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RESEARCH ARTICLE

Quantile Time-Frequency Connectedness Between Carbon Emissions, Traditional and New Energy: Evidence from COVID-19 and the Russia-Ukraine Conflict

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Abstract: This study investigates the spillover effects associated with diverse market conditions in energy and carbon markets, encompassing both new and traditional energy sectors. Using a quantile vector autoregression approach, this research explores the dynamic interactions among carbon emissions, traditional energy, and new energy from January 1, 2019, to July 28, 2023. Firstly, the research findings presented in this article reveal a significant spillover effect under extreme conditions, whether the change is highly positive or negative, with increases observed from 26.67% to 76.15% and 74.19%, respectively. Secondly, during the Russia-Ukraine conflict and COVID-19 pandemic, the interaction among carbon emissions, traditional energy, and new energy intensified, transforming their roles in the context of spillover effects. The negative spillover effects in the new energy and carbon markets position them as effective hedging tools. Finally, the pandemic and conflicts have underscored the increasing importance of new energy, particularly in the long run, as evidenced by the significant expansion of spillover effects in the new energy market. These findings inform policymakers and ecological investors in developing effective policies and tailored investment strategies across various frequency ranges.

Keywords: carbon emission, energy market, spillover effects, quantile vector autoregression (QVAR) method

1. Introduction

Carbon emissions are a pivotal factor in global warming. Following the release of the 2013 United Nations Intergovernmental Panel on Climate Change (IPCC) report on the impact of human activities on climate change, countries have pledged to reduce greenhouse gas emissions, which have increased since the Industrial Revolution. In light of the escalating economic risks associated with climate change, nations have generally recognized the imperative of achieving energy transformation and reducing carbon emissions [1]. To this end, countries are actively promoting the development of new energy sources [2], encouraging investment in green finance, and establishing mechanisms for carbon emission trading to advance sustainable development goals. However, the COVID-19 pandemic and the 2022 Russia-Ukraine crisis have posed significant challenges to energy transformation and upgrading, thereby threatening the stability of the energy sector [3]. Sustainable development constitutes an important component of the global economy [4, 5], prompting researchers to explore the significance of environmental sustainability for economic growth. Among the factors related to environmental sustainability, sustainable economic growth [6-8] and energy security [9] play crucial roles.

At the same time, carbon emissions, as a policy-driven indicator, are significantly influenced by the carbon market, which represents a relatively specialized segment within the energy market [10]. In the era of economic globalization, especially during financial crises, the increased integration of macroeconomics, finance, and commodity markets has become inevitable. Additionally, Jin's study demonstrated that speculators tend to focus on short-term transactions rather than long-term ones, and they often trade at levels that impact carbon emissions [11]. Finally, energy prices, government policies, and other unforeseen shocks are important factors contributing to high volatility in this market [12, 13] (path V in Fig1).

The significance of spillover effects between traditional and new energy sources has been increasingly acknowledged within low-carbon energy transformation. In the era of economic globalization, particularly amid financial crises, the increased integration of macroeconomics, finance, and commodity markets has become inevitable. Furthermore, Jin's study demonstrated that speculators tend to focus on short-term transactions rather than long-term ones, and they often trade at levels that impact carbon emissions [14].

Existing literature indicates that during pandemics and the Russia-Ukraine conflict, there is notable volatility connectivity; Coban found that COVID-19 influenced the renewable energy industry, providing a unique opportunity to incorporate renewable energy into the economic recovery plan [3] (path IV in Fig1). However, the degree of this increase varies [14]. The findings related to risk sender/receiver dynamics and the frequency of connectivity also demonstrate inconsistencies [15, 16]. Furthermore, the emergence of conflicts has disrupted commodity trade, leading to a shift in supply-side volatility connectivity [17] (path VI in Fig1).

Based on the analysis presented above, and considering the escalating trends in globalization and the advancement of carbon financialization, as highlighted by Berta et al, there is a pressing need for a comprehensive assessment of the flow of information and influences between the domestic market and its international counterparts [18]. This analysis is essential for equipping investors and market stakeholders with the insights necessary for informed decision-making concerning risk allocation and effective investment portfolio management. Furthermore, it is crucial for environmental policy analysts to develop accurate policies based on this evaluation.

An increasing body of empirical research has explored the relationship between carbon emissions and traditional markets. Several studies on interconnectivity in the energy carbon market employ the dynamic connectedness framework established by Diebold and Yilmaz [19, 20]; Feasible Quasi Generalized Least Squares (FQGLS) estimators [21], bidimensional empirical mode decomposition (BEMD) based on a multiscale approach [22], multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) techniques [23, 24], the wavelet approach [25, 26], vector autoregression (VAR) models [27] and Granger causality tests [28]. However, we found that existing models only provide preliminary analysis of risk spillovers and fail to accurately describe the spillover effects within the market or quantify their scale. To address these limitations, this study employs DY, BK, and QVAR models to depict the trajectory and magnitude of risk spillovers across segmented markets and evaluates the periodic characteristics of specific quantile tail risk spillovers at various frequencies in the energy market. In addition, it also studied the spillover effects of fluctuations in different conditional quantiles at specific frequencies, thereby enhancing its robustness and flexibility. This method helps evaluate the fluctuations in net risk spillover levels between different segmented markets.

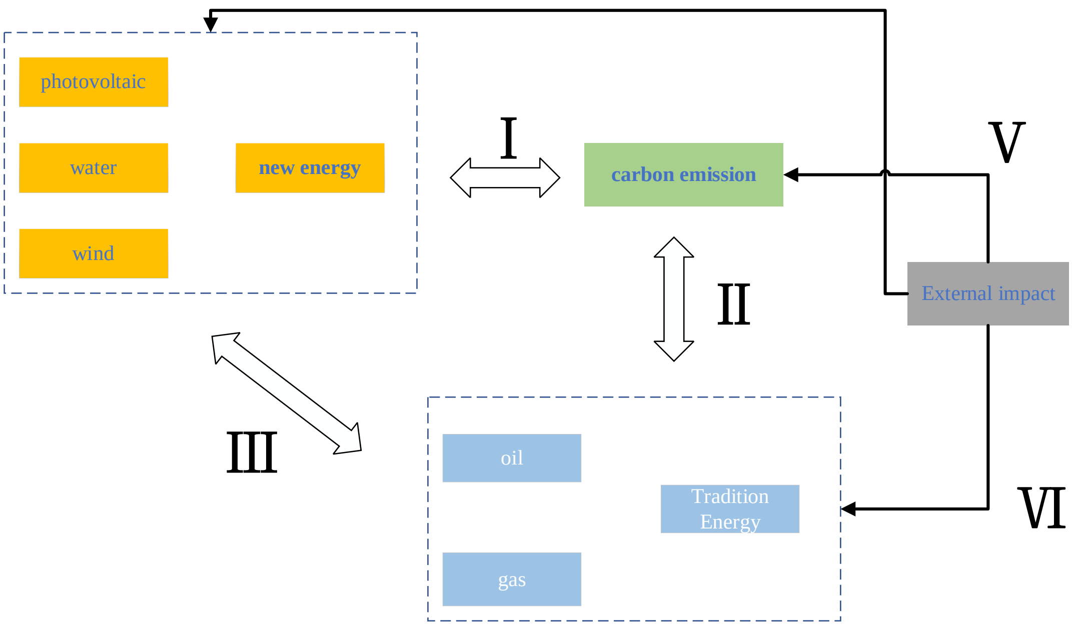
Briefly, this article offers a fresh perspective on the existing literature in the following areas: (I) The examination of variability in extreme states to provide more precise recommendations for market participants and policymakers. (II) A focus on the overlooked risk transmission associated with energy sources, highlighting the need for analyses in both the frequency domain and extreme conditions. (III) The introduction of the QVAR model to analyze the carbon emission index alongside traditional and renewable energy sources under extreme conditions. (IV) An investigation into return spillovers and interconnectivity effects among carbon markets, new energy, and traditional energy markets.

