the long run.
Fahmy, 2022 [29]	Jan 2009 and Dec 2019	Clean energy, technology, and crude oil	Exogenous STR model	Oil price has a stronger asymmetric persistence on the cycle of clean energy assets pre-Paris Agreement. In the period post Paris Agreement, Technology stock prices are the best regime drivers for clean energy assets with strong nonlinear asymmetric persistence.
Maghyereh et al., 2019 [30]	Jan 2001 to Feb 2018 (Daily)	Oil, clean energy, and clean energy technology	Wavelet, DCC-GARCH	Significant bidirectional return and risk transfer from oil and technology to the clean energy market in the long term.
Zhang et al., 2020 [31]	Jan 2006 to Dec 2018 (monthly)	Oil, clean energy, and clean energy technology	Wavelet-based quantile-on-quantile, Causality-in-quantiles	Strong predictability of the oil price shocks for the stocks in the long run.
Shahbaz et al., 2021 [32]	Mar 2005 to May 2021 (Daily)	Clean energy, technology, light crude oil, and stock	Granger causality, Quantile regression	Clean energy markets react to crude oil and stock markets depending on the market regime.
Qu et al., 2021 [33]	Jan 2011 to Mar 2016 (5-min)	New energy, high-tech, low-carbon notion, andcrude oil	Diebold and Yilmaz	High-tech and low-carbon are main contributors to the volatility spillover of new energy.

From the literature review above, it was found that scholars have carried out many beneficial explorations of the coal market, new energy market and high-tech market. However, there are still some areas that need to be improved. Compared with the existing literature, the contributions of this paper are through two distinct channels. First, most of the current research focuses on the crude oil market. Given China's coal-dominated energy structure, this paper expands the depth of analysis by incorporating coal, new energy, and high technology into a unified framework. Moreover, most of the research methods in the existing relevant literature can only reflect their time-varying characteristics and linkage relationship under normal market conditions. From the perspective of quantiles, using the nonparametric quantile Granger causality test and quantile connectedness model, we judge the qualitative causality and quantitative spillover degree of the coal market, new energy market, and high-tech market in different market conditions, which broadens the perspective of analyzing the problem.

3. Methodology

3.1. Nonparametric Quantile Causality Testing

Our methodology is twofold. We first apply the nonparametric quantile causality test that was developed by Balcilar et al. [34]. This methodology combines the approach of the k^{th} order nonparametric causality of Nishiyama et al. [35] and the framework of nonparametric causality in quantiles of Jeong et al. [36]. The Granger test is based on the idea that if x is a cause of y, but y is not a cause of x, then the past value of x can help predict the future value of y, but the past value of y cannot help predict the future value of x. Therefore, following Nishiyama et al. [35] and Jeong et al. [36], the Granger causality in quantile can be defined as the non-causality of y_t by x_t in the τ^{th} quantile with regard to the lag vector of $\{ y_{t-1}, \cdots, y_{t-p,}, x_{t-1,}, \cdots, x_{t-p}\}$, which can be verified if:

$$Q_\tau\{y_t | y_{t-1,}, \cdots, y_{t-p,}, x_{t-1,}, \cdots, x_{t-p}\} = Q_\tau\{y_t | y_{t-1,}, \cdots, y_{t-p}\} \tag{1}$$

On the other hand, x_t causes y_t in the τ^{th} quantile with respect to the lag vector of $\{y_{t-1}, \cdots, y_{t-p,}, x_{t-1,}, \cdots, x_{t-p}\}$ if:

$$Q_\tau\{y_t | y_{t-1,}, \cdots, y_{t-p,}, x_{t-1,}, \cdots, x_{t-p,}\} \neq Q_\tau\{y_t | y_{t-1,}, \cdots, y_{t-p}\} \tag{2}$$

where $Q_\tau\{y_t \cdot\}$ is the τ^{th} conditional quantile of y_t depending on t.

Let us define the following vectors $Y_{t-1} = (y_{t-1,}, \cdots, y_{t-p})$, $X_{t-1} = (x_{t-1,}, \cdots, x_{t-p})$ and $Z_t = (X_t, Y_t)$. Also, $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we define $Q_\tau(Z_{t-1}) = Q_\tau(y_t)|Z_{t-1}$ and $Q_\tau(Y_{t-1}) = Q_\tau(y_t)|Y_{t-1}$, then we obtain $F_{y_t|Z_{t-1}}\ \{Q_\tau(Z_{t-1})|Z_{t-1}\ \} = \tau$ with probability one. In this line, the hypothesis of causality in quantiles presented in Equations (3) and (4) can be expressed as:

$$H_0 : P\left\{F_{y_t|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right\} = 1 \tag{3}$$

$$H_1 : P\left\{F_{y_t|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right\} < 1 \tag{4}$$

