The impact of geopolitical risk on the connectedness between carbon and energy markets: A multiscale higher-moment analysis

Ling Xiao: ling.xiao@rhul.ac.uk

Qiujin Gao: qiujin.gao.2023@live.rhul.ac.uk

Matthew C. Li: matthew.li@rhul.ac.uk

Royal Holloway, University of London. TW20 0EX, Egham Hill, UK

Abstract

The strong interdependency between carbon and energy markets has been well documented. The existing research reports asymmetric, time-varying and heterogenic dependency in the short and/or long run between the carbon and energy market. The latest conflicts between Russia and Ukraine, and Israel and Hamas have been generating significant impact on the demand and supply of energy assets. Geopolitical risk (GPR), hence, as a noticeable example, evidently affects financial markets, energy, and commodity market. We aim to study how the risk transmits to carbon, energy market individually and as a whole unit. This study adopts the Baruník and Křehlík (2018) approach to discover the time-varying, heterogenic dependency features exhibited in the higher-moment connectedness at different time scales - short and long-run. Furthermore, GARCH-MIDAS is applied to investigate whether there is asymmetric dependence between geopolitical risk and carbon-energy network. Our results show a strong market-connectedness, asymmetric characteristics in risk spillover at higher moments. Natural gas and heating oil play an important role in risk spillover. In long-run, clean energy becomes the second largest transmitter after natural gas. In terms of net spillover, carbon, heating oil are the main transmitters at lower moment, but clean energy undergoes a role transformation and becomes net- transmitter at higher-moment skewness and kurtosis. GPR significantly affects the carbon market whereas clean energy is less impacted.

Keywords: geopolitical risk; carbon-energy market; higher-moments; risk connectedness; network

1. Introduction

The strong interdependency between carbon and energy markets has been well documented (see for example, Ji, Zhang and Geng, 2018; Dai *et al.*, 2021; Ren *et al.*, 2022; Zhou *et al.*, 2023; Ahmed *et al.*, 2024). The extant research reports asymmetric, time-varying and heterogenic dependency in the short and/or long run between the carbon and energy market. The main findings also shed light on the risk transmission in the multi-market network between these two markets with focuses on the implications for portfolio and risk management, energy policy making and addressing challenges of achieving low-carbon economy etc. In recent years, scholars have studied how economic uncertainties affect the price movements of various assets. In particular, the rise in geopolitical tensions has become more frequent in regions that are affluent in energy and mineral resources. The latest conflicts between Russia and Ukraine, and Israel and Hamas have been generating significant impact on the demand and supply of energy assets. Geopolitical risk, hence, as a noticeable example, evidently affects financial markets (Sohag *et al.*, 2022); energy and commodity market (Ha, 2023; Jin *et al.*, 2023). Furthermore, it can be observed in the European Union allowances (EUA) futures that geopolitical risk also changes the demand for the carbon future market. The carbon-energy network highlights the impact of geopolitical risk on the dependency between EUA and energy prices (Lu *et al.*, 2024). Carbon market plays a critical role in achieving net-zero and facilities sustainable finance. However, to our best knowledge, there is no research examining how geopolitical risk influences carbon-energy as a network. In order words, we aim to study how the risk is transmitted to carbon, energy market individually and as a whole unit.

Investors and policymakers are concerned about increasing likelihood of geopolitical tension/conflicts as extreme events. In light of the importance of portfolio and risk management of carbon-energy market, this paper aims to provide insights into how geopolitical risk impacts the connectedness between the carbon and energy markets through a multiscale higher-moment analysis. To perform our analysis, we model the geopolitical-carbon-energy network using GARCH-MIDAS method (Conrad and Kleen, 2020) to address the mixed frequency issue. Geopolitical risk is often measured in low frequency i.e. monthly whereas carbon-energy market commonly produces daily data. This study adopts the Baruník and Křehlík (2018) approach to discover the time-varying, heterogenic dependency features exhibited in the higher-order moments connectedness at different time scales - short and long-run. Furthermore, Quantile-on-Quantile regression is applied to investigate whether there exists asymmetric dependence between geopolitical risk and carbon-energy network. The sampling data covers 2013 to 2024 due to the reasons that EUA phase III commenced in 2013 and ended in 2020 and the Russia-Ukraine war began in 2014.