This paper makes significant contributions to the understanding of energy market dynamics through three primary avenues. First, it utilizes the QVAR model to analyze spillover effects and volatility in both traditional and renewable energy sectors. The results indicate a persistent high-risk spillover in the new energy sector, highlighting its critical role as a risk contributor. Notably, during the initial phases of COVID-19 and the Russo-Ukrainian conflict, the oil market transitioned from a negative to a positive net spill index, emerging as a risk transmitter. Furthermore, the study reveals varying spillover effects among distinct indicators under different quantile conditions, providing valuable insights for market participants and policymakers in identifying global price trends. Second, the analysis uncovers a pronounced high-risk spillover effect associated with emerging energy sectors. Post-pandemic and during the Russia-Ukraine conflict, the influence of specific new energy markets on risk spillover has significantly evolved. Given the discrepancies in supply chains, market demand, government policies, and financialization, not all commodities react uniformly to geopolitical conflicts [29]. Monitoring these shifts is essential, enabling investors to leverage diverse investment strategies tailored to specific events, thus enhancing returns through increased connectivity. Third, this study identifies market connectivity patterns across various frequency domains. Utilizing the DY model [30], it examines static spillover effects among carbon emissions, traditional energy, and renewable energy sectors, revealing a significant increase in overall connectivity following the pandemic and the Russia-Ukraine conflict. Additionally, the BK method is employed to evaluate interrelationships across various time horizons, which are vital for effective risk management during turbulent market conditions [31].

The structure of this article is summarized as follows: Section 2 is literature review, Section 3 provides a detailed introduction to data and methods, Section 4 discusses empirical results, Section 5 examines robustness, and Section 6 provides a conclusion with policy insights.

Figure 1

Workflow Diagram



2. Literature Review

Previous research has documented the association between energy market spillovers and levels of carbon emissions (path I II III in Fig1). In the Central European region of the European Union [19, 20], uel prices significantly impact market prices. However, other studies have highlighted the influence of new energy sources, particularly photovoltaic power generation, on carbon emission prices. Past research has also indicated that establishing a carbon emissions trading market effectively lowers carbon dioxide emissions [32, 33]. Simultaneously, the newly established unified carbon market in China holds significant potential for emissions reduction, while the spillover effects of regional markets have far-reaching implications [34, 35]. Li and Wang noted that among the pilot programs, Shenzhen's dynamic return spillover effect is the most pronounced, exhibiting the longest time-lagged correlations, making it China's leading market-oriented carbon trading initiative [36]. Moreover, research has examined how carbon quota prices affect conventional energy sources such as crude oil and coal. Researchers have examined the spillover effects of EUA pricing on new energy, indicating that short-term effects are particularly pronounced between clean energy and carbon prices. Additionally, long-term spillover effects are most prominent between the new energy index and carbon prices [37]. Wu identified spillover effects between the energy market and carbon emissions, with the most significant impact occurring between carbon and coal prices [38]. The substantial policy changes have led to significant shifts in the spillover index, with the oil market exhibiting a pronounced average effect on carbon prices [20]. However, much of the existing literature employs carbon prices as variables for analysis, which are significantly influenced by market fluctuations and policy changes. Therefore, this article uses carbon emissions as a factor variable, which can be regarded as an important output variable of the carbon market. Carbon emissions reflect the carbon production of enterprises or countries during a specific period, and can more directly reflect the actual carbon emissions of enterprises or industries. Monitoring Carbon emissions can serve as a long-term monitoring indicator for assessing the sustainability of carbon reduction efforts. By monitoring and analyzing carbon emissions, it can promote technological innovation, enhance resource allocation, and support the long-term objective of reducing emissions for enterprises.

Concurrently, a substantial corpus of scholarly research persists in examining the interplay between energy consumption and carbon emissions during times of crisis. Kirshner found that the outbreak of COVID-19 posed a considerable impediment to the advancement of global new energy [39]. The pandemic threatens the rapid expansion of the global new energy sector, drawing significant interest from investors and policymakers. The emergence of COVID-19 in 2020, along with the Russia-Ukraine crisis in 2022, poses major challenges to energy transformation and modernization, thereby jeopardizing the stability of the energy sector [3]. The profound ramifications of the pandemic on the global society and economy have resulted in mounting impediments to the attainment of sustainable development objectives. Hence, we deem it imperative to conduct more comprehensive research into the linkage between energy usage and carbon emissions.

Previous research has predominantly employed SVMODEL, Granger causality tests, VAR models, BEKK, GARCH models, and MES to quantify spillover effects across various markets [40, 41]. While these methodologies are indeed valuable, they fail to accurately capture the magnitude, timing, and directionality of safety spillovers across multiple asset markets within intricate financial networks. In order to mitigate this limitation, Diebold and Yilmaz introduced a metric for decomposing prediction error variances and developed a comprehensive total connectivity index, thereby furnishing a holistic framework for assessing spillover effects (Diebold and Yilmaz, 2012). However, the methodology possesses deficiencies in capturing the temporal dynamics of risk spillover effects. As a result, an expanding corpus of research is concentrating on the frequency-domain attributes of these spillover effects, employing variance decomposition in spectral representations to address this limitation (Asadi et al., 2022; Li et al., 2022). Baruník and Křehlík developed a framework for a spillover index rooted in frequency-domain analysis (Baruník and Křehlík, 2018). This method decomposes risk spillovers into distinct frequency bands, facilitating the assessment of connectivity among various frequency response variables and enabling the analysis of risk spillover effects over different time periods. Utilizing the BK method, Ferrer constructed a frequency-domain correlation network encompassing crude oil prices, diverse financial variables, and new energy stock prices. Subsequently, they conducted an in-depth analysis of the correlation levels and explored the underlying drivers of cross-market risk across various temporal horizons (Ferrer et al., 2018). Jiang and Chen utilized both temporal and frequency dimensions to quantify dynamic risk transmissions among financial markets and five energy markets in the context of the COVID-19 pandemic (Jiang and Chen, 2022). Additionally, Umar utilized the BK method to reveal the heterogeneity of volatility correlations between new and traditional energy across different time periods. The study confirmed that during the crisis, interdependence among energy markets intensified, with extreme events exacerbating risk contagion effects between them (Umar et al., 2022).

Both the DY and BK methodologies estimate the conditional expectation. however, shocks may not propagate similarly under different market conditions. Bouris' research has somewhat underestimated the influence of unforeseen events in extreme circumstances (Saeed et al., 2021). To mitigate the deficiencies of prior research, studies have refined the conditional mean VAR model by incorporating conditional quantile analysis. Khalfaoui utilized quantile regression to investigate spillover effects within the energy market during extreme scenarios. By employing the fitted quantile vector autoregressive (QVAR) model to quantify spillover at the 0.05 and 0.95 conditional quantiles, this research introduces an innovative methodology for examining spillover dynamics across varying shock intensities (Khalfaoui et al., 2022). Therefore, Ando's implementation of the quantile vector autoregressive model, based on the DY method, to explore the topological structure of networks and the diversity of risk spillovers across various quantiles, holds greater significance than merely focusing on mean-based risk spillovers (Ando et al., 2022). Furthermore, Chatziantoniou introduced a novel quantile-based time-frequency spillover framework that incorporates the repeated integration of the QVAR model with the BK method's frequency domain analysis. This methodology examines the cyclical attributes of risk spillovers, focusing on those occurring at specific quantiles and across multiple frequencies, within the realm of energy markets. Additionally, it examines the volatility spillover effects at specific frequencies across various conditional quantiles, thereby enhancing its robustness and flexibility (Chatziantoniou et al., 2022). Moreover, Ando underscored that, in comparison to conventional conditional mean estimation techniques, such as ordinary least squares, this methodology demonstrates reduced susceptibility to outliers, resulting in enhanced accuracy and reliability of the estimates (Ando et al., 2022). Saeed somewhat underestimates the influence of unforeseen events in extreme circumstances (Saeed et al., 2021). To address the limitations of prior research, existing studies have extended the VAR model by incorporating conditional quantile calculations. Khalfaoui utilized quantile regression to examine the spillover effects within the energy market during extreme conditions. Thus, Ando's utilization of the quantile vector autoregressive model, grounded in the DY method, to investigate the topological characteristics of networks and the variety of risk spillovers across different quantiles, carries greater importance than focusing solely on mean-based risk spillovers (Ando et al., 2022). Furthermore, Ando underscored that, in comparison to conventional conditional mean estimation techniques, including ordinary least squares, this methodology exhibits reduced susceptibility to the impact of outliers, thereby producing more precise and trustworthy estimation outcomes (Ando et al., 2022).