To obtain a metric measure for the practical implementation of the causality-in-quantile test, Jeong et al. [36] used distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t represents the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null in (5), which can only be true if and only if $E[1\{y_t \leq Q_\tau(Y_{t-1})|Z_{t-1}\}] = \tau$, where $1\{\cdot\}$ is an indicator function. Jeong et al. [36] specify the distance function as follows:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum\nolimits_{t=p+1}^{T} \sum\nolimits_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{5}$$

$K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, $\hat{\varepsilon}_t$ is the unknown regression error estimate, and its expression is:

$$\hat{\varepsilon}_t = 1\{y_t \leq \hat{Q}_\tau(Y_{t-1})\} - \tau \tag{6}$$

$\hat{Q}_\tau(Y_{t-1})$ is an estimate of the τ^{th} conditional quantile of y_t, given Y_{t-1}. Below, we estimate $\hat{Q}_\tau(Y_{t-1})$ using the nonparametric kernel method as: $\hat{Q}_\tau(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}(\tau|Y_{t-1})$, where $\hat{F}_{y_t|Y_{t-1}}(\tau|Y_{t-1})$ is the Nadaraya–Watson kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(\tau|Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{t-s}}{h}\right) 1(y_s \leq y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{t-s}}{h}\right)} \tag{7}$$

where $L(\cdot)$ is the kernel function and h is the bandwidth.

Balcilar et al. [34] developed a two-stage test to observe mean and variance causality between variables. Using the method of Nishiyama et al. [35], the assumptions of higher-order quantile causality are as follows:

$$H_0 : P\left\{F_{y_t^k|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right\} = 1 \tag{8}$$

$$H_1 : P\left\{F_{y_t^k|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right\} < 1 \tag{9}$$

We apply k = 1 to test the first-order moment mean causality between steam coal, new energy, and high-tech markets.

3.2. Quantile Connectedness

As indicated earlier, we qualitatively consider the predictability of the steam coal, new energy, and high-tech markets at different quantiles. Next, we employ the quantile connectedness approach proposed by Ando et al. [17] to identify how the strength and duration of spillovers between these markets will change under extreme upward and downward market movements. The approach answers the question of how much of the future uncertainty associated with variable i can be attributed to idiosyncratic shocks coming from variable j as the shock size varies [17]. We first estimate the quantile vector autoregression, QVAR(p):

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + \varepsilon_t(\tau) \tag{10}$$

y_t and y_{t-j} are $k \times 1$ dimensional endogenous variable vectors, τ stands for quantile, p represents the lag length of the QVAR model, $\Phi_j(\tau)$ is a $k \times k$ dimensional QVAR coefficient matrix, and $\varepsilon_t(\tau)$ demonstrates the $k \times 1$ dimensional error vector, which has a $k \times k$ dimensional variance–covariance matrix, $\Sigma(\tau)$. Converting QVAR(p) to QVMA(∞) is the key to variance decomposition, and we utilize Wold's theorem: $y_t = \mu(\tau) + \sum_{i=1}^{\infty} \Psi_i(\tau)\mathcal{E}_{t-i}$.

Then, the H-step ahead generalized forecast error variance decomposition (GFEVD) of Koop et al. [37] and Pesaran and Shin [38] is calculated, which illustrates the impact a shock in variable j has on variable i:

$$\phi_{ij}^{g}(h) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \Sigma(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h(\tau) \Sigma(\tau) \Psi_h(\tau)' e_i\right)} \tag{11}$$

This normalisation $\widetilde{\phi}_{ij}^{g}(h) = \frac{\phi_{ij}^{g}(h)}{\sum_{j=1}^{k} \phi_{ij}^{g}(h)}$, e_i represents a zero vector with unity on the i^{th} position. Therefore, $\sum_{j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(h) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(h) = k$. Using the GFEVD, we can construct connectedness indices, described in Table 2.