The contributions of this paper include: 1) reveals the risk transmission channels between geopolitical risk and the carbon-energy network; 2) provides investors with rich information on risk measures to manage the increasing risk exhibited in the carbon-energy market. In particular, this study takes clean energy markets into consideration which could encourage investors to shift towards sustainable finance with explicit risk measures; 3) informs policy and regulation makers of the prominent impact of geopolitical risk on carbon and energy markets so that pertinent considerations can be made.

2. Literature review

2.1. Theoretical motivation

The rapid developments of financial econometrics in the last few decades reflect the fact that academia and practitioners are keen to accurately capture the behaviour of financial markets and assets. Market data is often analysed to understand the price change, historic or implied volatility or actual price movements (De Clerk and Savel'ev, 2022). The statistical distribution provides an explicit measure to describe and predict the probability of price changes. Most of the financial models (e.g. Capital Asset Pricing Model, Portfolio Theory, Black-Scholes model etc.) and investors primarily concern about the first two moments i.e. expected return (mean) and risk (volatility). The higher-moments i.e. skewness and kurtosis measure asymmetry and tail conditions of the distribution with respect to the long-term loss (Li et al., 2020). Extreme events correspond with positive excess kurtosis or fat-tails from a statistical perspective, suggests that the distribution of returns in financial markets exhibit heavier tails than could be expected from a normal assumption (see Mandelbrot (1963), Longin and Solnik (2001), Longin (2005)). Negatively skewed or asymmetric distribution of asset returns implies that extreme negative events tend to happen more frequently than extreme positive events see Fama (1965), Ang and Chen (2002), Patton (2004) and Garcia and Tsafack (2011)).

Researchers argue that such higher-order moments information (Bali, 2008; Christoffersen et al., 2021; Harvey et al., 2010; Langlois, 2020) is precisely the primary risk that investors face and the main source of systemic risk that needs to be addressed by policy makers. For example, a risk-averse investor prefers positive skewness and small kurtosis of the investment return to avoid low-probability events with disastrous consequences, e.g. 2008 global financial crisis, Covid-19 pandemic, and recent and on-going conflicts between Russia and Ukraine, and Israel and Hamas. The Autoregressive Conditional Heteroscedasticity (ARCH) model which models the time-varying second-order conditional moment has been extremely popular since it was introduced by Engle (1982). Soltyk and Chan (2021) appraise its popularity and success to capture volatility in time-series data which advances the modelling and prediction risk of financial assets. As a natural extension of ARCH, literature has emerged to study higher-order conditional moments of the third (skewness) and fourth (kurtosis) moment in the last two decades.

There is a group of researchers supporting the significance of higher-order moments in asset pricing (Harvey and Siddique, 2000; Dittmar, 2002; Ang et al., 2006; Guidolin and Timmermann, 2008; Maheu et al., 2013; Chabi-Yo et al., 2014; Zambrano and Juan, 2019; Gormsen and Jensen 2020; Hu et al., 2023). Recently, there has been an increasing interest in examining the co-movements at higher-order such as co-skewness and tail dependency between different assets e.g. carbon and energy markets (Dai et al., 2021); stock and commodity markets (Ahmed, 2022); Bitcoin and SP500; Bouri, et al., (2022) amongst cryptocurrencies (Cui and Maghyereh, 2022; Nyakurukwa and Seetharam, 2023). There are studies of portfolio risk management which take the co-movements of higher-moments into account for example, Harvey et al., (2010); Cerrato et al., (2017) higher order co-movements are closely related with an asymmetric tail dependence in equity portfolio management; Nekhili and Bouri (2023) highlight that the use of higher-order moments and co-movements lead to higher expected utility and better performance of hedging; Mensi et al., 2024 point out that the spillovers in higher-order moments increase during different phases of the COVID-19 and Ukraine-Russia wars. Ignoring them can lead to suboptimal inferences on spillover and portfolio analysis. Ahmed et al., (2024) show the portfolio performance improved after considering the spillovers at higher-moments. In summary, it is critical to study higher-moments which drive asset pricing and asymmetric tail risk.

2.2. Connectedness between carbon-energy-clean energy

The strong interdependency between carbon and traditional energy market has been well documented (see for example, Ji, Zhang and Geng, 2018; Dai *et al.*, 2021; Ren *et al.*, 2022;

Zhou *et al.*, 2023; Ahmed *et al.*, 2024). The extant research reports asymmetric, time-varying and heterogenic dependency in the short and/or long run between the carbon and energy market. Recent development focuses on the higher-order co-movements between carbon, clean and green energy in the context of extreme events such as public health crisis, climate change and geopolitical tensions.

