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Time-Frequency and Quantile Connectedness Among Geopolitical Risks, Conventional and Clean Energy, Electricity, and Carbon Markets

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Abstract: Climate change, energy crisis, and geopolitical conflicts have become the triple dilemma of the world, which seriously hinders global sustainable development. Against this context, achieving net-zero emissions and promoting energy transition have been put on the urgent agenda. Therefore, it is necessary to have a deep understanding of the linkage among geopolitical risks, conventional/clean energy, electricity, and carbon markets, so as to stabilize energy and carbon markets and ensure the orderly progress of energy transition and carbon emission reduction. This study explores the dynamic and directional connectedness among these variables under multiple time frequencies and conditions by using two volatility spillover approaches and the quantile vector autoregression model. We find that the interconnectedness between variables is greatly strengthened during extreme conditions and dominated by the spillover effects in the short run. Electricity market is always the critical risk spillover contributor in situations of various scales of shocks. Fossil and clean energy are both net recipients of spillover effects from electricity and carbon markets. And notably, the geopolitical risks act as the net short-term spillover receiver and medium- and long-term spillover transmitter in the connectedness network. Additionally, we show that carbon market becomes a significant risk transmitter under extreme circumstances. Our findings have implications for preventing adverse effects of cross-risk spillovers and promoting global sustainability.

Keywords: geopolitical risks, traditional energy, clean energy, electricity, carbon market, spillover effects, quantile connectedness

1. Introduction

The global community has been confronted with a range of complex and pressing challenges in recent years, including heightened geopolitical tensions, persistent climate change, and intensifying energy crises [1–3]. Geopolitical conflicts such as the Russian-Ukraine war which exacerbate instability in global supply chains [4, 5] result in sharp swings in commodity markets [6, 7]. Climate change, mainly manifested as frequent extreme weather and global warming from burning fossil energy, is threatening the survival and development of human beings [8, 9]. Moreover, the global economic recovery after the COVID-19 crisis, supply chain disruptions, extreme climate, and unstable clean energy production have impacted the supply and demand of energy, ultimately leading to the energy crisis [10, 11]. Therefore, ensuring energy security, promoting energy transition, and achieving carbon emission reduction targets have been put on the urgent agenda of governments [12, 13]. In the scenario of increasingly complex geopolitical situations and accelerated energy transformation, this paper undertakes a holistic examination of the interconnectivity among geopolitical risks (GPR), fossil/clean energy, electricity, and carbon markets.

The outbreak of geopolitical conflict has significantly affected energy markets. For instance, the Russian-Ukraine conflict that erupted in 2022 has severely disrupted the supply structure of energy, contributing to extreme volatility in energy prices [6, 14, 15]. Arguably, as fossil fuels are mainly produced in areas where geopolitical conflicts are concentrated, including Russia and the Middle East, GPR inextricably triggers the price fluctuations of energy markets [16, 17]. Meanwhile, the price shocks of energy which remain important strategic reserves can lead to increased social and political instability in both energy-exporting and energy-importing economies [7, 18]. In addition, higher GPR stimulates the tilt of resources toward clean energy industries by sparking conventional energy crises and trade disputes [19]. Conversely, the expansion of the clean energy sector also has an impact on GPR by affecting fossil energy prices and inducing resource competition. In sum, the GPR raised by negative geopolitical events is intricately bound up with the energy markets (path I in Figure 1).

Additionally, there is also a linkage between conventional and clean energy (path II in Figure 1), which is determined by the substitution effect between them [20–23]. Electricity, as an increasingly important type of secondary energy resource, is generated by fossil fuels and clean energy. Due to the climate change and energy crisis, governments are progressively shifting

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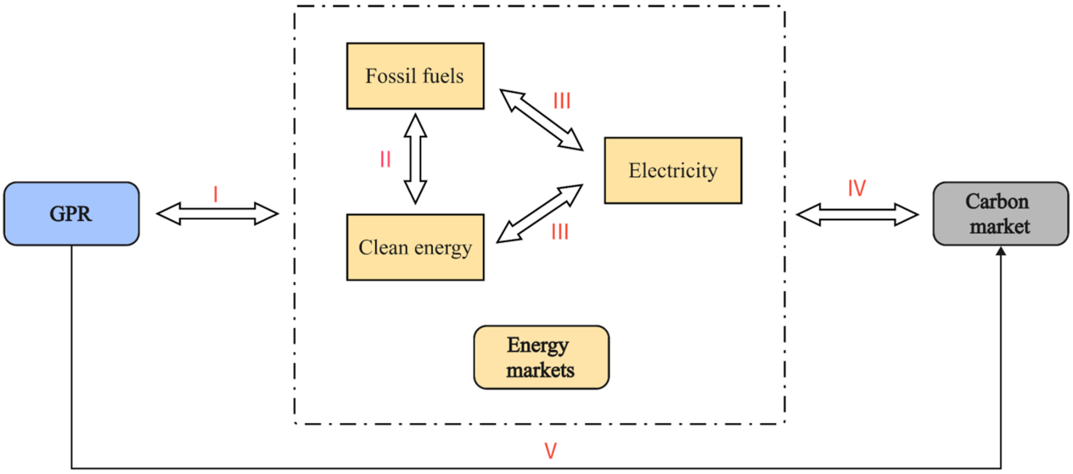
Figure 1
Conceptual framework



toward renewable power. According to Renewable Energy Policy Network for the 21st Century (REN21), during 2022, renewable power capacity increased by 13% to 348 GW, from 306 GW in 2021. And notably, renewable energy sources contributed 92% of the increase in global total power generation in 2022 [24]. The International Energy Agency (IEA) reveals that high electricity prices during the energy crisis in 2022 are mainly driven by high fuel prices which comprise 90% of the increase in the average costs of generating electricity [25]. The electricity market is inescapably connected with fossil and clean energy markets (path III in Figure 1).

The Paris Agreement is another landmark protocol to combat climate change after the Kyoto Protocol, aiming to limit the rise in the average surface temperature of the world to less than 2°C over pre-industrial levels [26, 27]. The emissions trading system (ETS) is an effective scheme to restrain CO_2 emissions by allowing carbon emission permits to be traded as a commodity [28, 29]. The prices of the emission rights are treated as the cost of corporations which are energy-intensive and further have an effect on the demand for conventional and clean energy [30, 31]. Likewise, carbon prices are closely connected with electricity prices by affecting electricity supply because the electricity sector is the largest CO_2 emitter of all sectors and accounts for about 40% of total global emissions, according to the report from Ember [32]. Therefore, the carbon market is inextricably associated with traditional/clean energy and electricity markets (path IV in Figure 1). In addition, it can be seen from the price data collected from the WIND database that since the outbreak of the Russian-Ukraine conflict, European Union Allowance (EUA) future prices have plummeted from 94.69 EUR/MT to their trough of 57.96 EUR/MT, partly because the conflict has intensified downward economic pressure and resulting in curtailed production, and finally reduced the demand for carbon allowances (path V in Figure 1).

In sum, there is a close interconnection among GPR, various energy submarkets (i.e., traditional fuels, clean energy, and electricity), and carbon markets. Theoretically, GPR directly affects these markets via the channels including supply and market risks. On the one hand, GPR has an impact on the stability of global supply chain, resulting in changes in the energy supply and carbon emission demand, and then affecting the energy and carbon prices. On the other hand, the GPR's rise intensifies uncertainty for energy producers and investors, which increases the market risk premium. Meanwhile, GPR also impacts investor expectations, which further leads to variations in prices of energy and carbon markets. On the contrary, the fluctuations in energy markets have an impact on GPR through triggering political and economic stability and economic policy uncertainty in energy-exporting and importing countries. Likewise, fossil and clean energy, electricity, and carbon markets are also connected with each other through the supply and market risk channels.

Moreover, as the financial liberalization and energy and carbon financialization deepen, the fossil/clean energy, electricity, and carbon emission allowance, which not only are affected by the fundamentals but also exhibit financial market features, are becoming more connected with each other [33]. More importantly, the multiple and consecutive black swan events, such as the COVID-19 crisis in 2019, the ongoing Russia-Ukraine war in 2022, and Hamas's attack on Israel in 2023, have left the interconnectivity more complex and changeable [1]. Based on the above, a detailed examination of the risk connectedness among GPR, various energy submarkets, and carbon markets during multiple market circumstances empirically can not only be of significance to the governments in figuring out the risk contagion mechanism among these markets, stabilizing the energy markets and achieving carbon emission reduction targets, but also offer the investors some suggestions on hedging options and portfolio management.

The paper contributes to related literature from three aspects. Firstly, this study conducts a holistic examination of the interconnectedness between GPR, various energy submarkets, and carbon markets. Considering the current international situation, the interconnectedness between them is increasing and becoming more intricate, but few papers focus on the relationship between them. Although some scholars have investigated the impact of one or several specific extreme events such as the Russian-Ukraine war on the interdependence among energy and carbon markets by simply dividing the sample period into several episodes based on the timing of the crises [34–37], they cannot examine the bidirectional spillovers between GPR, various energy submarkets, and carbon markets. In this regard, we innovatively integrate an index that can accurately measure global GPR and is derived from

Caldara and Iacoviello [38] in the research network to effectively capture the bidirectional spillovers between variations in GPR, various energy submarkets, and carbon markets. Second, in the connectedness network, we consider five energy submarkets including oil, natural gas, coal, electricity, and clean energy. The electricity and clean energy markets are gradually exerting a deeper influence over traditional energy and carbon markets because of the energy transition. Nonetheless, many studies investigate exclusively the linkages among fossil fuels, clean/ renewable energy, and carbon [2, 39]. Consequently, electricity sector's impacts on other markets are disregarded and need to be investigated. Thus, we construct a connectivity network that includes GPR, electricity, traditional/clean energy, and carbon prices to explore the role of different energy submarkets, especially the electricity market, in the system. Third, this paper employs Diebold and Yilmaz [40] (DY) and Baruník and Křehlík [41] (BK) spillover indices and a approach based on the quantile vector autoregression (QVAR) model to examine time-frequency spillover effects at different quantiles, which can capture the connectedness among variables under multiple market conditions. Some scholars have explored the spillover among GPR, fossil fuels, and carbon market during normal market states [42], which cannot obtain the relationship under extreme states. To address this gap, this study provides an in-depth view of the connectivity among GPR, traditional/clean energy, electricity, and carbon prices by using QVAR approach, which can support policymakers and investors in taking differentiated strategies in terms of different market states.