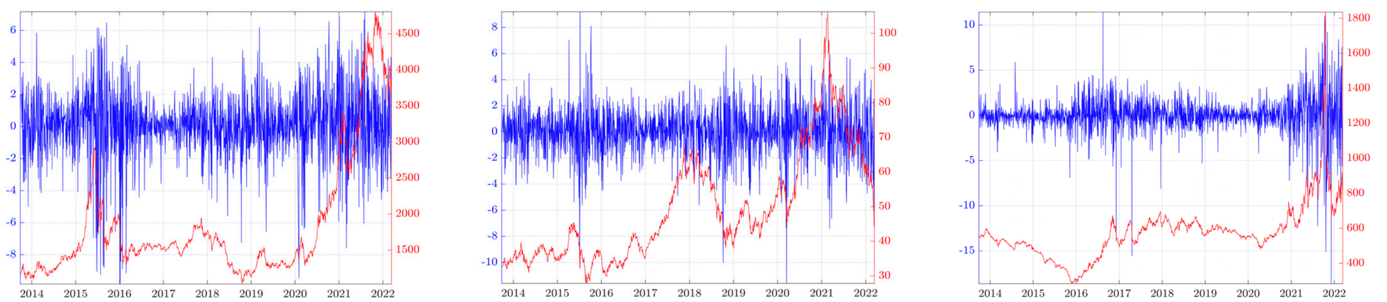
Table 2. The connectedness indices.

Meaning	Index and Calculation
Measuring the connectedness across all markets	Total ($TS_t(h) = \left(\sum_{i,j=1, i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(h)\right) / N \times 100$)
Measuring the total connectedness from others	Directional ($FROM_{i\leftarrow\cdot,t}(h) = \sum_{j=1, i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(h) \times 100$)
Measuring the total connectedness to others	Directional ($TO_{i\rightarrow\cdot,t}(h) = \sum_{j=1, i\neq j}^{N} \widetilde{\phi}_{ji,t}^{g}(h) \times 100$)
Measuring the net connectedness from market i to others	Net ($NET_{i,t} = TO_{i\rightarrow\cdot,t}(h) - FROM_{i\leftarrow\cdot,t}(h)$)
Measuring the net connectedness between i and j	Net pairwise ($NP_{ij,t} = \left(\widetilde{\phi}_{ji}^{g}(h) - \widetilde{\phi}_{ij}^{g}(h)\right) \times 100$)

4. Data and Descriptive Analysis

Zhengzhou Commodity Exchange launched the steam coal futures contract on 18 June 2013. The marketization of China's steam coal market enables the supply and demand of steam coal to be reflected through its price, thereby making it a suitable proxy to measure the coal market [11,39]. To account for the performance of the new energy market, we relied on the CSI Mainland New Energy Index. The index selects 50 samples with large-scale and relatively profitable new energy businesses from the securities of listed companies in the Shanghai and Shenzhen markets involving new energy production, new energy storage, and new energy vehicles. China technology ETF is a benchmark for high tech that tracks 110 leading technology companies listed in China [16]. Given the availability of steam coal futures data, the sample interval is from 26 September 2013 to 14 March 2022, and the daily closing price data of each index extracted from the Wind database with codes "ZC.CZC," "CQQQ.P," and "000941.CSI," respectively, in which the return is calculated by the first-order logarithmic difference.

Figure 2 shows the price and return trend of steam coal, new energy and high-tech. Note that the red line in each graph represents the price series and the blue line stands for the return series. Specifically, for the steam coal market, it is evident that the price of steam coal will soar and fluctuate sharply at the beginning of 2021. According to Kilian [40], coal prices are inherently determined by the following factors: (i) fundamentals of the coal market, such as coal supply and demand; and (ii) coal market-specific factors such as speculation and spillovers. There are two key channels to drive changes in China's coal prices. In recent years, the global trend of "de-coalification" has led to a decline in the elasticity of global coal supply. After the epidemic, due to the recovery of the manufacturing industry, the demand for electricity and coal surged. Supply and demand are unbalanced and prices have risen. In addition, from the perspective of spillovers, the price of bulk commodities such as oil and natural gas has risen, and the fuel substitution in the crude oil market and the market contagion in the international coal market have also driven up the price of coal to a certain extent [13]. Moreover, there are some speculative factors, which together promote the rise of the price of coal. Regarding the new energy market, the yield of the new energy market fluctuated sharply in 2015, which is consistent with the timeline of the Chinese stock crash in 2015 and the Paris Climate Agreement of 2015. Possibly due to the government's favorable policies on new energy, the stock price of new energy has risen sharply since the end of 2018. In September 2020, China proposed a carbon-neutral timetable, and favorable policies for new energy were introduced intensively, vigorously developing wind power, photovoltaics, and promoting energy innovation, and the price of new energy continues to rise. In addition, the price of high-tech reached a high point in early 2018 and early 2021, and the price fluctuation was relatively stable.



(a) (b) (c)

Figure 2. Price and return series plot of New energy, High-tech and Coal. (**a**) New energy; (**b**) High-tech; (**c**) Coal.