Nasreen et al., (2020) explore the dynamic linkages between oil returns, clean energy, and technology stock indices and report the three markets future returns while the persistence of long-term volatility is larger than short-term volatility. Ding et al., (2021) examine the time-frequency spillovers among carbon, fossil energy and clean energy markets. Their findings conclude that short-term spillovers are stronger than long-term spillovers. Carbon market is a net receiver of risk spillovers from the clean energy and oil markets in the short term. COVID-19 pandemic leads to stronger cross-market risk contagion in the long term. The attention to climate change has significant causal effects on spillovers. Tiwari et al., (2022) focus on the dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic. They find that clean energy dominated all other markets and is seen to be the main net transmitter of shocks in the entire network with Green Bonds and Solactive Global Wind, as the major recipients of shocks in the system. Su et al. (2023) investigate the connectedness between fossil fuel, renewables and carbon markets. Their findings suggest that the impact of extreme conditions on the connectedness network of underlying assets proves to be more pronounced compared to the mean quantile. However, the density of spillovers between the markets during the energy crisis does not increase significantly . It may be due to the correlation network may result from multiple shocks acting together. Qiu et al., (2023) study the carbon, stock and renewable energy market, they claim that the carbon market has a positive impact on the renewable energy market in the short term. In particular, the carbon market had a positive impact on the renewable energy stock market during Brexit. Furthermore, extreme event such as COVID-19 exacerbates the short-term impact between markets. Wang et al., (2024) examine the intricate relationship between the Chinese carbon, energy, and electricity markets and use the TVP-VAR model to explore the risk spillover effects among these markets. They report that risk spillover among the three markets is particularly evident in the downside or upside market, and during COVID-19, the carbon market amplifies the spillovers on other markets under market downside. Ahmed et al., (2024) also highlight that higher-moment nexus intensifies during crisis period. Interestingly, intensity of the total spillover index (TSI) measures jointly for conditional volatility, conditional skewness and conditional (excess) kurtosis is larger than the TSI measures individually for each moment, reflecting the significant cross - moment spillovers and their contribution to the total spillover in the system of the three moments.

2.3. Impact of geopolitical risk on carbon and energy, clean energy market

There have been a few attempts to examine the impact of GPR on carbon and energy market due to the escalation of the regional conflicts since 2022. Le Thanh Ha (2023) explores the dynamic connectedness between green energy and carbon risk during Russia-Ukraine conflict using a wavelet analysis. This study provides evidence of partial coherencies between these indicators during the conflict. However, such analysis does not take higher-moments into account. Lau, et al., (2023) investigate the interdependency between geopolitical risk, carbon and energy market using monthly data. One of the main findings is that the dependence structure across geopolitical risks and oil prices is positive at different periods and quantiles. However, it has a couple of limitations. First, carbon and clean energy price are often analysed on daily basis to capture its drastic movements. The use of monthly data to match the GPR created by Caldara and Iacoviello (2022) would lose important information. Second, the paper does not examine how the geopolitical risk affects the nexus of carbon-energy system.

2.4. Research gap

Different from the existing studies discussed above, we use a more comprehensive data set covering not only EUA, oil, natural gas, coal, but also electricity and clean energy markets given the electricity market is a major player in the EUA markets, whereas clean energy is relevant for the transition to cleaner energy and the recent literature on portfolio decarbonising. Furthermore, our sample period is much longer, covering the period 2013-2024, which allows us to reflect more phases of the EU ETS market and important recent extreme events such as the COVID-19 outbreak, the Russia-Ukraine war, and Israel and Hamas war. These events could have shaped the energy markets and possibly led to a large deviation of return series distribution away from normal and thus to realisation of spillover effects in higher-order moments. Moreover, we estimate the spillover for each higher-order moment separately and jointly, reflecting the cross-spillover effect and thus the contribution of each moment to the total spillover index jointly estimated in the system of the three moments. This evidence is new to the related literature on spillovers in higher-order moments (Bonato et al., 2020; Bouri et al., 2021, 2023; Dai et al., 2021; Zhang, Jin, et al., 2022), and can be recognised under the extreme market condition and extreme events, which can lead to more intense spillovers in the carbon and energy markets to the extent of initiating significant spillovers across high-order moments. Lastly, regarding the evidence showing that the impact of geopolitical risk on higher-order moments spillovers, we investigate how the GPR affect carbon-energy markets as a whole system and individually.