Hence, the scientific objective of this work is to capture the tail risk spillover effects of traditional energy, new energy, and carbon emissions across various market conditions and frequencies, employing the time-frequency spillover framework and the QVAR model. The focus of this research was to gain insights into the dynamic and time-varying attributes of these spillover effects, as well as the notable impact of investor sentiment on near-term outcomes, particularly during extreme events. This study contributes to the existing research by highlighting the substantial escalation of spillover effects during the initial phases of both the pandemic and the Russia-Ukraine conflict, underscoring the necessity for further exploration into the underlying factors that govern market dynamics and identifying effective hedging assets within the carbon and traditional energy markets.

3. Statistical Analysis and Methodology

3.1 Data

This study examines the spillover effects between energy and carbon emissions from January 1, 2019, to July 31, 2023. It selects the hydroelectric power generation index (water), the wind power generation index (wind), and the photovoltaic power generation index (photovoltaic) as representatives of new energy. In contrast, the NYMEX natural gas index (gas) and the ICE oil futures index (oil) represent the traditional energy market. The traditional energy data presented in this article refers to the closing prices of international energy markets, while the new energy data pertains to the closing prices of China's new energy index. All tables in this article were quantitatively analyzed using R and RStudio.

Table 1

Descriptive Statistics on carbon Emissions, traditional energy and new Energy

	carbon	water	photovoltaic	wind	gas	oil
mean	-0.0003	0.0006	0.0010	0.0008	0.0000	0.0004
maximum	0.1871	0.0647	0.0828	0.0933	0.4253	0.1544
minimum	-0.2202	-0.092	-0.1025	-0.1035	-0.1771	-0.3085
std. dev.	0.03	0.02	0.02	0.02	0.04	0.03
skewness	-0.5	-0.27	-0.11	0.05	0.87	-1.48
kurtosis	9.94	2.66	1.66	2.14	9.95	17.52
J-B	4456.37	330.71	126.8	207.07	4559.05	14074.33
ADF	-10.26***	-9.54***	-8.40***	-9.23***	-8.28***	-8.53***

Note: J-B represents the Jarque-Bratest statistic; *, * *** Significantly at levels of 10%, 5%, and 1%, respectively

The carbon emission index referenced in this article is derived from Carbon Monitor "https://www.carbonmonitor.org.cn/". Futures prices for both traditional and renewable energy indices are employed to represent their market values, with data sourced from the Wind database. The futures market, characterized by its ease of trading and higher volume compared to physical commodities, effectively reflects demand, pricing expectations, and global supply (Mei and Xie, 2022). The prices of energy futures exert a direct influence on a multitude of economic activities (Ren et al., 2022a). Furthermore, the energy market is frequently regarded as a haven for mitigating risks in financial markets through diversification strategies (Adams and Glück, 2015; Kang and Yoon, 2019).

Table 1 presents the descriptive statistics for each variable. According to the Jarque-Bera statistic, the volatilities of all data deviate from a normal distribution. Moreover, the unit root test confirms that all variables are stationary, fulfilling the prerequisites for the application of QVAR models.

3.2 Methodology

This article employs a generalized prediction error variance decomposition technique from the QVAR model introduced by Chatziantoniou et al (Chatziantoniou et al., 2022), to assess the tail risk spillover effects stemming from carbon emissions and the transition between traditional and new energy sources across varying scales of impact, timeframes, and cycles. Specifically, the conditional median is indicative of a normal state, while the 0.95 and 0.05 conditional quantiles reflect extreme downturns and upswings, respectively.

To derive the various connectedness measures, this paper begins with estimating a quantile vector autoregression (QVAR(p)), characterized as follows:

$$x_t = \mu(\tau) + \phi_1(\tau) x_{t-1} + \phi_2(\tau) x_{t-2} + \cdots + \phi_p(\tau) x_{t-p} + \mu(\tau) \tag{1}$$

Where x_t and x_{t-i} , $i=1,\ldots p$ represents vectors of endogenous variables with $N \times 1$ dimensions., τ is between $[0,1]$ and denotes the quantile of interest, p signifies the number of lags incorporated within the QVAR model, $\mu(\tau)$ is a conditional mean vector with $N \times 1$ dimensions, $\phi_j(\tau)$ is a QVAR coefficient matrix with $N \times N$ dimensions, and $\mu_i(\tau)$ demonstrates the error vector $N \times 1$ has an error variance-covariance matrix of dimension $N \times N$, $\sum(\tau)$. To transform the QVAR(p) model into its quantile vector MA representation, denoted as QVAR(∞), this paper employs the Wold theorem.:

$$x_t = \mu(\tau) + \sum_{j=1}^{p} \phi_j(\tau) x_{t-j} + \mu(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) u_{t-i}$$

Following this, the generalized forecast error variance decomposition (GFEVD) is computed as a means of implementing the central element of the connectedness methodology (Koop et al., 1996; Pesaran and Shin, 1998). The GFEVD proportion of forecast error variance indicates the impact of a disturbance in series j on series i . This measure quantifies the influence exerted by the specified disturbance and can be expressed mathematically in a defined formula:

$$\theta_{ij}(H) = \frac{\left(\sum(\tau)\right)_{jj}^{-1} \sum_{h=0}^{H} \left(\left(\Psi_h(\tau) \sum(\tau)\right)_{ij}\right)}{\sum_{h=0}^{H} \left(\Psi_h(\tau) \sum(\tau) \Psi^{'}(\tau)\right)_{ii}} \tag{2}$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N} \theta_{ij}(H)} \tag{3}$$

To ensure that the row sums of $\tilde{\theta}_{ij}(H)$ add up to one, it is necessary to normalize each row by its sum, resulting in $\tilde{\theta}_{ij}$. By normalizing, this paper obtain the following identities: $\sum_{i=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\theta}_{ij}(H) = N$. Therefore, the sum of each row in the matrix equals one, illustrating how a shock in one series impacts not only that specific series but also all others j .

In the subsequent stage, this paper compute several measures of connectedness. The first measure this paper calculate is the net pairwise connectedness (NPDC), can be obtained through the following procedure:

$$NPDC(H) = \tilde{\theta}_{ij}(H) - \tilde{\theta}_{ji}(H) \tag{4}$$

If $NPDC_{ij}(H) > 0 \left(NPDC_{ij}(H) < 0\right)$ this signifies that series j exerts a stronger (weaker) influence on series i than the influence of series i on series j . Hence, if $NPDC_{ij}(H) > 0$ Series j exerts dominance over series i and vice versa.

The measure of total directional connectedness to others (TO) quantifies how a shock in series i is transmitted to all other series j :

$$TO_i(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{ji}(H) \tag{5}$$

The measure of total directional connectedness to others (FROM) quantifies how a shock in series j is transmitted to all other series i :

$$FROM_i(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{ij}(H) \tag{6}$$

The net total directional connectedness highlights the imbalance between the connectedness series i extends to others and receives from them, signifying its net influence within the network.

$$NET_i\left(H\right)=TO_i\left(H\right)-FROM_i\left(H\right) \tag{7}$$

If $NET_i>0\left(NET_i<0\right)$ series i exerts more influence on all other series j than it receives from them, it is regarded as a net transmitter of shocks. Conversely, if it is influenced more than it influences others, it is regarded as a recipient of net shocks.