Table 3 gives the descriptive statistics of the data. To be specific, from the standard deviation, the returns of steam coal, high-tech and new energy stocks have similar fluctuations, and the skewness and kurtosis coefficients indicate that all the data deviate from the normal distribution. The JB statistic further confirms this deviation from the normal distribution, and market returns reject the normal distribution assumption at the 1% significance level; therefore, quantile analysis is essential. When the variables exhibit non normal distribution, the standard unit root cannot capture complete information in one case where stationary time series may have unit roots in one or more quantiles [19]. To this end, we use the quantile unit root test developed by Koenker and Xiao [41] and Galvao [42] to test for the existence of a unit root at all distribution levels for the series. As shown in Table 4, at the 5% confidence level, the test statistic is less than the critical value, the null hypothesis of the unit root will be rejected, and the variable is stationary in different quantiles so that we can carry out quantile causality analysis.

Table 3. Descriptive statistics and unit root.

	Mean	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
Coal	0.021	11.44	−18.629	1.914	−1.292 *	17.804 *	19365.0 *	−6.623 *
New energy	0.059	7.168	−9.828	1.975	−0.654 *	6.259 *	1057.6 *	−12.887 *
High-tech	0.014	9.203	−11.6	1.802	−0.358 *	6.179 *	910.6 *	−12.935 *

Note: JB denotes the Jarque–Bera statistic for normality, ADF test indicates the unit root test result, and * indicates statistical significance at the 1% level.

Table 4. Unit root test in quantiles.

τ	Coal		New Energy		High-Tech	
	$\alpha(\tau)$	T-Stat	$\alpha(\tau)$	T-Stat	$\alpha(\tau)$	T-Stat
0.05	0.086	−8.462	0.212	−7.475	0.227	−12.551
0.10	0.082	−15.935	0.134	−15.629	0.203	−16.889
0.15	0.046	−29.073	0.115	−22.746	0.146	−19.127
0.20	0.025	−39.420	0.097	−29.200	0.076	−25.608
0.25	0.020	−48.665	0.048	−36.549	0.048	−31.648
0.30	0.004	−55.148	0.018	−40.423	0.042	−36.087
0.35	−0.004	−63.372	−0.004	−47.970	0.020	−40.186
0.40	0.009	−66.118	−0.007	−50.903	−0.003	−49.137
0.45	0.003	−68.948	0.002	−51.778	−0.010	−46.189
0.50	0.003	−68.053	−0.011	−53.763	−0.003	−47.259
0.55	0.003	−67.890	−0.004	−52.082	−0.025	−46.413
0.60	0.001	−64.674	−0.014	−48.765	−0.009	−45.048
0.65	−0.005	−58.725	−0.036	−45.933	0.013	−38.796
0.70	−0.013	−54.399	−0.039	−41.464	0.005	−38.366
0.75	0.003	−45.676	−0.056	−37.131	−0.014	−35.884
0.80	0.014	−35.805	−0.029	−32.376	−0.006	−33.076
0.85	0.028	−25.387	−0.022	−29.464	−0.001	−29.649
0.90	−0.013	−22.414	−0.013	−22.795	−0.026	−25.764
0.95	−0.039	−14.557	−0.064	−15.816	−0.100	−19.923

Note: This table presents the results of the quantile unit root test for quantile orders τ = 0.05, ..., 0.95. We test the null hypothesis of the unit root $H0$: $\beta(\tau)$ = 1. The null hypothesis is rejected at the quantile τ order when the t-statistic is lower than the 5% critical value (CV).

5. Empirical Results and Discussion

5.1. Causality-Quantile Results

We performed a nonparametric quantile Granger causality test on a grid of 200 quantiles between 0.01 and 0.99 to test qualitative causality at different quantiles for steam coal, new energy, and high technology. The results are shown in Figure 3, which plots the different test statistics at the considered quantile orders. It can be observed that a unidirectional causality running from high technology to new energy between the quantile orders 0.1 and 0.4, indicating that the stock price of technology companies predicts the stock prices of new energy companies when the latter is relatively low. This is probably due to the fact that with the continuous expansion of domestic new energy investment and market scale, and the further strengthening of technology research and development, the capital market not only focuses on the concept of new energy but also on its technological content. Thus, new energy investors may need to consider high-tech shocks in their decisions, and policymakers need to formulate feasible economic policies considering the impact of high-tech shocks.