3. Methodology and data

3.1. Methodology

3.1.1. Higher-order moment risk measure

Three data series features, including non-normality, serial correlation, and leverage effect, need to be considered when modelling financial time series, such as futures prices (Nakagawa and Uchiyama, 2020). Firstly, because of the negative skewness and large kurtosis, the financial time series is left-skewed and fat-tailed but not normal. Secondly, the serial correlation of return or volatility, known as momentum or reversal effect, implies that high return and large changes of return in the past tend to increase and cluster together in one period thereafter. Thirdly, a negative correlation between return and volatility results in the leverage effect. Nakagawa and Uchiyama (2020) take all three characteristics of financial time series into account and construct a univariate GJRSK model by combining generalized autoregressive conditional heteroscedasticity (GARCH) with skewness and kurtosis (León, Rubio and Serna, 2005), and Glosten, Jagannathan, and Runkle GARCH (GJR) model (Glosten, Jagannathan and Runkle, 1993). We apply the following GJRSK model to measure our higher-order moments of market returns.

$$\begin{cases} r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \\ h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 \varepsilon_{t-1}^2 I_{\{\eta_{t-1}<0\}} \\ s_t = \gamma_0 + \gamma_1 \eta_{t-1}^3 + \gamma_2 s_{t-1} + \gamma_3 \eta_{t-1}^2 I_{\{\eta_{t-1}<0\}} \\ k_t = \delta_0 + \delta_1 \eta_{t-1}^4 + \delta_2 k_{t-1} + \delta_3 \eta_{t-1}^4 I_{\{\eta_{t-1}<0\}} \\ \eta_t = h_t^{-\frac{1}{2}} \varepsilon_t \\ \eta_t | I_{t-1} \sim g(0, 1, s_t, k_t) \end{cases} \tag{1}$$

where α_0 and α_1 are parameters from Autoregressive (AR) model, $I_{\{\eta_{t-1}<0\}}$ is an indicator function that returns 1 if $\eta_{t-1} < 0$ and 0 otherwise. Under the condition of I_{t-1}, η_t obeys a probability density function g with mean 0, variance 1, skewness s_t, and kurtosis k_t. . The parameters of this model are calculated by maximizing the following log-likelihood function l_t in equation (2).

$$l_t = -\frac{1}{2}\ln h_t - \frac{1}{2}\eta_t^2 + \ln\left(1 + \frac{1}{3!}(\eta_t^3 - 3\eta_t) + \frac{k_t - 3}{4!}(\eta_t^4 - 6\eta_t^2 + 3)\right)^2 - (1 + \frac{s_t^2}{3!} + \frac{(k_t-3)^2}{4!}) \quad (2)$$

3.1.2. Time-frequency connectedness

Based on the frequency connectedness theoretical framework suggested by Baruník and Křehlík (2018), and Diebold and Yılmaz (2014), we estimate dynamic frequency risk spillover connectedness among carbon and energy markets as Zhou et al. (2023) did. Basically, we need to know how to measure the degree and direction of risk spillover. Generalized Forecast Error Variance Decomposition (GFEVD) (Equation 3) used in the DY model is usually applied to measure how much the *n* th variable makes the contribution of the variance decomposition of the *m* th element. In Equation 3, H is the forecast horizon and Ψ_h is the $k \times k$ order matrix technique. The standardised equation (4) makes the value comparable.

$$(\vartheta_H)_{m,n} = \frac{\sigma_{nn}^{-1} \sum_{h=0}^{H} \left[(\psi_h \Sigma)_{m,n}\right]^2}{\sum_{h=0}^{H} \left(\Psi_h \Sigma \Psi_h^{'}\right)_{j,j}} \quad (3)$$

$$(\tilde{\vartheta}_H)_{m,n} = \frac{(\vartheta_H)_{m,n}}{\sum_{n=1}^{k} (\vartheta_H)_{m,n}}, \sum_{n=1}^{k} (\tilde{\vartheta}_H)_{m,n} = 1 \quad (4)$$

There are several ways to study the strength of the risk spillover effects, such as the total risk spillover effect of the carbon and energy system, the strength of the total risk spillover effect of market *n* on (TO) and receiving from (FROM) all other remaining markets, the effect obtained from the difference between TO and FROM (net spillover), and the size of the effect calculated from the difference between the total volatility shocks transmitted from market *m* to *n*, and from *n* to *m* (net pairwise spillover). Equation (5) shows the total risk spillover, TO, FROM, net spillover, and net pairwise spillover effect from above to below.