The degree of interconnectedness within the network, as signaled by the total connectedness index (TCI), is specified by the subsequent equation:

$$TCI\left(H\right)=N^{-1}\sum_{i=1}^{N}TO_i\left(H\right)=N^{-1}\sum_{i=1}^{N}FROM_i\left(H\right) \tag{8}$$

This metric essentially summarizes the average impact that a disturbance in one series exerts on all the other series within the system. A higher value of the total connectedness index (TCI) implies heightened market risk, whereas a lower value suggests decreased ris.

Till to date, the emphasis has been on assessing connectedness in the time domain; however, this study will now redirect its focus to the frequency domain. Firstly, the Fourier transform of the QVMA (∞) can define the spectral density at frequency ω for x_t.

$$S_x\left(\omega\right)=\sum_{h=-\infty}^{\infty}E\left(x_t x_{t-h}^{'}\right)e^{-i\omega h}=\Psi\left(e^{-i\omega h}\right)\sum_t\Psi^{'}\left(e^{+i\omega h}\right) \tag{9}$$

By combining spectral density and generalized prediction error variance decomposition, we obtain the frequency generalized prediction error variance decomposition. Here, $\theta_{ij}\left(\omega\right)$ indicates the conditional quantile τ , indicating the portion of the spectrum of variable i influenced by variable j. Additionally, the standards equation (9) is derived from chemical treatment.

$$\theta_{ij}\left(\omega\right)=\frac{\left(\sum(\tau)\right)_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi(\tau)\left(e^{-i\omega h}\right)\sum(\tau)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\Psi\left(e^{-i\omega h}\right)\sum(\tau)\left(e^{i\omega h}\right)\right)_{ij}} \tag{10}$$

$$\tilde{\theta}_{ij}\left(\omega\right)=\frac{\theta_{ij}\left(\omega\right)}{\sum_{k=1}^{N}\theta_{ij}\left(\omega\right)} \tag{11}$$

To investigate the spillover effects of tail risks among energy markets within distinct frequency bands, this paper establishes a specific frequency band segmentation: $d=\left(a,b\right):a,b\in\left(-\pi,\pi\right),a<b$. The magnitude of spillover from variable j to variable i within a particular frequency band is quantified by the measurement of $\tilde{\theta}_{ij}\left(d\right)=\int_a^b\tilde{\theta}_{ij}\left(\omega\right)d\omega$. From this, directional spillovers and total spillover indices can be obtained for different quantiles and specific frequency domains.

$$TO_i\left(d\right)=\sum_{i=1,i\neq j}^{N}\tilde{\theta}_{ji}\left(d\right),FROM_i\left(d\right)=\sum_{i=1,i\neq j}^{N}\tilde{\theta}_{ij}\left(d\right) \tag{12}$$

$$TCI\left(d\right)=N^{-1}\sum_{i=1,i\neq j}^{N}TO_i\left(d\right)=N^{-1}\sum_{i=1,i\neq j}^{N}FROM_i\left(d\right) \tag{13}$$

As per equation (13), the net overflow index (NET) can be defined in the quantile frequency domain, $NET_i\left(d\right)=TO_i\left(d\right)-FROM_i\left(d\right)$. Moreover, utilizing the net spillover index within the frequency domain facilitates the evaluation of each market's role in the transmission of tail risks across various time horizons.

4. Empirical Results and Discussion

4.1 Time-domain and -frequency average connectedness

4.1.1 Time-domain average spillover effects

To construct a Vector Autoregression (VAR) model with an optimal lag order of 1, we utilize the Hannan-Quinn criterion (HQ), Akaike information criterion (AIC), Schwartz criterion (SC), and final prediction error (FPE) as model selection criteria. Employing the DY method, we determine that the VAR model with a lag order of 1 yields the most favorable outcomes across these criteria. Table 2 presents the spillover matrix in a static state for carbon emissions affecting both new energy and traditional energy sectors. The diagonal elements of the matrix signify the self-contribution of each variable to the variance of its prediction error, reflecting the influence of its own lagged effects. Conversely, the numerical values along the off-diagonal elements represent the interdependencies among variables within the network of volatility spillovers. Notably, the diagonal elements play a pivotal role in capturing the autoregressive characteristics of the variables. Furthermore, the "TO" row and the corresponding "FROM" column within the "TO" row signify the aggregate inflow influence and the comprehensive spillover impact of tail risk in a particular energy market, respectively. Additionally, the "NET" row illustrates the net magnitude of tail risk spillover within the confines of the market.

Table 2

Static Spillover Table of Carbon Emissions and Traditional Energy, Clean Energy

	carbon	water	photovoltaic	wind	gas	oil	FORM
carbon	99.14	0.44	0.13	0.08	0.07	0.14	0.14
water	0.10	53.94	17.87	27.67	0.01	0.41	7.68
photovoltaic	0.10	16.39	49.46	32.85	0.10	1.10	8.42
wind	0.14	23.40	30.29	45.57	0.02	0.58	9.07
gas	0.16	0.04	0.17	0.02	98.31	1.31	0.28
oil	0.02	0.71	2.35	1.39	1.36	94.16	0.97
TO	0.09	6.83	8.47	10.34	0.26	0.59	
NET	-0.05	-0.85	0.05	1.27	-0.02	-0.38	TCI
NPT	0	3	5	6	1	2	26.57

Figure 2

Total Spillover Effect

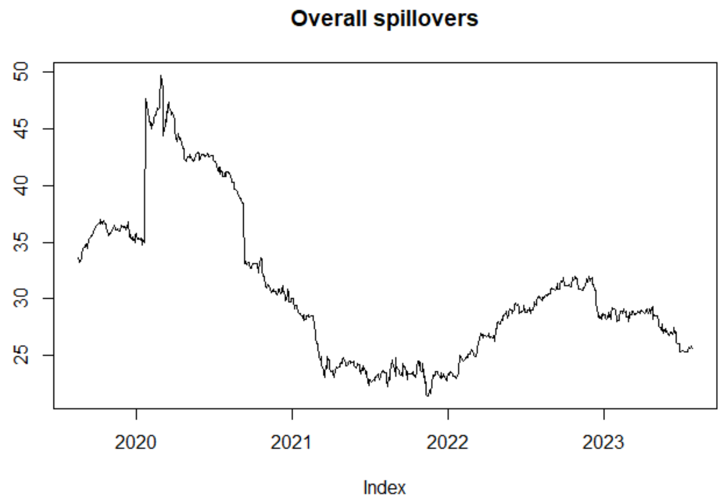


Table 2 illustrates the static spillover effects between the carbon emission index and both new and traditional energy sources under normal market conditions. Firstly, in terms of risk spillover (TO), the wind energy index exhibits the highest spillover level at 10.34%, followed by the photovoltaic index at 8.47%. The carbon emission index shows the lowest spillover level, amounting to 0.09%. Regarding the risk spillover effect (FORM), photovoltaic power generation displays the highest spillover level at 8.42%, followed by hydroelectric power generation at 7.68%. The minimum spillover effect of carbon emission indicators is 0.14%. From this, it can be seen that in time-domain analysis, photovoltaic power generation index and hydraulic power generation index are the main risk spillovers and also the main risk bearers. This further indicates that indices with higher spillover levels are more vulnerable to the influences of other indices. From the aforementioned table, it is evident that the traditional energy market, owing to its well-established market mechanism, exhibits relatively weak transmission of uncertainty shocks to other markets, resulting in a comparatively low risk spillover level. Secondly, in terms of net effect NET, both the carbon emission index and the traditional energy index have negative net spillover effects as receivers, with the crude oil index exhibiting the highest net spillover effect of -0.38% as the largest risk taker. Regarding new energy, aside from the hydropower index, all other indicators show positive effects, with the wind power index reaching a peak of 1.27%, playing a role in risk spillover. Additionally, based on the NPT index, the net spillover index of carbon emissions is entirely negative, greatly influenced by energy indicators. Meanwhile, the wind power generation index is entirely positive, suggesting that wind power generation is more mature in China and drives the fluctuations of other energy indices. Furthermore, Figure 2 clearly illustrates a noticeable rise in the overall connectivity index during the onset of the epidemic and the Russia-Ukraine conflict. This signifies an enhanced connection between energy and carbon emissions throughout these periods.