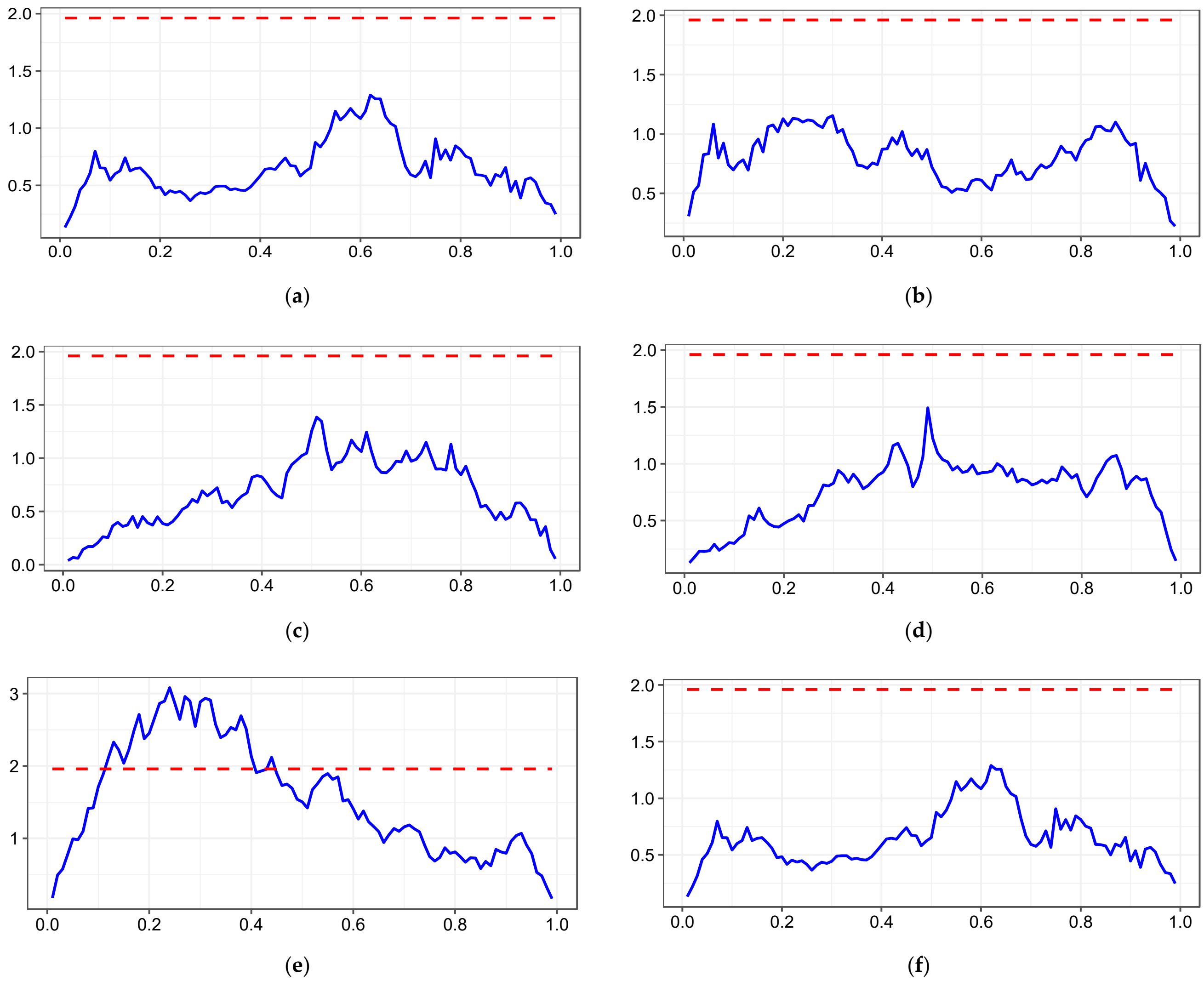


Figure 3. Nonparametric quantiles causality in means. (**a**) New energy $\nRightarrow$ Coal; (**b**) New energy $\nRightarrow$ High-tech; (**c**) Coal $\nRightarrow$ New energy; (**d**) Coal $\nRightarrow$ High-tech; (**e**) High-tech $\nRightarrow$ New energy; (**f**) High-tech $\nRightarrow$ Coal.

The causality is not significant from new energy to high-tech, so new energy does not improve high-tech forecasts. Bondia et al. [28] indicated that alternative energy prices are impacted by technology stock prices and oil prices in the short run, while there is no causality running towards prices of alternative energy stock prices in the long run. Our research confirms no causality running towards new energy market under any market conditions. Besides, the causality direction presented in row 2 of Figure 3 shows that the null hypothesis cannot be rejected, indicating that none of the considered coal Granger causes the high-tech or new energy. This result implies that the coal has no predictive power in the system, considering all quantiles of the distribution. Such results are novel compared to prior studies and probably are of great interest to investors in the coal market.