The remaining sections of this article are organized in the following manner. Section 2 provides a summary of the pertinent literature. Section 3 explains the methods and data. Sections 4 and 5 provide our empirical analysis and robustness test, and conclusions and policy implications are presented in Section 6.

2. Literature Review

This study investigates the linkages between GPR, fossil/clean energy, electricity, and carbon allowance markets. Accordingly, we divide relevant literature on this theme into three groups. The first group of studies is about GPR's impact on the interconnectedness among energy and carbon markets. The second group of research discusses the spillovers between GPR, energy, and carbon markets. The third group of research examines the relations between various energy submarkets and carbon prices. In addition, we illustrate how our study complements the above three groups of research.

Regarding the GPR's impact on the connectedness among energy and carbon, there has been an increase in attention recently due to the emergence of some crucial geopolitical events especially the Russian-Ukraine conflict. In this regard, Jiang et al. [36] and Xing et al. [37] both take China as an example and reveal the strengthened interconnectedness among traditional fuels and renewable energy since the Russian-Ukraine conflict breaks out by using DY approach. In addition, they also find the net spillover effects from renewable energy stocks to traditional energy prices during the Russian-Ukraine conflict. Applying the TVP-VAR model and data from the global dimension, Rubbaniy et al. [43] discover that the linkages between fossil fuels and renewable energy increase when in time of the COVID-19 crisis and the Russian-Ukraine conflict. Likewise, Naeem and Arfaoui [34] highlight the strong tail-risk spillovers between electricity and clean energy during tension episodes including the Russian-Ukraine conflict. They also find the oil market plays a role as the net risk recipient. Additionally, Si Mohammed et al. [44] capture a higher volatility interconnectedness between metal, clean energy, and conventional energy prices during the Russia-Ukraine war. However, Hoque et al. [45] report a lower degree of overall connectivity among carbon, climate, and fossil energy during the war through the TVP-VAR approach. In addition, they argue that oil market is a spillover transmitter in the short term while switching into a risk recipient in the long term. By partitioning the sample period into several episodes based on the timing of the crises, these studies of the impacts of GPR on market interconnectedness show varying results, which might be attributed to the application of different samples. The risks caused by the outbreak of geopolitical events may weaken over time, so it is difficult to accurately reflect the GPR's impact on the relations between markets by simply grouping the sample periods they selected. Unlike them, we apply a newly constructed daily GPR index of Caldara and Iacoviello [38] and directly explore the accurate influence of GPR on each market.

The second group of research is gaining attention as some indicators to measure GPR are put forward. For instance, Lau et al. [7] analyze the connectedness among GPR in five BRICS economies, fossil fuels, and carbon allowance prices through using five monthly regional GPR indices. The authors find that GPR in Russia contributes the highest spillovers on fossil energy returns and the risk spillovers between GPR and oil prices are measurably varying in time and frequency domain and positive at different quantiles. Jiang et al. [42] further reveal the higher short-term spillover effects at the conditional mean among GPR, fossil energy, and carbon prices. They find that GPR primarily plays a role as the net spillover transmitter while GPR is more affected by carbon allowance market, particularly in the short term. Moreover, Gong et al. [18] confirm fossil fuel markets exhibit more significant spillover effects than clean energy and GPR boosts the risk connectedness among energy markets. Equally importantly, based on the energy-GPR two-tier network, the authors also confirm that the energy markets show positive net spillover effects on GPR. However, these papers do not consider the role of the power market. Energy transformation is imminent as world fossil energy crisis frequently break out, which indicates that the power market is playing an increasingly critical role. The relations between GPR and electricity are gradually increasing. In addition, since energy markets consist of various submarkets, the studies that exclude certain energy or carbon markets may omit the critical sources of spillover effects, which results in the change of connectedness paths, and eventually come to different conclusions. Therefore, this paper conducts a holistic and systematic examination of the relationship between GPR, various energy sub-sectors including electricity, traditional/clean energy, and carbon allowance markets, which contributes to the literature.

The third group of research examines the relationship among various energy submarkets and carbon markets. Theoretically, carbon market and energy market are connected through two channels, that is, the correlated information and the risk premium, which transpires in the process of price discovery and risk identification [46–49]. In turn, fossil energy influences carbon market through the effects of substitution, production constraint, and aggregate demand [46, 50]. Additionally, clean energy stocks are connected with energy and carbon markets by substitution effects and financial investment/speculation [51]. In this context, a detailed study on the nexus of carbon market and various energy submarkets is conducive to both the risk management for investors and achievement of carbon reduction goals for governments [30, 52]. Thence, a majority of extant papers have empirically studied the linkages between carbon and various energy submarkets [31, 46, 49, 50, 53–58]. For example, Kumar et al. [59] investigate the causal relations between EUAs and US clean energy indices during the period 2005–2008. They find no evidence of statistical causality between these two variables. Supporting the conclusions drawn by Kumar et al. [59], Dutta [60] extend the sample period to 2007–2016 and also find variations of EUA prices do not influence returns on US clean energy stock. However, Hanif et al. [31] find evidence of the relations in conditional mean and tails between carbon allowance prices and clean energy stock prices by using DY, BK, and copula models. In addition, Jiang et al. [30] believe that there is a significant Granger causality in lower and higher conditional quantiles between carbon and fossil fuel prices while the causal relations in the median quantiles are not significant. Nonetheless, by employing the TVP-VAR-SV method, Qiao et al. [53] highlight that the interconnectedness between carbon, fossil fuels, and electricity is significant and time-varying. Additionally, they argue that the variations in carbon prices more significantly affect fossil energy and China's electricity market, which is different from the work of Naeem and Arfaoui [34] who take the conventional and alternative electricity indices into account and find the alternative electricity index in the network play a role as the risk transmitter. In sum, these studies on the nexus between carbon and various energy markets present heterogeneous results, partly because the connection between these markets is becoming closer and more intricate as the financial liberalization and the financialization of energy and carbon continue to move forward, and the global geopolitical landscape and policy environment change [46]. Moreover, the difference in conclusions may also be due to the selection of samples. In this spirit, we select the more mature representative market in Europe as our research object to present a holistic view on the interconnectedness among GPR, conventional/clean energy, electricity markets, and carbon markets.

After reviewing these articles, we find that the studies on GPR, energy markets, and carbon market connectivity are still limited and fail to conduct a more holistic examination of the interconnectivity between GPR, traditional/clean energy, electricity, and carbon allowance prices. Moreover, to examine the interconnectedness among these variables, various techniques are applied in the above-mentioned articles, for instance, GARCH family models [58], TVP-VAR method [43, 53], BK and DY spillover indices [36, 42, 46], asymmetric slope Value-at-Risk approach (CAViaR) [34], and Tail Event driven NETwork technique (TENET) [18]. However, as the economic environment becomes increasingly complex, the spillover effects among markets during upside and downside periods may be different, and the above methods are unable to capture such changes. Therefore, for the purpose to explore the spillover effects in different market states, this paper adopts the DY and BK approaches and the QVAR framework which can analyze the time-frequency spillovers in quantiles among variables to further supplement existing literature, provide investment recommendations for market participants with different investment cycles under different scales of shocks, and help for policymakers to formulate carbon reduction policies and promote energy transition.

3. Methodology and Data

3.1. Methodology

The DY spillover index is calculated by the generalized forecast error variance decomposition (GFEVD). In contrast to the classic variance decomposition approach based on the traditional VAR framework, the DY method is able to avoid the problem of the dependence on variable ordering and can be used to conduct dynamic spillover analysis, which helps us investigate bidirectional static and dynamic spillover effects among variables in the time domain. The structural VAR(p) with n-dimensional variables $Y_t = (y_{1t}, y_{2t}, \dots y_{Nt})'$ can be written as follows:

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t, \tag{1}$$

where $t = 1, \dots, T$ and $\varepsilon_t \sim N(0, \Sigma)$. We simplify Equation (1) as $\Phi(L)Y_t = \varepsilon_{t-i}$, where $\Phi(L) = \Phi_0 - \Phi_0 L - \dots.. - \varphi_p L^p$ and Φ_0 denotes the unit matrix. If Equation (1) is stable, we can further express Y_t as the moving average (MA) formula: $Y_t = \psi(L)\varepsilon_{t-i}$, $\psi(L) = [\Phi(\mathrm{L})]^{-1}$. We define the forecast horizon as $H$and the connectedness as θ_H. Hence, $(\theta_H)_{j,k}$ denotes the variable k's contribution to the element j's forecast error variance, which is computed as:

$$(\theta_H)_{j,k} = \frac{(\Sigma)_{k,k}^{-1} \sum_{h=0}^{H-1} (\psi_h \Sigma)^2}{\sum_{h=0}^{H-1} (\psi_h \Sigma \psi_h')_{j,j}}, \tag{2}$$

where we set H equal to 100 in this study. Furthermore, the standardized spillover effects $(\tilde{\theta}_H)_{j,k}$ can be written as:

$$(\tilde{\theta}_H)_{j,k} = \frac{(\theta_H)_{j,k}}{\sum_{k=1}^{N} (\theta_H)_{j,k}}, \tag{3}$$

where $\sum_{k=1}^{N} (\tilde{\theta}_H)_{j,k} = 1$ and $\sum_{j,k=1}^{N} (\tilde{\theta}_H)_{j,k} = N$. Further, we can calculate the net spillover effects from the element j to k by using the following equation:

$$NPC_{j,k}^H = (\tilde{\theta}_H)_{j,k} - (\tilde{\theta}_H)_{k,j}. \tag{4}$$

Then we define the spillover effects of the variable j to the other variables and those of other variables to the variable j as TO_j^H and $FROM_j^H$, respectively, which are calculated as:

$$TO_j^H = \sum_{j=1, j\neq k}^{N} (\tilde{\theta}_H)_{k,j}, \tag{5}$$

$$FROM_j^H = \sum_{j=1, j\neq k}^{N} (\tilde{\theta}_H)_{j,k}. \tag{6}$$

Thus, we can denote the net spillover effects of the variable j as follows:

$$NET_j^H = TO_j^H - FROM_j^H. \tag{7}$$

Then, we can obtain the total connectedness, which is defined as:

$$TC^H = N^{-1} \sum_{j=1}^{N} TO_j^H = N^{-1} \sum_{j=1}^{N} FROM_j^H. \tag{8}$$