4.1.2 Time-frequency average spillover effects

In addition to the time-domain analysis, this paper employs the BK method to categorize spillover effects into long-term, medium-term, and short-term components.

Table 3

frequency-domain spillover index

	carbon	water	photovoltaic	wind	gas	oil	FROM-ABS	FROM-WTH
carbon	77.99	0.28	0.08	0.05	0.06	0.08	0.09	0.11
water	0.06	43.48	14.16	22.25	0.01	0.27	6.13	7.59
photovoltaic	0.06	13.66	39.67	26.95	0.06	0.87	6.93	8.59
wind	0.09	19.33	24.38	36.93	0.02	0.48	7.38	9.14
gas	0.10	0.04	0.12	0.02	81.41	1.01	0.21	0.26
oil	0.02	0.49	1.64	0.96	0.97	76.28	0.68	0.84
TO_ABS	0.06	5.63	6.73	8.37	0.19	0.45	21.43	TCI
TO_WTH	0.07	6.98	8.34	10.37	0.23	0.56		26.54
NET	-0.03	-0.5	-0.2	0.99	-0.02	-0.23		

The spillover table for band: 3.14 to 0.63 Roughly corresponds to 1 days to 5 days.

	carbon	water	photovoltaic	wind	gas	oil	FROM-ABS	FROM-WTH
carbon	17.78	0..14	0.05	0.03	0.00	0.05	0.04	0.27
water	0.03	8.80	3.12	4.56	0.00	0.12	1.30	8.04
photovoltaic	0.03	2.30	8,24	4.98	0.03	0.19	1.26	7.73
wind	0.04	3.44	4.98	7.28	0.00	0.08	1.42	8.77
gas	0.05	0.00	0.04	0.00	14.24	0.26	0.06	0.36
oil	0.00	0.19	0.60	0.36	0.33	15.05	0.25	1.52
TO_ABS	0.03	1.01	1.46	1.65	0.06	0.12	4.33	TCI
TO_WTH	0.16	6.23	9.01	10.19	0.38	0.71		26.68
NET	-0.01	-0.29	0.2	0.23	0.00	-0.13		

The spillover table for band: 0.63 to 0.10 Roughly corresponds to 5 days to 30 days.

	carbon	water	photovoltaic	wind	gas	oil	FORM-ABS	FORM-WTH
carbon	3.37	0.03	0.01	0.01	0.00	0.01	0.01	0.28
water	0.01	1.66	0.59	0.86	0.00	0.02	0.25	8.07
photovoltaic	0.01	0.43	1.55	0.93	0.01	0.04	0.23	7.68
wind	0.01	0.64	0.94	1.36	0.00	0.02	0.27	8.75
gas	0.01	0.00	0.01	0.00	2.65	0.05	0.01	0.36
oil	0.00	0.04	0.12	0.07	0.06	2.83	0.05	1.55
TO_ABS	0.01	0.19	0.28	0.31	0.01	0.02	0.81	TCI
TO_WTH	0.17	6.19	9.06	10.17	0.38	0.72		26.69
NET	0.00	-0.06	0.05	0.04	0.00	-0.03		

The spillover table for band: 0.10 to 0.00 Roughly corresponds to 30 days to Inf days.

As demonstrated in Table 3, the overall spillover index remains stable at approximately 26.6%, indicating that the spillover between carbon emissions and energy is not significantly affected by time in the absence of major events. Furthermore, the table reveals a greater short-term spillover effect compared to the long-term effect, suggesting intensified competition between renewable and traditional energy sources in the carbon reduction process. This phenomenon is primarily driven by investor sentiment. Notably, the photovoltaic power generation index has gradually shifted from a negative net overflow in 2019 to a positive value, signifying a change in the position of the photovoltaic market in both the medium and short to long term.

4.2 Dynamic quantile connectedness

To investigate the spillover effect between carbon emissions and traditional energy sources in extreme scenarios, this article employs the QVAR model for comprehensive analysis.

Table 4

Carbon emissions in the time domain and tail risk net spillover table of traditional and new energy sources

(conditional median)

	carbon	water	photovoltaic	wind	gas	oil	FROM
carbon	99.14	0.44	0.13	0.08	0.07	0.14	0.86
water	0.10	53.94	17.87	27.67	0.01	0.41	46.06
photovoltaic	0.10	16.39	49.46	32.85	0.10	1.10	50.54
wind	0.14	23.40	30.29	45.57	0.02	0.58	54.43
gas	0.16	0.04	0.17	0.02	98.31	1.31	1.69
oil	0.02	0.71	2.35	1.39	1.36	94.16	5.84
TO	0.52	40.99	50.81	62.02	1.55	3,54	
NET	-0.34	-5.07	0.26	7.59	-0.14	-2.30	TCI
NPT	2	3	4	4	1	1	26.57

Table 5

Carbon emissions in the time domain and tail risk net spillover table of traditional and new energy sources (0.05 conditional quantiles)

	carbon	water	photovoltaic	wind	gas	oil	FORM
Carbon	24.75	15.01	15.17	16.17	13.78	15.12	75.25
Water	13.15	21.96	17.78	19.46	12.61	15.04	78.04
Photovoltaic	12.60	17.31	22.51	20.63	12.23	14.71	77.49
Wind	12.42	18.53	19.75	22.71	12.02	14.57	77.29
Gas	14.10	14.63	14.58	15.24	25.61	15.85	74.39
Oil	13.64	15.33	15.29	15.73	14.44	25.57	74.43
TO	65.91	80.81	82.58	87.23	65.08	75.28	
NET	-9.34	2.77	5.09	9.94	-9.31	0.85	TCI
NPT	1	3	4	5	0	2	76.15

Table 6

Carbon emissions in the time domain and tail risk net spillover table of traditional and new energy sources (0.95 conditional quantiles)

	carbon	water	photovoltaic	wind	gas	oil	FORM
carbon	29.22	14.22	13.94	14.73	14.30	13.59	70.78
Water	11.65	23.86	18.60	19.77	13.02	13.10	76.14
Photovoltaic	11.26	17.91	23.97	20.95	12.61	13.31	76.03
Wind	11.67	18.62	20.19	23.24	12.88	13.39	76.76
Gas	12.68	14,61	14.60	15.17	27.92	15.01	72.08
Oil	12.19	15.11	15.57	15.34	15.13	26.67	73.33
TO	59.44	80.46	82.91	85.97	67.94	68.40	
NET	-11.33	4.32	6.88	9.21	-4.13	-4.94	TCI
NPT	0	3	4	5	2	1	74.19

Figures 4, 5, and 6 demonstrate that total connectivity exhibits dynamic and symmetrical quantile characteristics. During extreme conditions, the risk spillovers between these markets are more robust（$\tau < 0.10, \tau > 0.90$）, with total connectivity fluctuations exceeding 70. The findings of this paper are consistent with recent research that indicates an intensification of risk spillovers between markets during periods of economic shocks or downturns (Li et al., 2016; Naeem et al., 2020). A comprehensive understanding of the Russia-Ukraine conflict's unique impact on connectivity has been achieved. The conflict not only significantly increased connectivity between low and high quantiles but also notably elevated the connectivity of the median during the initial phases of the conflict. The research findings of (Tiwari et al., 2022) diverge from this observation, revealing an increasing trend in risk spillovers caused by the COVID-19 at both low and high quantiles.

The aforementioned static spillover results highlight, from a time-domain perspective, a significant escalation in tail risk spillover levels among energy markets during extreme conditions. However, spillover indices that rely on conditional median measures face challenges in accurately capturing the impact of tail risk spillovers in such scenarios. Furthermore, the emerging energy market is particularly affected by market conditions, demonstrating a substantial increase in directional spillover levels. Despite these dynamics, traditional energy markets and carbon emission indices continue to maintain their dominant positions as risk bearers, exerting a considerable influence on spillover effects. Additionally, the propagation of risk shocks can lead to varying frequency responses, which can be attributed to economic cyclical fluctuations and the diverse nature of investors. Consequently, the analysis of tail risk contagion across different time periods is not effectively captured through time-domain analysis. Consequently, the adoption of a frequency-domain approach is crucial for analyzing tail risk spillovers in the global energy market, encompassing a range of frequency domains, such as high-frequency short cycles and low-frequency long cycle.