5.2. Quantile Connectedness Results

This section, regarding the quantile connectedness, measures the quantitative degree of the interaction between steam coal, new energy and high-tech under different quantiles. Table 5 presents the spillover results for the 0.5 quantile, as well as the 0.05 and 0.95 quantiles corresponding to extreme market conditions. First, the 0.5 quantile can be used as a reference to compare the upper and lower tail connectedness results. On the 0.5 quantile, the total spillover between markets is minimal, only 11.41%, mainly contributed by the spillover between high-tech and new energy, and the spillover between new energy and high-tech is larger than that of new energy and steam coal market. This evidence suggests that the steam coal market should not be used as a weather vane for new energy fluctuations, since it is most affected by its own fluctuations, accounting for 97.84%, and has a weaker ability to transmit shocks to other markets. These results are in accordance with the findings in previous studies that Chinese high tech is the main contributor to the volatility spillover of new energy [8,29,33]. Moreover, they are in line with the fact that big tech companies are major buyers of new energy and pioneers in important new technologies and materials. Large tech companies can facilitate the rollout of other key new energy technologies, including green hydrogen, long-term energy storage, advanced nuclear and geothermal energy. Although leading tech companies consume relatively little energy, due to their large financial footprints, coupled with their enormous cultural and scientific influence, big tech companies can play a key role in the new energy transition [43]. The quantile connectedness allows us to capture the network of connectedness associated with extreme large positive and negative shocks, i.e., shocks in the 95th and 5th percentiles of the size distribution of shocks, which is more useful and informative than concentrating on the median quantile only [44]. We find that the value of the connectedness measure was greater than the value of the median quantile for both the left and right tails of the conditional distribution. On the 0.95th and 0.05th quantile, the total spillovers between markets are 53.24% and 54.91%, respectively, the connectedness strength of the left tail is more significant in comparison, and both are much higher than the median level of 11.41%. Specifically, at the 0.05th quantile (downward), the impact of new energy on steam coal and high-tech markets is 24.12% and 32.45%, respectively. At the 0.95th quantile (up), the impact of new energy on steam coal and high-tech markets is 23.19% and 31.04%, respectively. The contribution of new energy to other markets (to) and from other markets is more substantial than the median, consistent with claims that financial contagion can occur under extreme market conditions [2,33,44]. This result suggests that risk shocks do not propagate strongly at the median, but have strong spillover effects in both tails [17]. If considering the difference of spillover and inflow received by each market, the steam coal market is the net recipient in the high and low quantiles, with a weak ability to transmit shocks and vulnerability to external shocks. In the low quantile, high technology is the main net transmitter, while in the high quantile, the net transmission effect of new energy is further enhanced.

To further illustrate the time-varying structure of connectedness strength at different quantiles, Figure 4 provides a graphical summary of the time-varying results of the total dynamic connectedness. The warmer the hue, the higher the connectedness strength. The connectedness is very strong for both spills below the 0.2 quantile and above the 0.8 quantile, showing a significant time-varying tail dependence, and the overall connectedness strength appears symmetric. Reboredo and Ugolini [24] also showed that the impact of energy prices on renewable energy prices is symmetric, so extreme increases and decreases in energy prices have similar effects on stock prices. Geng et al. [22] had different views, arguing that the earnings of oil and clean energy companies have an apparent asymmetry in information connectedness, which indicates a significant leverage effect, and the impact of bad news on information connectedness than good news. The 0.5 quantile corresponds to the total average connectedness of the whole cycle, and these important characteristics of shock risk transmission are masked in the model using traditional conditional mean estimation [45]. Through the dynamic total connectedness map, the evidence is obvious, i.e., the total connectedness has a significant value in a specific time interval (around 2016), which corresponds to the timeline of China's stock market crash. A plausible explanation is that a milestone in the scientific and political process of global climate governance was reached in December 2015, the Paris Agreement, which reaffirmed the goal of limiting global temperature rise to 2 degrees and proposed efforts to achieve the 1.5-degree target. In November 2016, the Paris Agreement entered into force. As a contracting party to the Paris Agreement, China responded positively. Specifically, in October 2016, the State Council issued the "13th Five-Year Plan for Controlling Greenhouse Gas Emissions," which proposed to accelerate the development of non-fossil energy, optimize the use of fossil energy, and strengthen low-carbon technological innovation. The 13th Five-Year Plan (2016–2020) further emphasizes the importance of developing renewable energy as part of the upgrading of the national energy structure. The development of renewable energy is the main focus of the work while promoting new technologies to improve the efficiency and cleanliness of traditional energy. The government will further support the development of hydropower, wind energy, solar energy and nuclear energy projects [46]. Fahmy [29] found that investors' awareness of climate risk and attention to green investment was rising after the Paris Agreement. Clearly, this increased awareness may have impacted the link between clean energy prices and coal and technology stock prices. Additionally, the total connectedness is statistically significant from late 2019 to 2021. This result may be related to the COVID-19 pandemic that began in late 2019 when various markets were affected to some extent due to a sudden halt in economic activity and an extreme global recession. The increase in connectedness during the COVID-19 pandemic is also consistent with the financial contagion and asymmetric price adjustment hypotheses, which predict faster spillovers of bad news across markets [47]. At the same time, in September 2020, China put forward the goal of carbon peak and carbon neutrality, which also provides important guidance for accelerating the green and low-carbon transformation after the domestic epidemic. This indicates the fact that connectedness is highly dependent on events.