Nevertheless, the DY index fails to capture the information spillovers at different time frequencies. Meanwhile, the spillover effects may change in different frequency domains because of the economic cyclicality, the heterogeneous investment cycles of market participants, and differences in external shocks. Based on the BK method put forward by Baruník and Křehlík [41], the interconnectedness among variables in different time frequencies including high-, medium-, and low-frequencies can be examined. Thus, we can obtain the short-, medium-, and long-term static and dynamic spillovers among variables. Based on the generalized causation spectrums, the GFEVD on frequency ω, where $\omega \in (-\pi, \pi)$, can be formulated as:

$$(f(\omega))_{j,k} = \frac{\sum_{k,k}^{-1} \left| (\psi(e^{-i\omega})\Sigma)_{j,k} \right|^2}{(\psi(e^{-i\omega})\Sigma\psi\psi'(e^{+i\omega}))_{j,j}}, \tag{9}$$

where ψ is the Fourier transformation and $\psi(e^{-i\omega}) = \sum_h e^{-i\omega m}\psi_m$, $m = 1, \ldots, H$ and i denotes the imaginary unit. Subsequently, the variance decompositions under the frequency b and d, where d is equal to (a, b) and $a, b \in (-\pi, \pi)$ is given by:

$$(\theta_d)_{j,k} = \frac{1}{2}\int_d^{\infty} \Gamma_j(\omega)(f(\omega))_{j,k} d\omega, \tag{10}$$

where $\Gamma_k(\omega)$ represents the weighting function. $(\theta_d)_{j,k}$ denotes the interconnectedness of the frequency band d. We can rewrite Equation (10) as:

$$(\tilde{\theta}_d)_{j,k} = \frac{(\theta_d)_{j,k}}{\sum_{k=1} (\theta_\infty)_{j,k}}, \tag{11}$$

where $(\theta_\infty)_{j,k} = (1/2)\int_{-\pi}^{\pi} \Gamma_j(\omega)(f(\omega))_{j,k} d\omega$. Consistent with DY index, the TO_j^d, $FROM_j^d$, and NET_j^d under the given frequency band d are given by Equations (4–7). Moreover, the directional connectedness between variables on frequency band $d$is:

$$C_d^w = 100 \times (1 - Tr\{\tilde{\theta}_d\} / \sum \tilde{\theta}_d). \tag{12}$$

However, it is challenging that the DY and BK methods under the traditional linear VAR framework are applied to examine the risk spillovers among markets in different conditions (quantiles). Therefore, Ando et al. [61] propose a quantile connectedness approach for the purpose of calculating the spillover effects in multiple quantiles of the conditional distribution. Based on the quantile VAR (QVAR) framework, this method is not sensitive to the outliers, is conducive to the analysis of asymmetric and nonlinear effects between variables, and is not subject to the constraints of heteroscedasticity and normality assumptions as required in the traditional VAR model.

We define the QVAR(p) process and the moving average representation of it at the τ-quantile as:

$$Y_t = \mu(\tau) + \sum_{i=1}^{p}(\tau)Y_{t-i} + \varepsilon_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau)\varepsilon_{t-i}, \tag{13}$$

Likewise, the time- and frequency-domain spillover effects among variables can be calculated by the GFEVD. For instance, from the time-domain perspective, the spillover effects at the τ-quantile are given by:

$$(\theta_H)_{j,k} = \frac{(\Sigma(\tau))_{k,k}^{-1} \sum_{h=0}^{H=1} (\psi_h(\tau)\Sigma(\tau))^2}{\sum_{h=0}^{H-1} (\psi_h(\tau)\Sigma(\tau)\psi_h'(\tau))_{j,j}}, \tag{14}$$

$$(\tilde{\theta}_H)_{j,k} = \frac{(\theta_H)_{j,k}}{\sum_{k=1}^{N} (\theta_H)_{j,k}}. \tag{15}$$

Next, "TO" spillovers (TO_j^d), "FROM" spillovers ($FROM_j^d$), and "NET" spillovers (NET_j^d) can be measured via the Equations (4–8).

3.2. Data

A GPR indicator and six relevant asset prices are applied in our analysis. First, we use the daily global GPR index of Caldara and Iacoviello [38]. As defined by them, GPR arises from the threats, occurrences, and escalations of geopolitical conflicts. Accordingly, based on the text-searching approach, they tally the percentage of articles with keywords associated with geopolitical events in ten representative newspapers such as the Daily Telegraph, and normalize it to 100. The keywords are determined and searched in terms of 8 groups (e.g., War threats, Terrorist threats, Beginning of war) from two aspects including threats and acts. Specifically, compared with other measurement methods of GPR, there are three advantages regarding this index according to Caldara and Iacoviello [38]. First, compared to the construction of dummy variables according to the realization of specific geopolitical events, this index identifies the threat of a negative event that hasn't realized, which pinpoints the timing of various geopolitical events and allows us to accurately explore their impact. Second, relative to the War Deaths, another indicator of adverse geopolitical events, the values of the GPR index have always been larger since World War II because of higher global attention to the geopolitical conflicts, indicating that the index can reflect the strength of the adverse events more effectively. Third, the calculation method of the GPR index is more robust compared to the Boolean operators employed by Baker et al. [62] who construct the economic policy uncertainty index. Moreover, the newspaper-based index is more effective to reflect GPR's impact on financial markets since investors rely on news reports to access timely information [63]. We collect the data of this GPR index from https://www.matteoiacoviello.com/gpr.htm.

Regarding conventional energy, we consider the futures settlement price of three important fossil energy sources, including Brent crude oil futures (hereafter OIL), UK natural gas futures (hereafter NG), and Rotterdam coal futures (hereafter COAL). The price data of OIL, NG, and COAL are collected from the WIND Database. About the electricity market, we select the Phelix-DE Power Baseload Year Future (hereafter ELEC) of the European Energy Exchange (EEX), given that EEX Phelix-DE Power Future contracts have the most liquidity for European electricity. As for clean energy, we focus on the European Renewable Energy Index (hereafter ERIX) that comprises the ten biggest European clean energy sector stocks. The carbon market is reflected by the price of EUA Future. ERIX and EUA are both obtained from the Bloomberg Database. Given the EUA prices were chronically low in the first and second phases (2005–2012) of EU ETS due to a large surplus of EUAs, and the allocation of EUAs becomes more reasonable and their prices are higher and more robust since Phase III, we use the seven daily data from January 2, 2013 to March 28, 2024. Meanwhile, we transform the seven time series into the logarithmic growth rates by the equation $r_t = \ln(Y_t) - \ln(Y_{t-1})$ to ensure the time series stationarity and identify the connectedness of growth rates.

Table 1
Descriptive statistics for the log-difference data

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX
Mean	−0.0020	0.0000	0.0004	0.0004	0.0007	0.0008	0.0005
Median	−0.0040	0.0010	−0.0004	0.0000	0.0000	0.0010	0.0010
Minimum	−3.00	−0.28	−0.36	−0.54	−0.20	−0.43	−0.13
Maximum	2.34	0.19	0.41	0.33	0.23	0.25	0.10
Std. Dev.	0.43	0.02	0.05	0.02	0.02	0.03	0.02
Skewness	−0.04	−0.99	0.62	−2.82	0.55	−0.98	−0.26
Kurtosis	1.71	17.78	10.46	117.91	13.78	16.36	4.06
J-B test	339***	37,044***	12,839***	1,612,260***	22,130***	31,416***	1,942***
ADF	−58.89***	−36.77***	−39.09***	−34.08***	−37.53***	−39.48***	−35.34***
PP	−87.55***	−51.71***	−51.46***	−49.46***	−48.58***	−53.84***	−51.16***
KPSS	0.01	0.04	0.05	0.06	0.17	0.09	0.05
Observations	2773	2773	2773	2773	2773	2773	2773

Note: *** indicates 1% significance level.

Table 1 displays the summary for each time series. The standard deviation for each variable is low except for GPR, implying GPR is the most volatile among all seven variables. Every time series has asymmetry distribution and is significantly non-normal in the application of the Jarque and Bera [64] test. Moreover, according to the ADF [65], PP [66], and KPSS [67] tests, all the series are stationary, which applies to the BK and DY methods. In addition, in order to more fully and intuitively observe the trends of variables of the trend of target variables during the sample period, we plot the original data and log-difference data simultaneously. As depicted in Figure 2, all the index/price series generally exhibit similar trends, especially after 2021. The GPR index experiences multiple spikes throughout the whole sample interval, which stems from several major adverse geopolitical events, e.g., the Paris terror attacks of 2015, the US-Iran conflict of 2020, the Russia's invasion of Ukraine of 2022, and Hamas's attack on Israel of 2023 [38]. Notably, the Russian-Ukraine conflict causes energy and carbon prices to hit new highs during the sampling period. The ERIX index steeply increases since the middle of 2020 and peaks around the beginning of 2021, after which the index experiences large fluctuations. Among the seven series, the logarithmic growth rates of GPR have the higher volatility across the whole sample duration, which supports the results of Table 1.

4. Empirical Results

The time-frequency connectedness in conditional mean and quantiles between GPR, fossil/clean energy, electricity, and carbon markets under the mean- and quantile-based framework is examined in this section. The lag lengths in the VAR model and QVAR model are both set to one according to the Schwartz information criterion. The "TO" spillovers capture the shocks of the specific market or GPR to other six variables, and "FROM" spillovers measure the shocks to the market or GPR from other series. The "NET" spillovers are equal to the "TO" spillovers minus "FROM" spillovers.