4.3 Net quantile connectedness

Table 7 presents the tail risk spillover effects in the energy market under normal conditions. The short-term spillover index is 21.34%, while the medium-term index is 4.33%. The tail risk spillover index for the short term is 21.34%, while it is 4.33% for the medium term. In contrast, the long-term spillover index is 0.81%. The analysis indicates that short-term risk spillovers primarily drive the overall tail risk spillover in the energy market. Furthermore, when assessing risk spillovers across both short-to-medium and long-term horizons, it becomes clear that the new energy market, especially the wind energy sector, demonstrates the highest level of risk spillover. The dominant risk spillover between carbon emissions and both traditional and new energy sources positions new energy as a significant systemic risk. Consistent with the time-domain analysis, new energy exhibits a stronger spillover effect on carbon emissions, highlighting its higher risk compared to traditional energy sources. Moreover, the net spillover of tail risk within the new energy sector exhibits significant heterogeneity across frequency domains. Specifically, in the short term, the photovoltaic market emerges as the primary bearer of risk, demonstrating distinct patterns of heterogeneity across various frequency domains; however, in the medium to long term, it evolves into a risk spillover agent. From a risk spillover perspective, the wind energy sector within the new energy market demonstrates the most prominent characteristics of spillover across both short- and long-term horizons.

Table 7

Averaged joint connectedness.

	Carbon	water	photovoltaic	wind	gas	oil
Carbon	99.14	0.44	0.13	0.08	0.07	0.14
Water	0.10	53.94	17.87	27.67	0.01	0.41
Photovoltaic	0.10	16.39	49.46	32.85	0.10	1.10
Wind	0.14	23.40	30.29	45.57	0.02	0.58
Gas	0.16	0.04	0.17	0.02	98.31	1.31
Oil	0.02	0.71	2.35	1.39	1.36	94.16
TO	0.52	40.99	50.81	62.02	1.55	3,54
NET	-0.34	-5.07	0.26	7.59	-0.14	-2.30
NPT	2	3	4	4	1	1

1-5

	carbon	water	photovoltaic	wind	gas	oil	FROM
Cabon	77.99	0.28	0.08	0.05	0.06	0.08	0.55
Water	0.06	43.48	14.16	22.25	0.01	0.27	36.75
Photovoltaic	0.06	13.66	39.67	26.95	0.06	0.87	41.61
Wind	0.09	19.33	24.38	36.93	0.02	0.48	44.29
Gas	0.10	0.04	0.12	0.02	81.41	1.01	1.28
Oil	0.02	0.49	1.64	0.96	0.97	76.28	4.08
TO	0.33	33.79	40.37	50.23	1.11	2.71	
NET	-0.21	-2.96	-1.23	5.94	-0.17	-1.36	TCI
NPT	2	3	4	4	0	2	21.43

5-30

	carbon	water	photovoltaic	wind	gas	oil	FROM
Carbon	17.78	0.14	0.05	0.03	0.00	0.05	0.26
Water	0.03	8.80	3.12	4.56	0.00	0.12	7.83
Photovoltaic	0.03	2.30	8.24	4.98	0.03	0.19	7.53
Wind	0.04	3.44	4.98	7.28	0.00	0.08	8.54

Gas	0.05	0.00	0.04	0.00	14.24	0.26	0.35
Oil	0.00	0.19	0.60	0.36	0.33	15.05	1.48
TO	0.16	6.07	8.78	9.93	0.37	0.69	
NET	-0.10	-1.76	1.25	1.38	0.02	-0.78	TCI
NPT	2	2	5	2	3	1	4.33

30-inf

	carbon	water	photovoltaic	wind	Gas	oil	FROM
Carbon	3.37	0.03	0.01	0.01	0.00	0.01	0.05
Water	0.01	1.66	0.59	0.86	0.00	0.02	1.48
Photovoltaic	0.01	0.43	1.55	0.93	0.01	0.04	1.48
Wind	0.01	0.64	0.94	1.36	0.00	0.02	1.40
Gas	0.01	0.00	0.01	0.00	2.65	0.05	1.60
Oil	0.00	0.04	0.12	0.07	0.06	2.83	0.07
TO	0.03	1.13	1.66	1.86	0.07	0.13	0.28
NET	-0.02	-0.34	0.25	0.26	0.00	-0.15	TCI
NPT	2	2	5	2	3	1	0.81

Figure 3

Total Spillover Effect

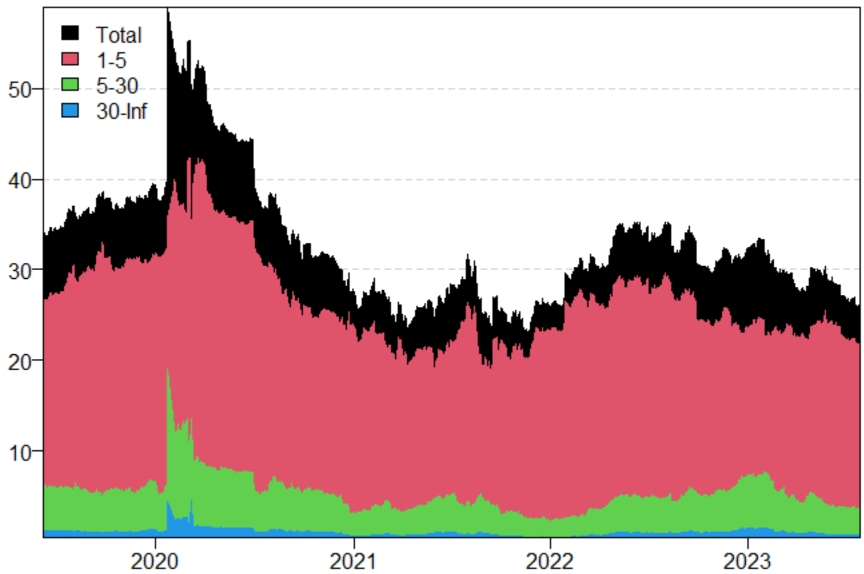
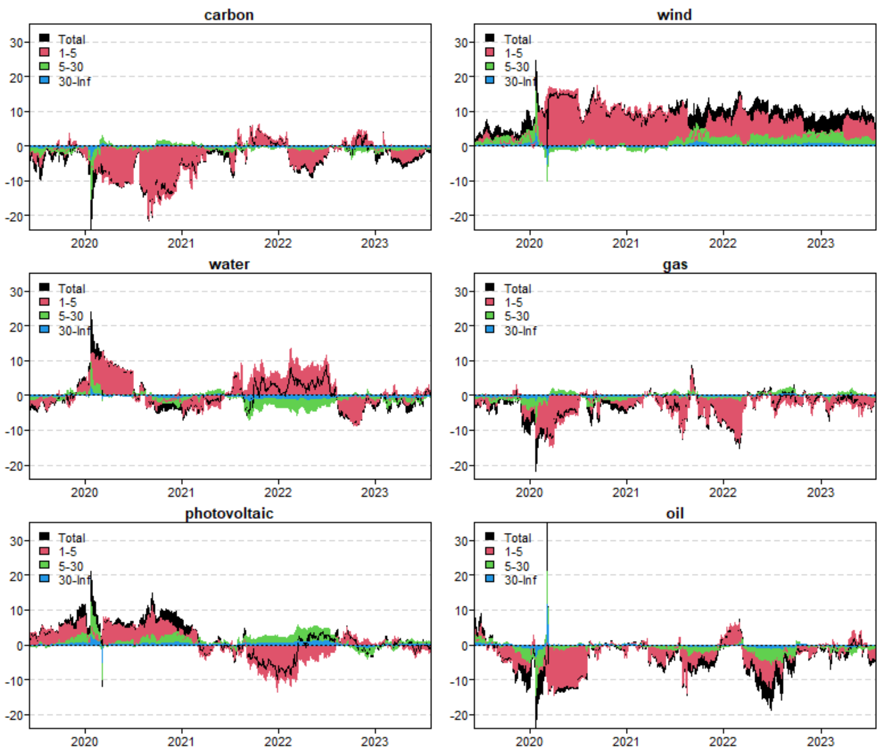


Figure 4

Univariate connectivity index



The results of the complete dynamic connectivity index for a single quantile are illustrated in Figure 5. Warmer colors on the chart signify a higher degree of correlation. Notably, there is a strong correlation—both positive and negative—between carbon emissions and both traditional and renewable energy sources. Notably, in 2020, the dynamic total connectivity index observed an increase, signifying a substantial augmentation in the correlation between carbon emissions and the energy market, potentially attributed to the pandemic's influence. This heightened relationship has resulted in increased market risks.