Table 5. Directional spillovers.

0.5	Coal	New Energy	High-Tech	FROM Others
Coal	97.84	0.98	1.18	2.16
New energy	1.23	83.52	15.26	16.48
High-tech	1.52	14.07	84.4	15.6
TO others	2.75	15.05	16.44	**TCI**
NET	0.59	−1.43	0.84	11.41
0.05				
Coal	47.28	26.45	26.27	52.72
New energy	24.12	43.42	32.45	56.58
High-tech	24.71	30.73	44.55	55.45
TO others	48.84	57.19	58.72	**TCI**
NET	−3.88	0.61	3.27	54.91
0.95				
Coal	48.97	25.97	25.06	51.03
New energy	23.19	45.77	31.04	54.23
High-tech	23.42	31.04	45.53	54.47
TO others	46.61	57.01	56.11	**TCI**
NET	−4.42	2.78	1.64	53.24

Next, we focus on net directional results (Results are based on a 200-day rolling-window QVAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast. However, our results are robust to other choices of the forecast horizons and window length. Those results are available on request). The warmer shadows on these graphs indicate that the market is a net transmitter. We note that in general, the net spillover effect of high technology is the strongest, and the spillover in the low quantile is higher than that in the high quantile, and the upper tail and lower tail are asymmetric. Over two time intervals (around 2016, mid-2018 to early 2020), the net transmission of high technology has increased significantly under various market conditions, which provides empirical evidence that high tech is more likely to become a net transmitter during the stock panic and crisis. Most of the time, the color of steam coal is colder, and the net transmission effect of steam coal is the weakest in the three markets, which is roughly the continuous net receiver of shocks in the whole sample period, especially under extreme market conditions. New energy varies over time between transmitter and receiver roles, and the transmission of new energy is mainly traced to the extreme quantile region.