4.1. Time-frequency connectedness of spillovers

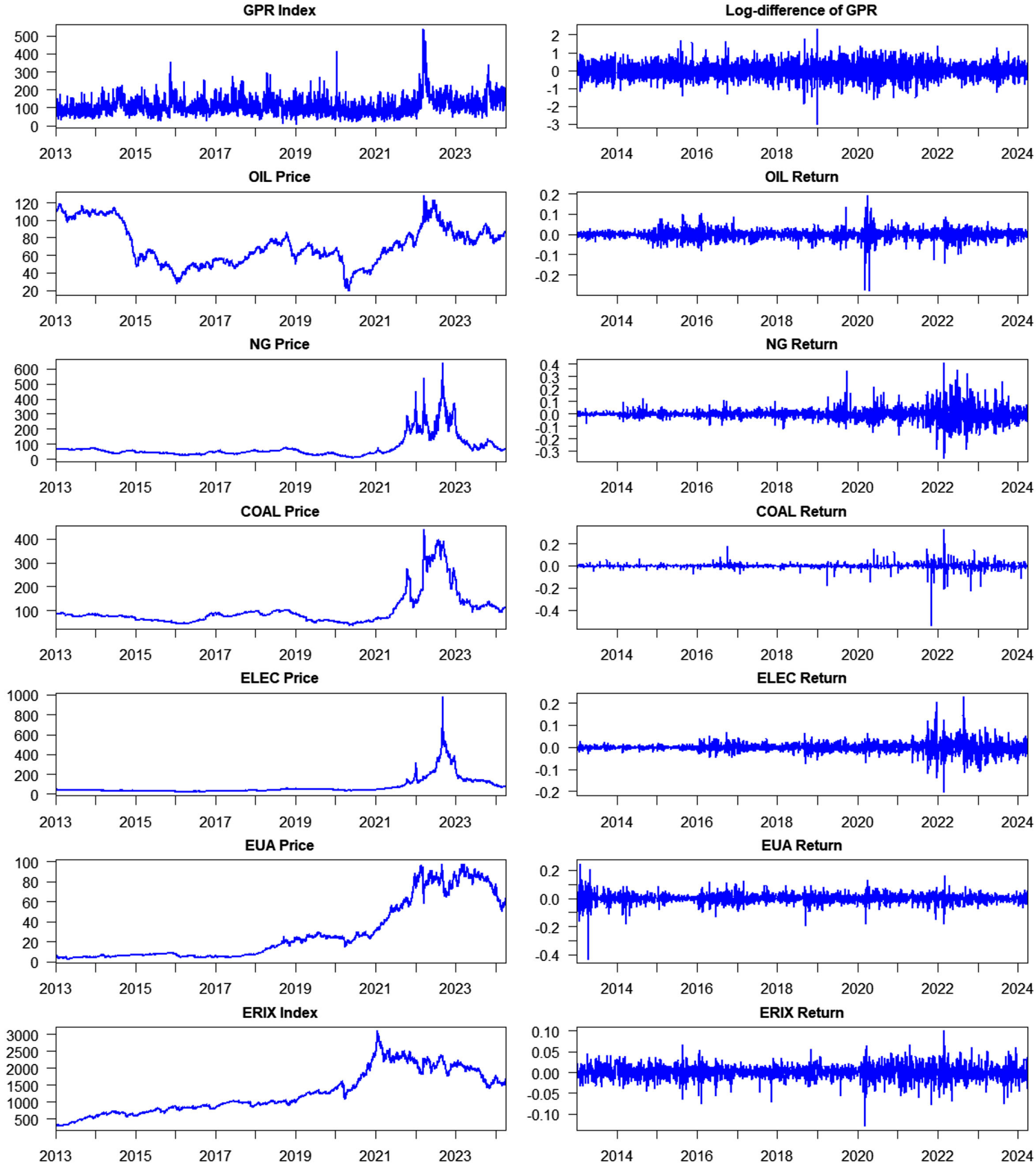
4.1.1. Time-domain connectedness

Table 2 shows the results of time-domain average spillover effects at the conditional mean estimated by the VAR model. The TCI value denotes the total inter-variable connectedness level and is equal to 21.17%, revealing the spillover effects between geopolitical risk, traditional/clean energy, electricity, and carbon prices. However, GPR occupies a small proportion of the inter-variable spillovers. GPR's effects on the other six variables account for 0.18%, and the spillovers received from the six markets to GPR reach 0.51%. This finding is consistent with Jiang et al. [42]. They uncover the weak interaction among GPR, traditional energy, and carbon markets. Under normal circumstances (conditional mean), the small fluctuations in GPR do not have a significant impact on the stability of the energy supply chain and weakly affect the investor expectations and market uncertainty. In turn, under normal market conditions (conditional mean), the weak fluctuations in energy markets do not lead to large economic or political pressure on countries or economies. Thus, in this scenario, GPR is less connected to financial markets, including energy and carbon markets. However, during periods of extreme states, the degree of tail-risk contagion between GPR and markets may be quite different (discussed in Section 4.2).

By contrast, the connectivity among the five energy submarkets and the carbon market is stronger, which supplements the research of Su et al. [2]. They reveal the weak interconnectedness between traditional/clean energy and EUA prices during normal market states. In terms of the connectedness among the six markets, the ELEC contributes to the biggest impact on the other markets, followed by the NG and EUA (30.77% and 16.72%, respectively). Also, the ELEC receives the most significant return spillover effects from the five other markets (40.69%–0.07% = 40.62%), followed by the NG and EUA (32.32% and 20.95%, respectively). Meanwhile, the ELEC plays a role as the largest net spillover transmitter (10.74%), while GPR and other markets in the system are the net information receivers.

The reason of electricity market as the biggest risk transmitter may be its lower liquidity level compared with other markets, which adds to the difficulty of trading this asset and the possibility of bigger investment losses [34]. Hence, the fluctuations in electricity prices can have a larger effect on the traditional/clean energy and carbon prices. Additionally, the electricity sector is responsible for the highest carbon emissions, which means that variations in power prices have a relatively significant influence on carbon allowance market [53]. Moreover, although the percentage of clean energy generation increases rapidly, the primary sources of generating electricity are still coal and natural gas, implying a stronger correlation of electricity with gas and coal prices than that with clean energy market. In addition, global crude oil consumption

Figure 2
Dynamics of the level values and the log-difference of the related variables



accounts for the largest share of conventional energy consumption, leading to clean energy as a substitute closely connected with the oil market [68]. Significantly, the ERIX yields larger spillover effects to OIL and EUA relative to the spillovers from it to other variables, implying that the clean energy market has a stronger ability to transmit the risk information to oil and carbon markets. One possible explanation for that is the fluctuations in the clean energy market can have an impact on allocation of crude oil and carbon assets in the portfolios of investors due to the strong substitution between clean energy and crude oil and the emission reduction ability of clean energy, ultimately resulting in price changes in OIL and EUA.

Table 2
Time-domain connectedness

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
GPR	99.49	0.00	0.04	0.05	0.15	0.15	0.11	0.51
OIL	0.01	89.02	1.11	1.58	3.23	2.39	2.66	10.98
NG	0.03	0.84	67.65	4.45	25.23	1.71	0.09	32.35
COAL	0.03	1.56	5.48	84.23	7.89	0.62	0.20	15.77
ELEC	0.07	2.16	21.98	5.52	59.31	10.44	0.51	40.69
EUA	0.04	2.27	2.16	1.08	14.13	79.02	1.30	20.98
ERIX	0.01	2.94	0.04	0.42	0.80	1.55	94.25	5.75
TO	0.18	9.76	30.81	13.11	51.42	16.87	4.87	**TCI**
NET	−0.32	−1.22	−1.54	−2.66	10.74	−4.11	−0.88	21.17

Note: the element of the static matrix (m, n) represents the directional spillovers from the $n-$th variable on the $m-$th variable.

4.1.2. Time-frequency connectedness

Given that the investor behavior may also have different cyclical characteristics [33], we further decompose the time-domain spillover effects into the connectedness in three frequency domains by using BK method. As displayed in Table 3, the short-term TCI (17%) contributes to the prominent part of the total connectedness (21.7%), while the medium- and long-term TCIs only account for 3.51% and 0.66%, respectively. This finding indicates that information spillovers are mainly concentrated within 5 five trading days, which is aligned with the conclusion of Qiao et al. [53]. They also suggest the higher short-term spillovers among fossil fuels, electricity, and EUA prices. One potential explanation for that is the investment behavior of investors with short-term horizons contributes more to the fluctuations of financial markets and the markets are sensitive to shocks [1]. As a result, the information spillovers of markets are quickly responded to and digested by other markets in the short term. In line with the results of Table 2, the interconnectedness in the mean of the distribution remains concentrated among the five energy markets and carbon market no matter in which frequency domains. Noteworthily, in the short run, the GPR and EUA both act as the net risk recipients, while they switch into the information transmitter in the lower frequency domains. This suggests that the GPR's impact on the traditional/clean energy, electricity, and carbon prices is gradually larger than that of the six asset prices on GPR risk as time prolongs, which supports the conclusions of Jiang et al. [42]. One explanation for that is that GPR, as one of the macro-economic factors, has a continuous and far-reaching impact on the markets by affecting the macro-economy, which is reflected by the net spillover effects of GPR in low-frequency domains (medium and long term). However, the fluctuations of financial markets tend to be affected by short-term factors such as investor sentiment, with larger high-frequency (short-term) spillover effects.

4.2. Quantile connectedness of spillovers

4.2.1. Time-domain spillover effects in quantiles

In view of the fact that the DY and BK spillover indices under the VAR framework fail to capture the degree of interconnectedness under extreme shocks [69], this study further investigates the connectedness in quantiles by using DY and BK methods based on QVAR model. Tables 4 and 5 show the spillovers at the extremely low ($\tau = 0.05$) and high ($\tau = 0.95$) tails of the distribution among the GPR and the six markets using the DY approach, respectively. In contrast to the results in Table 2, the TCI values at the quantiles 0.05 and 0.95 are 0.37% and 89.90%, respectively, implying the much stronger interconnectedness among variables during periods of extreme falling and rising states. The findings are supported by Chen et al. [69] and Gong et al. [33]. They also reveal a stronger bond between the underlying markets during extreme market states. Nevertheless, they find evidence of around 70% tail connectedness, while the 0.05- and 0.95-quantile connectedness in our system reaches 90.37% and 89.9%, respectively. The reason may be that we consider the GPR and electricity market which exhibit critical spillover effects in our connectedness network.