In this section, the paper investigates the dynamic network connectivity across all quantiles. The blue shadow represents a negative net overflow, while the red shadow indicates a positive net overflow. As illustrated in Figure 5, the net overflow of these products fluctuates between negative and positive values, underscoring the importance of examining dynamic connections. The analysis indicates that during the epidemic, the spillover effect of new energy significantly increased, while at the onset of the Russia-Ukraine conflict, traditional energy's spillover transitioned from negative to positive. Throughout the entire spillover effect, new energy and traditional energy primarily serve as signal transmission agents, although they exhibit high sensitivity within a limited timeframe. In contrast, carbon emissions predominantly function as recipients during most periods.

Figure 6 illustrates the net spillover effects of various variables across different time periods and quantiles. This phenomenon can be ascribed to an elevated sensitivity in the dynamic connectivity among energy markets in response to various external shocks, such as financial crises, policy adjustments, and geopolitical conflicts. Notably, the emerging energy market tends to act as a net disseminator of short-term spillover effects, while carbon markets and traditional energy exhibit the opposite trend, particularly during periods of conflict, when traditional energy serves as a hedge against short-term risks. In extreme market conditions, the energy market undergoes a notable transformation in its role over the medium to long term, alternating between being a net risk transmitter and a net risk receiver. However, the hedging function of traditional energy diminishes over time. Furthermore, the carbon market demonstrates a greater susceptibility to influences from other markets, as evidenced by its predominantly negative net connectivity across all time and frequency domains.

Figure 5

Dynamic total connectivity index on quantiles

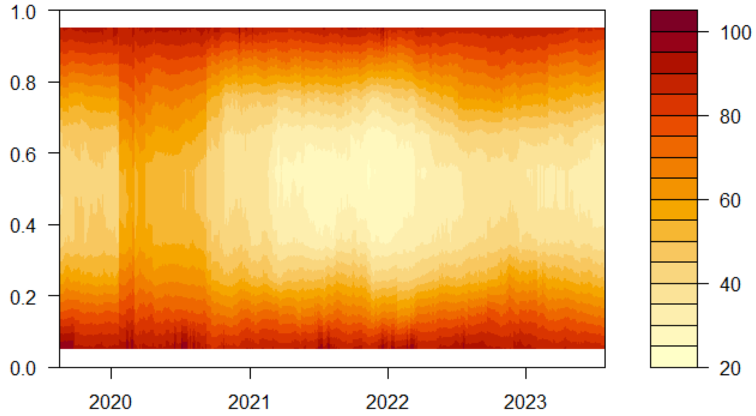
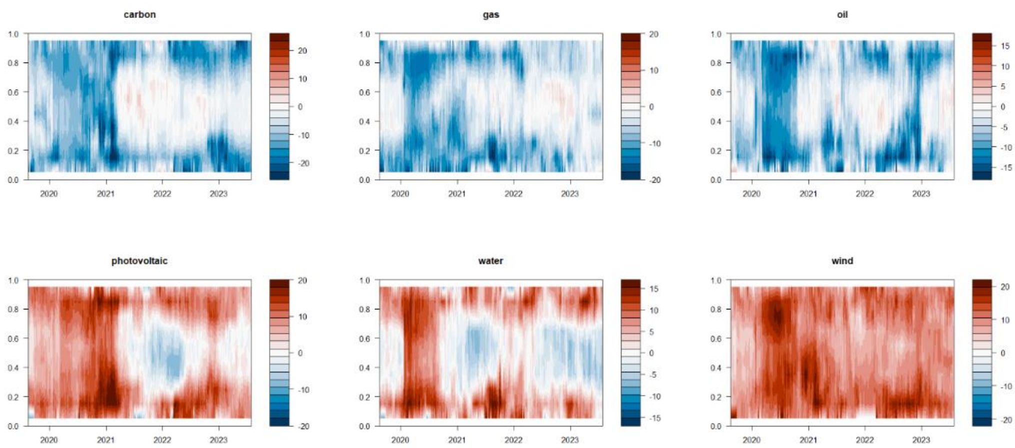


Figure 6

Total directional connectivity of dynamic networks on quantiles



4.4 Connectedness network results

Expanding upon this foundational understanding, the study delves deeper into the contagion effect of tail risk among carbon emissions, traditional energy markets, and new energy sources. To investigate this phenomenon, the study utilizes complex network analysis to examine the topological structure of the network. Utilizing the generalized prediction error variance decomposition of the QVAR model, this paper constructs a tailored tail risk contagion network specifically for carbon emission energy markets. The network comprises six indicator variables as nodes and represents the spillover relationships between energy and carbon emissions fluctuations through the network edges. From a time-domain perspective, Figure 7 visually represents the tail risk spillover network under normal market conditions, while Figures 8 and 9 depict the energy market's spillover network analyzed from a frequency-domain perspective, considering conditional quantile conditions.

Firstly, the tail risk spillover network demonstrates a stronger connection among its nodes, indicating a robust transmission of tail risk between markets. Secondly, upon examining individual markets, the interdependence between wind and hydropower emerges as the most significant, highlighting a strong bidirectional risk spillover between these two energy sources. In contrast, the correlation in volatility between new energy and traditional energy markets appears relatively weak, as evidenced by the low levels of tail risk transmission. This suggests that the interconnectedness among traditional energy markets plays a dominant role in determining the volatility of the global energy market and serves as a crucial channel for tail risk contagion. Therefore, in scenarios where extreme events impact the traditional energy market and lead to increased levels of tail risk spillover, the new energy market can serve as a viable option for mitigating risks associated with the traditional energy market.

Figure 7

(conditional median)

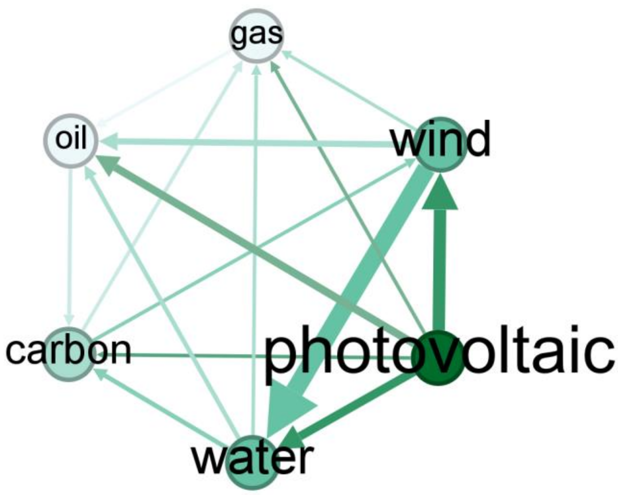


Figure 8

(0.05 Quantiles)