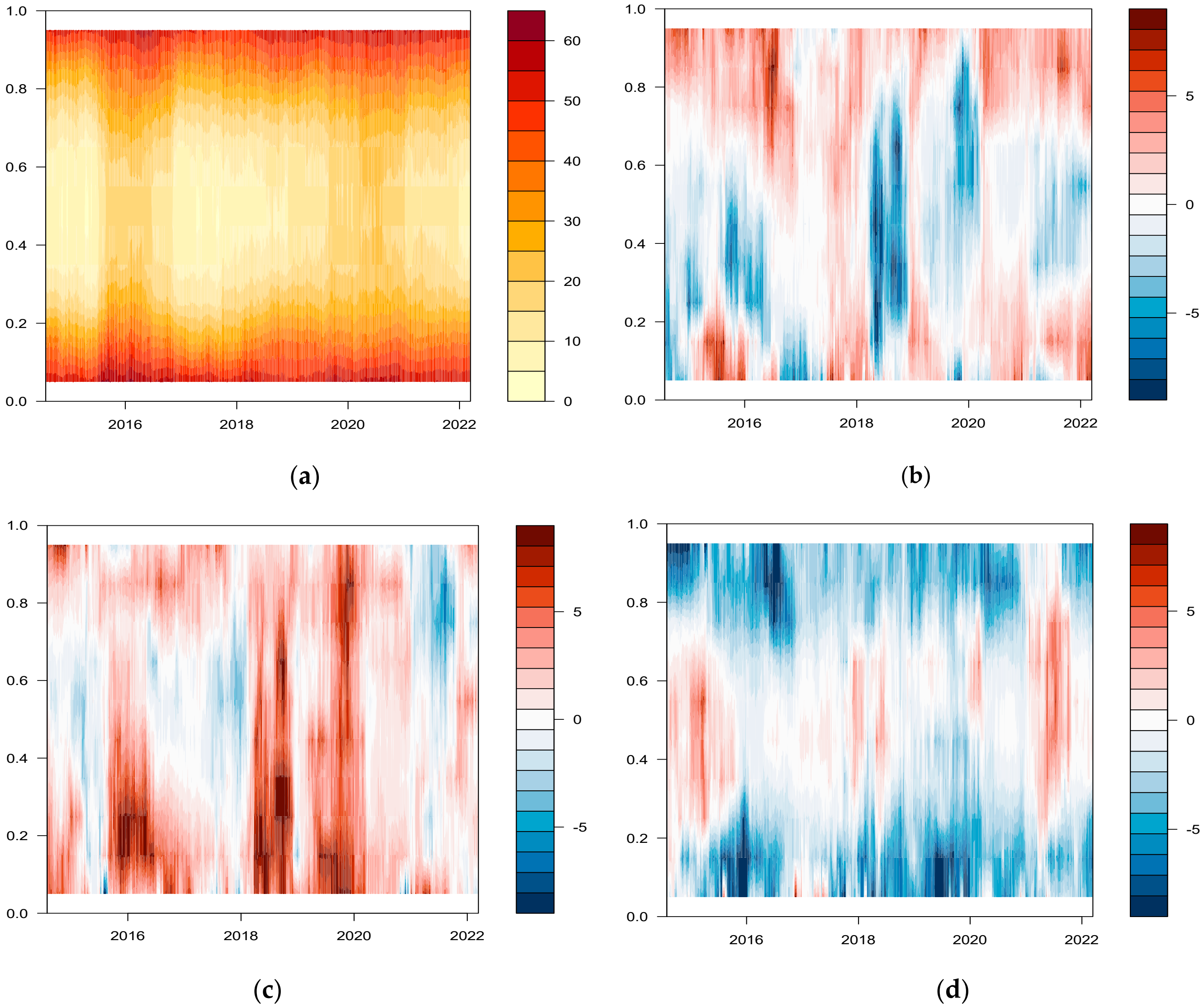


Figure 4. Dynamic connectedness. (**a**) Dynamic total connectedness; (**b**) Net total directional connectedness (New energy); (**c**) Net total directional connectedness (High-tech); (**d**) Net total directional connectedness (Coal).

6. Conclusions

China's energy transition should be based on the basic national conditions of coal dominance and further promote the optimal combination of coal and new energy, in which technological progress is the key. In order to deeply explore the correlation between coal, new energy and high-tech, this paper studies the risk transmission direction and spillover effect of the three under normal and tail conditions from the quantile perspective. First, from the results of quantile causality, steam coal has no prediction ability in the system. High-tech is the Granger causality of new energy between the quantiles of 0.1 and 0.4, which shows that high technology is predictive when new energy prices are low. Secondly, the quantile connectedness results show that the bi-directional risk spillover of high-tech and new energy is significantly higher than that of steam coal and new energy at different quantile levels, and high-tech has a substantial risk output capacity. In addition, we find that the total system spillovers increased significantly during the financial crisis or market overheating.

Our empirical results have reference value for investors and policymakers. The price of steam coal is not the critical factor affecting the share price of new energy. Investors can create hedging opportunities by taking advantage of the weak links between the steam coal market, new energy and high-tech. High technology is predictable for new energy in the low quantile, which helps investors understand the transmission mechanism of high technology in the new energy stock market and establish prediction models related to different market conditions. In addition, the research results on the extreme connectivity measurement of the upper and lower tails provide a subtle perspective on the importance of tail risk transmission. Furthermore, from the perspective of time-varying characteristics, in such events as China's stock market crash in 2015 and the COVID-19 pandemic, the total spillover between markets has intensified. Therefore, to deal with the adverse impact of the epidemic on the development of new energy, the government needs to take countercyclical measures and provide financial support to reduce the impact of COVID-19 on energy innovation and speed up the progress in key technology areas.

Considering the similar power supply structure dominated by coal power between China and emerging economies such as India and Chile, these conclusions may be useful to those countries that are highly dependent on the coal market and have low development of high-tech. These countries need to make great efforts in technological progress and policy formulation. Strengthening green technology cooperation and investment will also be the focus of China and these countries to jointly build new energy-related international infrastructure under the Belt and Road initiative [48].

In terms of limitations of this paper, due to the heterogeneity of investors, this work can be expanded by using quantile frequency connectedness [49] to expand the scope of time investment. Furthermore, the three markets system can be expanded to include the raw material market, such as crucial metals (rare earths, etc.). The price of fossil energy affects the cost of raw materials in the metal industry, and metals are the critical raw materials for developing new energy [50]. Risk transmission between these markets is another possible avenue of research.

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