Moreover, the static connectedness between GPR and energy and carbon prices in extreme conditions is much higher compared to the case of normal circumstances. More specifically, GPR shows a significant increase in "to" and "from" spillovers (0.18%–72.27%, 0.51%–75.19%) at the extreme right tail ($\tau = 0.05$), and the same is true (0.18%–69.83%, 0.51%–74.63%) at the extreme right tail ($\tau = 0.95$). This suggests that the drastic fluctuations in geopolitical risk significantly affect the five energy and carbon markets, and vice versa. Similarly, the tail connectedness among the six markets in the network exhibits excess connectedness relative to the connectedness under mean conditions [70]. In line with Table 2, the GPR is still a net risk receiver in both extreme rising and falling states, which indicates that the extreme fluctuations of GPR are more affected by these six markets. Driven by the setting of net-zero emissions goals, the electricity and carbon market are getting more and more global attention. We can see that the electricity market remains the critical net contributor of spillover effects during extreme periods. Moreover, the carbon market turns from the net risk recipient at the conditional mean into the transmitter at the tails of distribution (the largest transmitter at the 0.95-quantile, especially). Moreover, the NG becomes the important net transmitter at the right tail, which supports the conclusions of Li et al. [71] which argue that NG is more dominant than OIL against the backdrop of rising GPR and global energy supply shortages. At the left tail, the net risk spillover of NG is close to zero, revealing the possibility of natural gas as the diversification option in hedging the risks in other assets under extreme falling states. Similarly, under extreme conditions, the absolute values of the net spillover index of OIL are relatively low, which means the oil asset can act as a haven asset. Moreover, it is worth noting that ERIX has a larger effect on GPR during periods of large fluctuations than that on other markets, which differs from the results in Table 2. This may be because large variations in the clean energy market trigger competition among countries for clean energy technologies and scarce resources and indirectly lead to changes in GPR. In addition, ERIX acts as a net spillover contributor to COAL, implying the possibility of using clean energy markets to reduce coal

Table 3
Time-frequency connectedness

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
Short-term spillovers: 1 day to 5 days								
GPR	92.15	0.00	0.04	0.05	0.15	0.15	0.10	0.49
OIL	0.01	71.69	0.85	1.28	2.58	2.01	2.17	8.90
NG	0.03	0.71	54.30	3.24	20.01	1.40	0.09	25.48
COAL	0.02	1.13	4.04	66.33	6.13	0.57	0.12	12.02
ELEC	0.05	1.84	17.46	4.34	46.30	8.27	0.43	32.39
EUA	0.03	2.05	1.96	1.07	12.04	64.77	1.15	18.30
ERIX	0.01	2.19	0.04	0.40	0.67	1.16	75.65	4.45
TO	0.14	7.93	24.38	10.38	41.57	13.55	4.05	**TCI**
NET	−0.34	−0.97	−1.10	−1.64	9.19	−4.74	−0.40	17.00
Medium-term spillovers: 5 days to 30 days								
GPR	6.22	0.00	0.00	0.00	0.00	0.00	0.01	0.02
OIL	0.00	14.59	0.21	0.25	0.55	0.32	0.42	1.75
NG	0.00	0.11	11.23	1.01	4.39	0.26	0.00	5.78
COAL	0.00	0.35	1.21	15.04	1.48	0.04	0.06	3.15
ELEC	0.02	0.27	3.81	0.99	10.93	1.83	0.06	6.98
EUA	0.01	0.18	0.17	0.01	1.77	12.01	0.13	2.27
ERIX	0.00	0.63	0.00	0.02	0.11	0.33	15.66	1.09
TO	0.03	1.55	5.40	2.30	8.29	2.79	0.69	**TCI**
Net	0.02	−0.21	−0.37	−0.86	1.31	0.52	−0.40	3.51
Long-term spillovers: 30 days to Infinite days								
GPR	1.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OIL	0.00	2.74	0.04	0.05	0.10	0.06	0.08	0.33
NG	0.00	0.02	2.12	0.20	0.83	0.05	0.00	1.10
COAL	0.00	0.07	0.23	2.85	0.28	0.01	0.01	0.60
ELEC	0.00	0.05	0.72	0.19	2.08	0.35	0.01	1.32
EUA	0.00	0.03	0.03	0.00	0.32	2.25	0.02	0.41
ERIX	0.00	0.12	0.00	0.00	0.02	0.06	2.94	0.21
TO	0.01	0.29	1.02	0.44	1.56	0.53	0.13	**TCI**
NET	0.01	−0.04	−0.07	−0.17	0.24	0.12	−0.08	0.66

Table 4
Time-domain connectedness in the quantile $\tau = 0.05$

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
GPR	24.81	12.97	12.60	10.03	12.70	13.84	13.06	75.19
OIL	12.56	22.07	12.59	10.67	14.03	14.71	13.38	77.93
NG	12.25	12.70	21.74	11.25	15.75	14.47	11.84	78.26
COAL	11.57	12.28	13.24	23.86	14.06	13.28	11.71	76.14
ELEC	11.29	13.13	14.59	11.38	20.44	17.09	12.08	79.56
EUA	12.06	13.23	13.01	10.66	16.57	21.87	12.60	78.13
ERIX	12.54	14.14	12.11	10.30	13.46	14.44	23.01	76.99
TO	72.27	78.45	78.13	64.28	86.58	87.83	74.66	**TCI**
NET	−2.92	0.51	−0.13	−11.85	7.03	9.69	−2.33	90.37

Table 5
Time-domain connectedness in the quantile $\tau = 0.95$

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
GPR	25.37	12.57	12.76	10.94	12.78	12.66	12.93	74.63
OIL	11.77	23.30	13.03	11.56	13.90	13.18	13.25	76.70
NG	11.72	12.34	22.69	12.12	15.94	13.36	11.83	77.31
COAL	11.26	12.35	13.77	23.38	14.33	12.61	12.31	76.62
ELEC	11.16	12.50	15.12	12.12	20.73	16.25	12.12	79.27
EUA	11.45	12.46	13.10	11.26	17.04	22.02	12.67	77.98
ERIX	12.47	13.69	12.54	11.33	13.45	13.39	23.13	76.87
TO	69.83	75.91	80.32	69.32	87.44	81.45	75.11	**TCI**
NET	−4.80	−0.79	3.01	−7.30	8.17	3.47	−1.77	89.90

use. On the contrary, ERIX always is the net spillover recipient from OIL and NG under extreme conditions, but not for COAL. Against the context of energy transformation, the role of the clean energy sector in fossil fuels and further reducing their use is still limited except for coal.

4.2.2. Time-frequency spillover effects in quantiles

Likewise, we break the tail connectedness in the time-domain down into short-, medium-, and long-term spillover effects at the extreme quantiles (i.e., $\tau = 0.05,\ 0.95$). Tables 6 and 7 represent the results of time-frequency connectedness of spillovers among variables at the quantiles 0.05 and 0.95, respectively. In line with Table 3, the total connectedness across the time series is mainly attributed to the short-term factors (73.17% for $\tau = 0.05$ and 72.69% for $\tau = 0.95$). In addition, the mean-based connectedness analysis underestimates the connectedness under the extreme falling and rising states no matter in which frequency domains. That is, compared to the short-, mid-, and long-term interconnectedness among GPR, traditional/clean energy, electricity, and carbon prices during normal states, the risk spillover degrees of these three frequency domains between each pair of variables under extreme circumstances are all considerably greater [33]. GPR and EUA act as the net tail-risk contributors in the medium and long run. In general, the geopolitical risks and carbon market have an impact on the energy price mainly by influencing the fundamentals (e.g., supply and demand), which are often associated with long-term spillovers. In addition, we find the potential hedging capacity of EUA under extremely falling states in the short term due to its net spillover index close to zero. Differing from the times of normal conditions, EUA turns into the net short-term transmitter at the extremely high quantile, implying carbon market exerts more short-term influence on GPR and energy markets in extremely rising states.

In addition, OIL becomes a net spillover transmitter (4.15%) at the left tail in the short run, second only to ELEC (6.23%). NG switches into a net transmitter (6.93%) at the right tail in the short run, second only to ELEC (10.04%). However, the net spillovers from OIL, NG, and ELEC to other variables are mainly significant in the short run. Fossil fuels and electricity serve on the net receivers under extreme falling and rising states in the long run, except for the weak net transmitter for oil under rising states. In the case of ERIX, at the left tail, the positive net spillover effects are found over a short term, while negative net effects are examined over the medium and long term. However, these results are quite the opposite for the right tail, which means, for each frequency domains, the clean energy market plays distinct roles in the research network during different market states.

Table 6
Time-frequency connectedness in the quantile $\tau = 0.05$

	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
Short-term spillovers: 1 day to 5 days								
GPR	22.50	11.43	11.24	8.94	11.37	11.62	11.47	66.07
OIL	9.92	17.31	9.79	8.34	10.87	10.76	10.24	59.93
NG	10.47	10.68	18.20	9.42	13.14	11.40	9.80	64.91
COAL	9.33	9.46	10.34	18.65	10.90	9.79	8.98	58.79
ELEC	9.36	10.70	11.99	9.48	16.69	13.09	9.72	64.35
EUA	10.51	11.37	11.36	9.34	14.27	17.74	10.72	67.57
ERIX	9.69	10.44	9.17	7.88	10.02	10.17	17.19	57.37
TO	59.27	64.07	63.89	53.41	70.58	66.83	60.93	**TCI**
NET	−6.80	4.15	−1.02	−5.39	6.23	−0.74	3.57	73.17
Medium-term spillovers: 5 days to 30 days								
GPR	1.87	1.15	1.06	0.85	1.04	1.46	1.19	6.75
OIL	2.10	3.77	2.23	1.86	2.53	2.86	2.45	14.03
NG	1.42	1.57	2.90	1.47	2.10	2.17	1.56	10.28
COAL	1.79	2.20	2.34	4.26	2.55	2.51	2.11	13.50
ELEC	1.51	1.82	2.06	1.49	3.02	2.87	1.78	11.53
EUA	1.23	1.39	1.31	1.03	1.84	2.97	1.42	8.21
ERIX	2.28	2.92	2.35	1.94	2.76	3.12	4.67	15.36
TO	10.31	11.05	11.35	8.64	12.81	14.99	10.51	**TCI**
NET	3.56	−2.99	1.07	−4.85	1.28	6.78	−4.85	13.28
Long-term spillovers: 30 days to Infinite days								
GPR	0.44	0.38	0.30	0.23	0.29	0.76	0.40	2.37
OIL	0.54	0.98	0.56	0.47	0.63	1.09	0.69	3.97
NG	0.36	0.46	0.64	0.36	0.51	0.90	0.48	3.06
COAL	0.46	0.63	0.56	0.96	0.61	0.97	0.62	3.85
ELEC	0.43	0.61	0.54	0.41	0.74	1.12	0.57	3.68
EUA	0.33	0.47	0.34	0.29	0.46	1.16	0.46	2.34
ERIX	0.57	0.79	0.58	0.48	0.69	1.15	1.16	4.27
TO	2.68	3.33	2.88	2.23	3.19	6.00	3.22	**TCI**
NET	0.32	−0.65	−0.18	−1.61	−0.49	3.66	−1.05	3.92