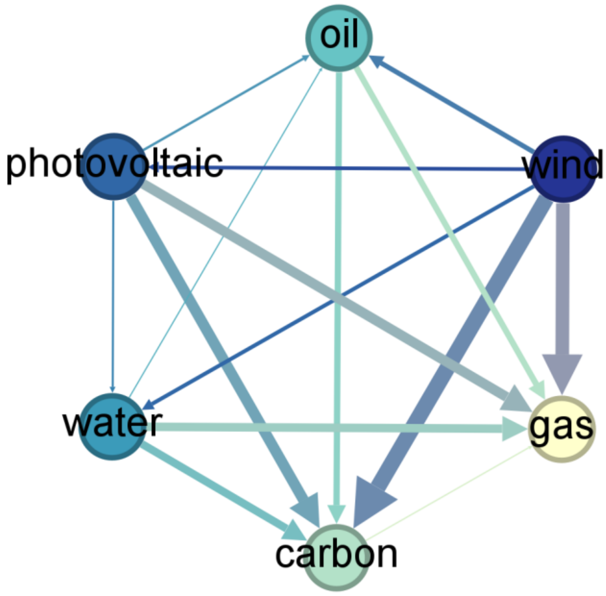
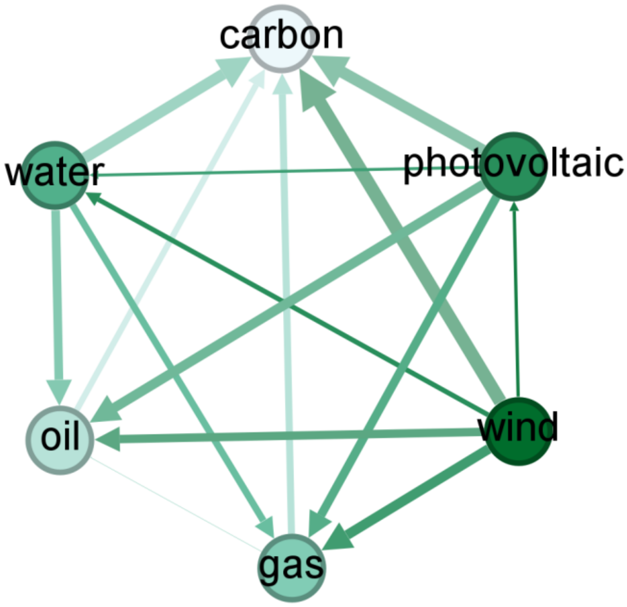


Figure 9

(0.95 Quantiles)



5. Robust Test

Figure 10

Total Spillover Effect (robust test)

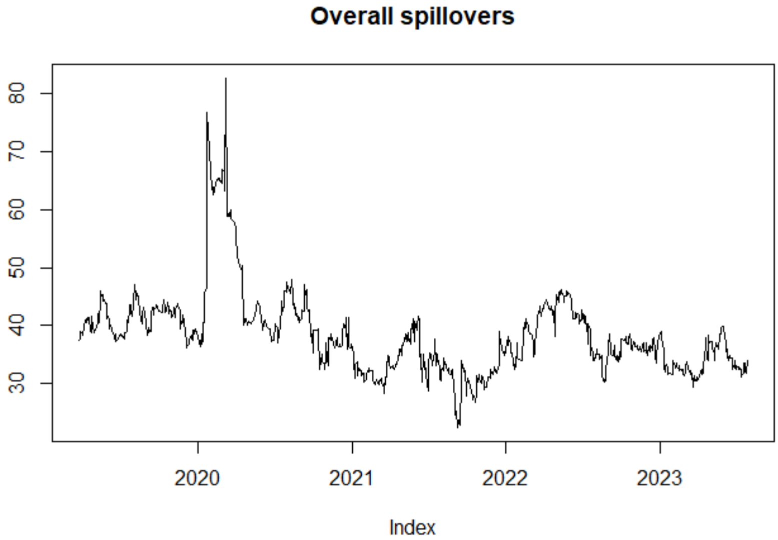
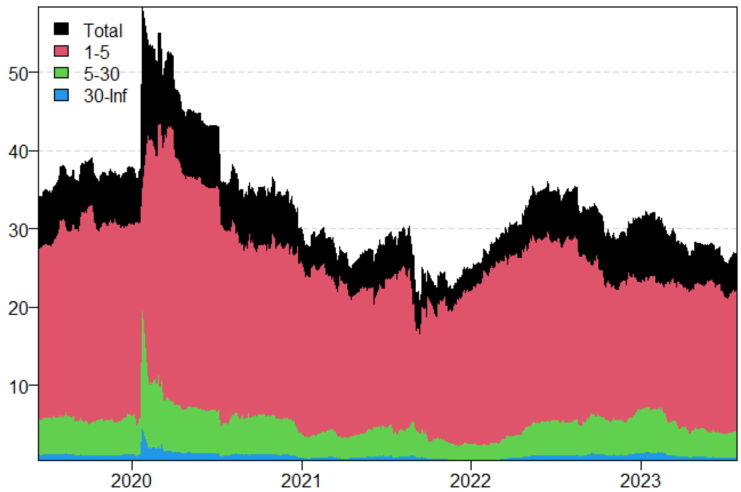


Figure 11

Total Spillover Effect (robust test)



In this section, the study performs a robustness test by substituting the ICE Brent crude oil price with the NYMEX crude oil futures price. The results, as shown in Figure 10-11, demonstrate a high degree of similarity between the two curves. This confirms that the findings of this study remain unaffected by changes in oil futures prices, thereby indicating the robustness of the conclusions presented in this paper.

6. Conclusion and policy implications

At present, the global economy is actively focused on promoting energy conservation and reducing emissions, while the energy industry is undergoing a transition toward cleaner and more sustainable practices. The objective of this study is to investigate the risk spillover effects of carbon emissions and traditional energy sources during periods of extreme events. To achieve this, the paper employs Vector Autoregression (VAR) models and quantile VAR models across three time-frequency domains and over time. Building on this foundation, the study further explores dynamic spillover effects and constructs a network of spillovers to investigate the directionality between markets. Lastly, this paper conducts a robustness test. Of course, this paper also has limitations. the existence time of new energy technologies is relatively short and the scale is small, which means that existing data may not be able to fully capture long-term trends or cyclical changes. We also have identified the spillover effects of energy and carbon emissions, which will also be a pathway for future research. And we will also introduce more energy variables for comparative analysis to enhance the reliability of the research results.

Our research has yielded intriguing findings. Firstly, this paper utilizes the time-frequency spillover framework and QVAR model to effectively analyze the spillover effects of carbon emissions, traditional energy, and new energy across different market conditions and frequencies. The tail risk spillover among carbon emissions, traditional energy, and new energy exhibits dynamic and time-varying features, making it susceptible to extreme events. Secondly, the findings of this paper indicate that the spillover effect primarily operates in the short term, highlighting the significant influence of investor sentiment on near-future outcomes. Thirdly, a substantial increase in the overall spillover effect is noted during the initial stages of both the epidemic and the Russia-Ukraine conflict. This escalation can be attributed to the heightened impact of these events on energy prices. Our research results underscore the importance of conducting more comprehensive investigations into the underlying factors that drive market dynamics. Finally, our findings indicate that the carbon market and traditional energy market are the main net recipients of spillover effects and can serve as effective hedging assets.

This paper propose relevant policy recommendations based on the research findings mentioned above. Market participants are advised to adjust their investment portfolios according to the targeted spillover effects among different assets. This proactive strategy can help mitigate the adverse impacts of extreme events. Short-term investors should remain vigilant about the negative repercussions of cross-risk spillovers across different time frames. For policymakers, a crucial step involves strengthening regulations in traditional energy markets. Close monitoring of fluctuations in energy prices and preventing chain reactions among assets should be prioritized. Furthermore, recognizing the long-term spillover risks from the new energy market underscores its significance in both traditional energy and green finance sectors. Enhancing the pricing mechanisms for new energy and leveraging its potential for sustainable environmental development may prove beneficial. Simultaneously, during the policy formulation process, policymakers should carefully consider the risk transmission mechanisms between various markets and take appropriate measures to effectively respond to crisis events. By implementing these recommendations, both market participants and policymakers can contribute to a more resilient and stable financial system in the face of spillover effects and extreme events.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Wei Jiang: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing - review & editing, Funding acquisition. **XiaoLiang Guo:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Sifeng Bi:** Data curation, Writing - review & editing, Supervision.

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