Table 7
Time-frequency connectedness in the quantile $\tau = 0.95$

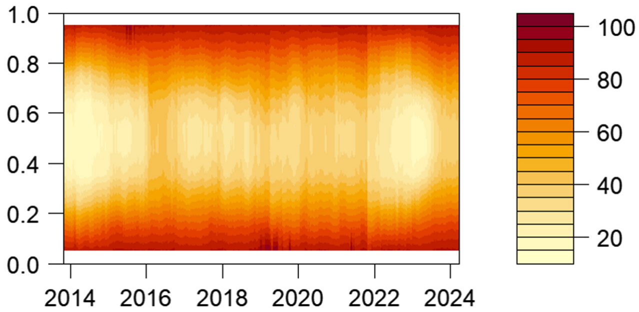
	GPR	OIL	NG	COAL	ELEC	EUA	ERIX	FROM
Short-term spillovers: 1 day to 5 days								
GPR	23.39	11.55	11.76	10.06	11.73	11.68	11.97	68.76
OIL	9.79	19.22	10.55	9.48	11.53	10.98	10.99	63.32
NG	8.93	9.31	17.04	8.91	11.87	10.01	8.95	57.98
COAL	8.50	9.39	10.01	17.72	10.78	9.66	9.13	57.47
ELEC	8.61	9.69	11.54	9.23	15.76	12.67	9.22	60.95
EUA	9.35	10.26	10.73	9.23	13.96	18.06	10.25	63.77
ERIX	10.47	11.42	10.35	9.37	11.12	11.15	19.28	63.88
TO	55.64	61.61	64.95	56.28	70.99	66.15	60.51	**TCI**
NET	−13.11	−1.71	6.97	−1.19	10.04	2.38	−3.37	72.69
Medium-term spillovers: 5 days to 30 days								
GPR	1.67	0.83	0.81	0.70	0.86	0.82	0.80	4.82
OIL	1.59	3.33	1.96	1.63	1.91	1.80	1.83	10.73
NG	2.22	2.40	4.52	2.50	3.26	2.69	2.31	15.38
COAL	2.21	2.35	2.97	4.55	2.86	2.37	2.56	15.32
ELEC	2.09	2.30	2.91	2.33	4.07	2.96	2.38	14.97
EUA	1.76	1.84	1.96	1.67	2.58	3.35	2.05	11.85
ERIX	1.68	1.89	1.81	1.61	1.94	1.89	3.26	10.82
TO	11.56	11.62	12.42	10.43	13.42	12.52	11.93	**TCI**
NET	6.74	0.89	−2.97	−4.89	−1.56	0.67	1.12	13.98
Long-term spillovers: 30 days to Infinite days								
GPR	0.32	0.18	0.18	0.18	0.19	0.16	0.16	1.05
OIL	0.39	0.75	0.52	0.45	0.46	0.41	0.42	2.65
NG	0.57	0.63	1.14	0.71	0.81	0.66	0.57	3.94
COAL	0.55	0.61	0.79	1.11	0.69	0.57	0.62	3.83
ELEC	0.46	0.52	0.67	0.56	0.90	0.62	0.52	3.34
EUA	0.34	0.37	0.40	0.36	0.51	0.62	0.38	2.35
ERIX	0.32	0.38	0.38	0.36	0.39	0.35	0.59	2.18
TO	2.63	2.68	2.95	2.61	3.04	2.77	2.67	**TCI**
NET	1.58	0.03	−1.00	−1.22	−0.31	0.42	0.49	3.22

4.3. Dynamic quantile connectedness

Furthermore, we employ the 200-period rolling window analysis to investigate the dynamic quantile connectedness. Figure 3 shows the dynamic time-domain information spillovers for $\tau \in (0.05, 0.95)$ the equally spaced grid of 10 quantiles (). As seen from the figure, the spillovers are symmetrical on quantiles and time-varying [1]. More specifically, the total connectedness index is greater than 80% in both the lower tail ($\tau \leq 0.10$) and upper tail ($\tau \geq 0.90$) and continues to decline as the quantiles gradually converge to the median. For the time-varying characteristics, we can note the increases in connectedness over the four distinct periods: between 2015 and 2016, from 2018 to early 2019, from 2020 to early 2022, and after late 2023. Global financial market turbulence and the oil crisis are the possible agents of the rising connectedness during 2015 and 2016 [72]. Heightened global trade frictions, volatile oil and natural gas markets subject to shocks of supply and demand, and fluctuating carbon prices caused by a series of reforms to the EU carbon market may have been the driving forces behind the increased spillover effects in 2018 and early 2019. The COVID-19 and the Russian-Ukraine conflict have witnessed the closer relations among the variables from 2020 to early 2022, which is in line with Tiwari et al. [73]. Finally, for the period after late 2023, the consequence may be attributed to the Hamas's attack on Israel. Figure 4 presents the dynamic quantile connectedness on three frequency bands. First, the risk spillovers among variables are larger at the extreme quantiles than that at the mean quantile over the short-, mid-, and long-term, which is in line with the static spillover effect analysis results in the previous section. Second, the dynamic connectedness in all quantiles mainly focuses on the short term, once again confirming the previous findings. Third, the short-, mid-, and long-term spillovers all show time variant characteristics.

Based on the analysis above, it is found that during the entire sample period, the connectivity among GPR, various energy submarkets, and carbon market at the low and high tails is much stronger than that at the mean quantiles, indicating the presence of significant tail contagion. The findings suggest that policymakers should closely monitor periods of high changes in GPR, energy markets, and carbon prices to manage tail-risk contagion. Additionally, it is observed that connectedness increases at all quantiles during major geopolitical conflicts and public health events. Nevertheless, this paper does not empirically analyze how different external events such as government debt crises, interest rate changes, and extreme weather events affect variables at different quantiles, which could be explored in future research.

Figure 3
Dynamic time-domain total connectedness in quantiles



4.4. Net quantile connectedness

We further calculate the dynamics of net quantile spillover effects for each variable. Through this analysis, we can identify whether the variable acts as a net information recipient or contributor under different scales of shocks in certain periods. Figure 5 shows the dynamic time-domain net connectedness in quantiles for each related variable in our system. GPR is the net spillover receiver over most of the sample period. Notably, GPR turn into the net transmitter under extreme conditions during 2014 in which the Ukraine crisis occurs, and 2022 when the Russia-Ukraine war breaks out. At the extreme low ($\tau = 0.05$) and high ($\tau = 0.95$) quantiles, OIL shifts between the risk transmitter and receiver during the sampling period. As for other quantiles ($0.15 < \tau < 0.85$), Oil primarily acts as the net recipient except for the period 2015–2016 (oil crisis), and 2022 (Russia-Ukraine war). Before 2022, NG is the risk receiver around median quantiles and shifts between risk transmitter and receiver at the lower and higher quantiles. However, the net spillovers of NG are positive and larger in almost all quantiles during the ongoing Russian-Ukraine conflict. In line with the results of previous sections, COAL is shown as the net risk recipient at the lower and higher quantiles, and ELEC mostly acts as the net spillover transmitter in all quantiles. EUA has had an increasing impact on energy markets and GPR since the adoption of the Paris Agreement in 2015. Particularly during the COVID-19, the carbon market has shown resilience under the market stability reserve (MSR) mechanism despite the global economic

Figure 4
Dynamic frequency-domain total connectedness in quantiles

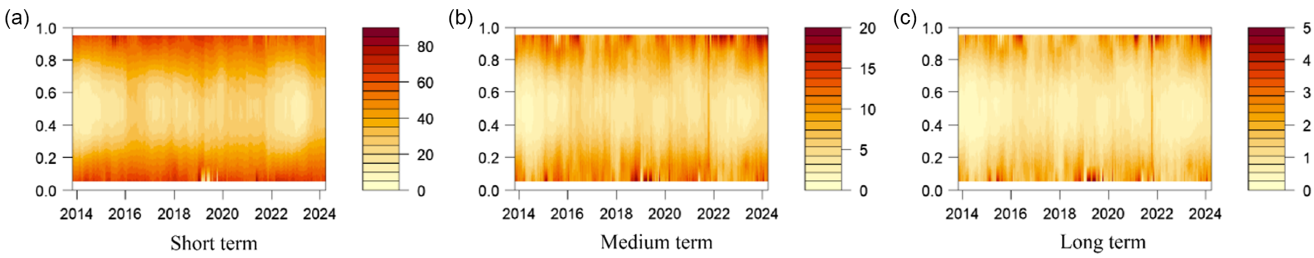
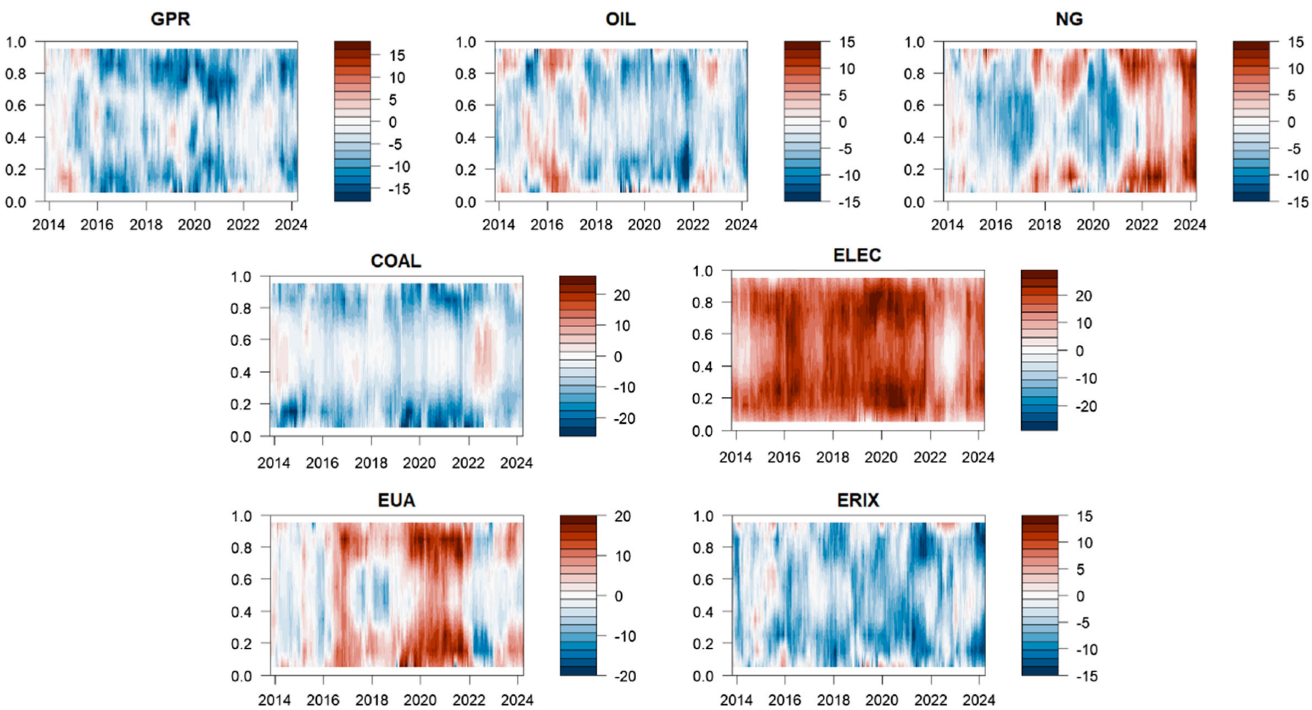


Figure 5
Dynamic time-domain net connectedness in quantiles



slowdown and the weak energy market, ensuring the long-term prospect of rising EUA prices and the market effectiveness of EUAs. However, EUA switches into the net receiver across all quantiles from the beginning of 2022, which is due to the fact that the energy crisis aggregated by the Russia-Ukraine war has to some extent weakened the role of EUA in reducing fossil energy usage. Most of the time, ERIX acts as the net receiver, implying the clean energy market has taken more shocks from other variables.

Figure 6 presents the dynamic frequency-domain net connectedness in quantiles. For each variable, the subplots from

Figure 6
Dynamic frequency-domain net connectedness in quantiles

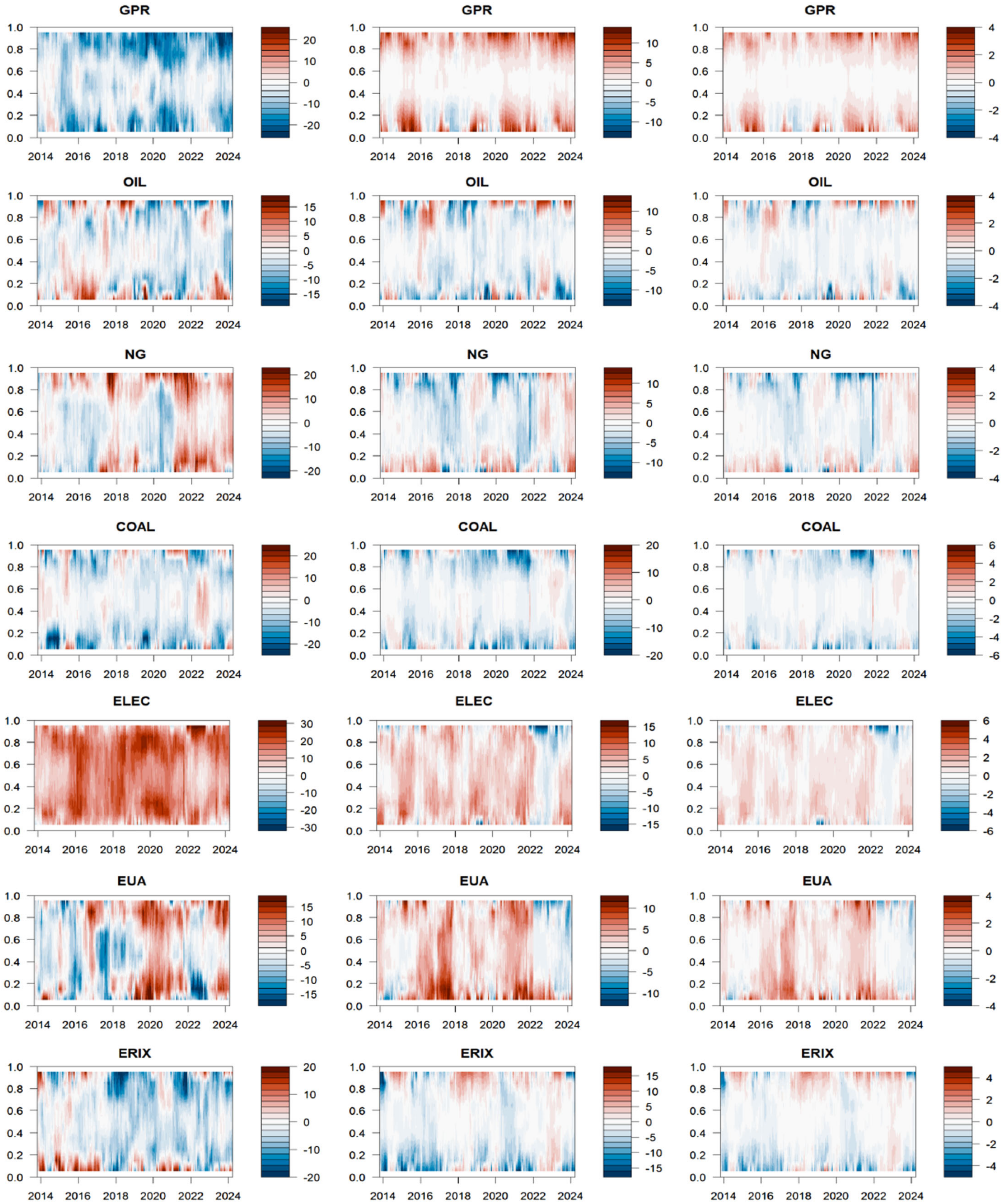
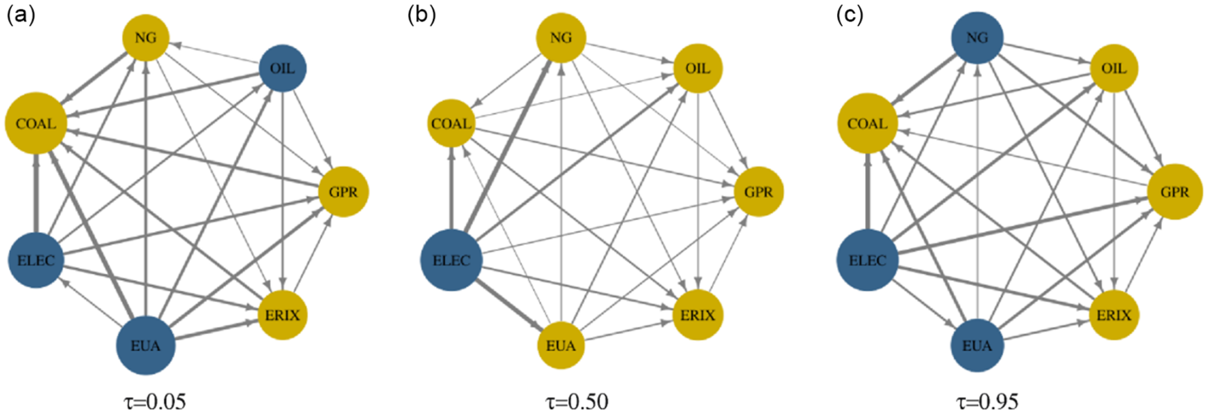


Figure 7
Time-domain connectedness networks in three quantiles



left to right in Figure 6 represent the dynamic net spillover effects for the equally spaced grid of 10 quantiles ($\tau \in (0.05, 0.95)$) in the short-, mid-, and long-term, respectively. It can be seen that net spillovers of each variable change with different frequency bands. Among that, the GPR shows the most significant difference among the three frequency domains. In the short run, GPR is shown as a net risk recipient. However, for almost the entire sample period, GPR becomes the net spillover contributor over the mid- and long-term, particularly significant at higher quantiles. This implies that rising geopolitical risks have more implications for energy and carbon prices over the mid- and long-term. Generally, the market behavior of short-term investors is responsible for the high-frequency spillover effects. Over a longer time frame, low-frequency spillover tends to be attributed to macro-economic factors which include GPR [33]. Therefore, the risk transmission of GPR lasts longer. Over the mid- and long-term, ELEC acts as the risk recipient during 2022. In the short run, the role of EUA oscillates dramatically between spillover transmitter and receiver. Nevertheless, over the mid- and long-term, EUA exerts a greater influence on other markets as its net spillover effects are positive in most sample periods except after early 2022, which indicates the EUA market plays a critical part in aspect of carbon abatement, with a lasting impact on energy markets. However, the Russian-Ukraine conflict and subsequent energy dilemma weaken the role of carbon markets in the system.

4.5. Connectedness network analysis

Lastly, the net pairwise directional interconnectedness is depicted in Figures 7 and 8. The arrow represents the direction of the net spillover effects between each pair of variables, and the thickness of each line reflects the strength. Each vertex's size and color denote the level and sign of overall net spillovers between the specific variable and the other six variables, with gold-colored and blue-colored vertex representing negative and positive net spillovers, respectively. Figure 7 shows the time-domain net pairwise directional connectedness under extreme ($\tau = 0.05, 0.95$) and normal ($\tau = 0.50$) conditions. From this network, we find that ELEC is the prominent information transmitter to fossil/clean energy and GPR. COAL is susceptible to the shocks of other variables. Under extreme conditions, EUA acts as a net information transmitter to fossil/clean energy, as the carbon market is playing an increasingly important role in promoting net-zero emissions and energy transition. The clean energy sector is still at an early stage and is more vulnerable to shocks from other variables.

Figure 8 presents the frequency-domain net pairwise connectedness in three quantiles ($\tau = 0.05, 0.50, 0.95$). Over the short run, GPR is the net receiver of information from OIL, NG, ELEC, ERIX, and EUA. Among that, OIL, ELEC, and ERIX occupy the major proportion of net spillover effects on GPR under extremely falling states, and NG, ELEC, and EUA occupy that on GPR under extremely rising states. In the medium term, GPR and EUA become the significant risk transmitters. In this regard, EUA is the major risk transmitter to the fossil/clean energy and electricity under extreme falling state, and GPR dominates the fluctuations in fossil/clean energy, electricity, and carbon prices in the extremely falling state. In addition, ERIX becomes a net transmitter to COAL and NG at the right tail, mostly due to the enhanced substitution effects in the aspect of power generation between them under the pressure of the global energy transformation [2].

5. Robustness Test

Considering that DY and BK spillover indices have sensitivity to the rolling window width [1], we further alter it to test the robustness and validity of our results. Figure 9 shows the dynamic time-domain total connectedness across all quantiles by employing 150- and 250-period rolling window. It can be seen that these results follow a similar trend to those of Figure 4, indicating our findings are robust to different settings of different rolling window.

Figure 8
Time-frequency-domain connectedness networks in three quantiles

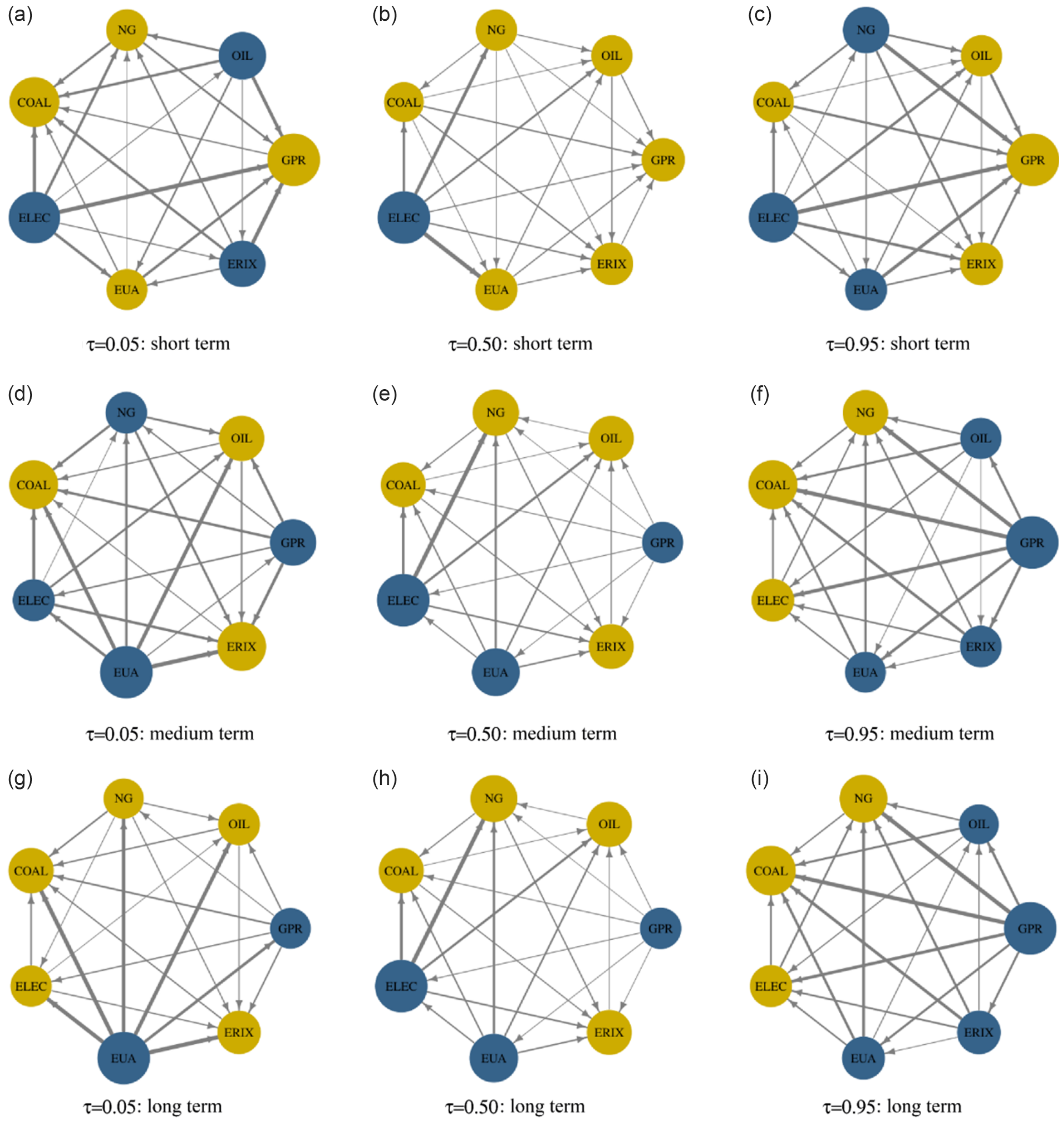
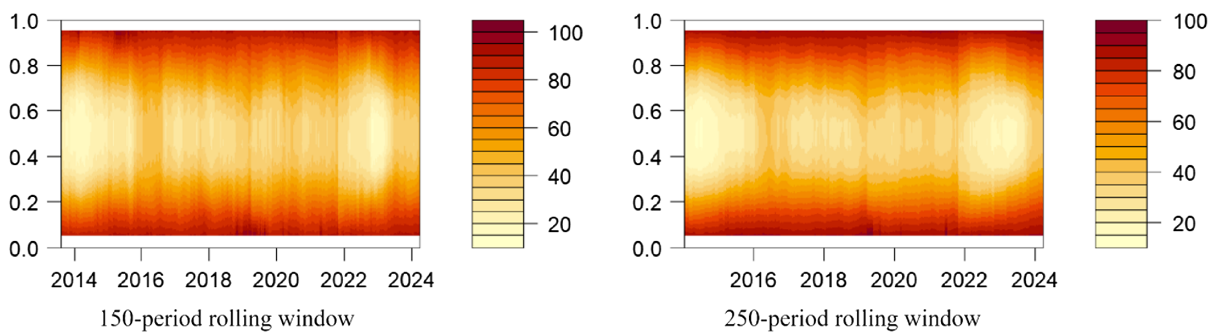


Figure 9
Overall spillovers across all quantiles



6. Conclusion and Recommendation

In this paper, we provide new insights into the time-frequency and quantile interconnectedness between geopolitical risks (GPR), traditional/clean energy, electricity, and carbon prices by applying the Diebold and Yilmaz [40] approach, the Baruník and Křehlík [41] approach and the QVAR framework. The following are several notable findings. Firstly, the overall time-domain interconnectedness among variables is much more significant in extremely low ($\tau = 0.05$) and high ($\tau = 0.95$) quartiles than in the median ($\tau = 0.50$) quantile, with 90.37%, 89.9%, and 21.17%, respectively. Second, the geopolitical risks receive more spillover effects from the variations in energy and carbon prices in both normal and extreme circumstances. Third, the risk spillovers under normal conditions are dominated by electricity market, while carbon markets become another source of risk spillovers in extreme cases. Fourth, through decomposing the spillover effects into the short-, mid-, and long-term spillovers, we find evidence that the geopolitical risks and carbon market have positive net spillover effects over the medium and long run.

The paper explores the risk transmission mechanism between GPR, various energy markets, and carbon markets from time-frequency and quantile perspectives through the connectedness analysis. We reveal the time-frequency spillover effects among them under normal conditions, which aligns with the existing research. However, the analysis using the conditional mean regression fails to capture the connectedness in extreme circumstances. Empirically, larger fluctuations in an asset price tend to attract more attention from market participants, which prompts them to adjust the investment portfolios and ultimately leads to a deeper correlation between different assets. On this basis, we use quantile-based analysis and uncover more significant risk contagion (spillover effects) and paths of risk contagion among GPR, various energy markets, and carbon markets in extreme states, which adds to the existing research.

According to our findings, some implications are provided for the investors. First, considering the increased connectedness between markets in extreme states, investors should be mindful of tail-risk contagion. As the geopolitical situation and market environment evolve, a flexible investment strategy should be taken into account by investors to get greater benefits. Furthermore, short-term investors in the fossil fuel markets should pay closer attention to abnormal fluctuations in the electricity and carbon markets, thereby benefiting from information spillovers from the electricity and carbon markets. Thirdly, investors with long-term objectives may consider incorporating oil assets into their investment portfolios to achieve diversification benefits due to the relatively weak long-term connections between oil and other energy prices.

Moreover, the findings of this paper also have certain implications for policymakers. From the perspective of risk regulation and prevention, policymakers need to focus on the risk connectedness among GPR, energy markets, and carbon markets under multiple circumstances and time-frequency bands and develop specific policies accordingly. To be specific, in extreme cases with increased market interconnectedness, both electricity and carbon markets are crucial sources of risk spillovers. For instance, the fossil energy crisis results in the prices of fossil fuels fluctuate considerably, which further affects the power, clean energy, and carbon prices through the channels including the behavior of energy producers and investors, ultimately intensifying the market tail-risk contagion. At this point, the prices of fossil fuels are susceptible to the changes in electricity and carbon markets according to our conclusions. Moreover, in the context of finance deepening, the local risks may gradually evolve into systemic financial risks. Therefore, when an energy crisis breaks out, the government should regulate the tail risks promptly and utilize the power and carbon markets to stabilize energy markets. Also, the government should take similar measures to stabilize markets when the outbreak of geopolitical conflicts causes fluctuations in GPR and then affects the energy markets. In addition, macro-economic factors including interest rate fluctuation and inflation can have an effect on the interconnectedness among markets. For instance, lower interest rates can boost demand, resulting in the higher energy and carbon prices and creating market upside risk. Likewise, inflation, which is usually caused by high demand or production costs, is often linked to rising energy and carbon prices. The larger fluctuations in energy and carbon prices correspond to higher market connectedness. As a result, interest rate changes, inflation, and deflation may exacerbate market tail-risk contagion. Other external shocks such as global pandemics, technological disruptions, and environmental events can also exert a considerable influence on energy prices, which intensifies the tail connectedness. During these periods, policymakers should also consider the function of information transmission of carbon and electricity markets. Meanwhile, policymakers can draw on the role of central banks and international institutions in stabilizing energy markets. In extreme economic circumstances, central banks can employ monetary policy instruments to adjust interest rates, curb inflation, and ultimately stabilize financial markets. International bodies, including the International Monetary Fund and the World Bank, can offer financial assistance to countries facing economic crises.

Under normal conditions, the risk spillovers are mainly from the electricity market. Hence, policymakers should necessitate attention to its volatility. Geopolitical risks and carbon market become the primary sources of net risk spillovers in the long run, which requires the government to monitor the geopolitical situation and take timely measures to mitigate shocks of geopolitical risks to energy markets. In addition, specific measures including adjusting the pricing of carbon allowances can be applied to influence other markets, ultimately reducing the fossil energy use.

From the perspective of sustainability, policymakers should ensure clean energy and carbon market stability by minimizing the impact of traditional energy and geographical risks. Policymakers are supposed to enhance the carbon market's operation mechanism and accelerate energy transformation by giving tax incentives or subsidies in the clean energy industry. Moreover, policymakers should also prioritize international cooperation to prevent and mitigate geopolitical risks. Notably, the formulation of differentiated measures against different market and geographical circumstances to manage risks and the tax incentives and subsidies to develop the clean energy sector are conducive to preventing systemic risks, avoiding energy crises, and obtaining long-term benefits, but at the same time, these measures increase government operating costs and fiscal expenditure. Therefore, the government should uphold the principle of cost-effectiveness by improving the efficiency of government operation, in order to increase the economic feasibility of the above measures. Specific measures include promoting digital transformation and strengthening internal control construction.

This study focuses on the time-frequency spillovers of geopolitical risks, traditional/clean energy, electricity, and carbon prices under different states. Nonetheless, there are still some aspects that need to be further explored. For instance, future studies can look into the Granger causality in quantiles among GPR, energy, and carbon prices and establish a model to predict the movement of prices for effective decision-making. Moreover, future research can further investigate the effects of various external shocks (e.g., climate change) on the connectedness across different quantiles.

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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, Writing – review & editing, Supervision. **Jingang Jiang:** Software, Data curation, Writing – original draft, Visualization. **Jinyan Hu:** Funding acquisition.

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