$$\begin{cases} C(H) = 100 \times \frac{\sum_{m,n=1,m\neq n}^{K}(\tilde{\vartheta}_H)_{m,n}}{\sum_{m,n=1}^{K}(\tilde{\vartheta}_H)_{m,n}} \\ C_{\cdot n}(H) = 100 \times \frac{\sum_{m=1,j\neq k}^{K}(\tilde{\vartheta}_H)_{m,n}}{\sum_{m=1}^{K}(\tilde{\vartheta}_H)_{m,n}} \\ C_{n\cdot}(H) = 100 \times \frac{\sum_{m=1,m\neq n}^{K}(\tilde{\vartheta}_H)_{n,m}}{\sum_{m=1}^{K}(\tilde{\vartheta}_H)_{n,m}} \\ C_n(H) = C_{\cdot n}(H) - C_{n\cdot}(H) \\ C_{m,n}(H) = 100 \times (\frac{(\tilde{\vartheta}_H)_{m,n}}{\sum_{n=1}^{K}(\tilde{\vartheta}_H)_{m,n}} - \frac{(\tilde{\vartheta}_H)_{n,m}}{\sum_{m=1}^{K}(\tilde{\vartheta}_H)_{n,m}}) \end{cases} \tag{5}$$

where $Tr\{\cdot\}$ is the Trace Operator, $C_{\cdot\cdot}(H)$ represents the risk spillover effect.

Regarding the frequency spillover effect, we need to study the spectral representation of variance decomposition. Frequency response function written in Equation (6) applied in the BK model help characterize the frequency dynamics.

$$S_X(w) = \sum_{h=-\infty}^{\infty} E(X_t X_{t-h})e^{-iwh} = \varphi(e^{-iw})\Sigma\varphi'(e^{+iw}) \tag{6}$$

In Equation (6), $i = \sqrt{-1}$, $\varphi(e^{-iw}) = \sum_{h=0}^{\infty} \varphi_h e^{-iwh}, h = 1,2,\cdots H$, and w means frequency. $S_X(w)$ refers to the Power Spectrum which describe how the sequences are distributed over the frequency component w. Generalized causation spectrum can be constructed by assuming $w = \in (-\pi, \pi)$, which is presented in Equation (7):

$$[f(w)]_{m,n} = \frac{\sigma_{nn}^{-1}|(\varphi(e^{-iw})\Sigma)_{m,n}|^2}{[\varphi(e^{-iw})\Sigma\varphi'(e^{+iw})]_{m,m}} \tag{7}$$

where $\varphi(e^{-iw})$ means the Fourier Transform of pulse effect function Ψ. Under the condition of an arbitrary frequency band: $d = (a,b), a, b\epsilon(-\pi,\pi)$, the total connectedness and the frequency connectedness indices can be specified as the following sub-equations (8) specifically.

$$\begin{cases} C_d^W = 100 \times (1 - \frac{Tr(\{\tilde{\vartheta}_d\})}{\Sigma(\tilde{\vartheta}_d)_{m,n}}) \\ C_d^F = 100 \times (\frac{\sum_{m\neq n}(\tilde{\vartheta}_d)_{m,n}}{\Sigma(\tilde{\vartheta}_\infty)_{m,n}} - \frac{Tr(\{\tilde{\vartheta}_d\})}{\Sigma(\tilde{\vartheta}_\infty)_{m,n}}) \end{cases} \tag{8}$$

3.1.3. GARCH-MIDAS framework

In order to study the role of monthly geopolitical risk indices in explaining daily risk spillover effects between carbon, energy, and clean energy markets, we apply a mixed frequency data model, the GARCH-MIDAS model. There are some reasons explaining why we use this model. The first reason is that the mixed frequency data sampling (MIDAS) framework can combine data from different frequencies into one model, which helps investigate high-frequency risk spillover effects at low-frequency geopolitical risk. Secondly, the GARCH model is combined with the MIDAS framework, which considers the error term of dependent variables series and the information on external geopolitical risk. Thirdly, the existing literature implies that the GARCH-MIDAS model performs best in capturing mixed-frequency information and forecasting among models such as the GARCH, heterogeneous autoregression, and high-frequency-based volatility models (Ghysels, Santa-Clara and Valkanov, 2004; Conrad and Kleen, 2020). Therefore, we use a mixed-frequency data model to explore whether geopolitical risk indices impact high-order moments total and net risk spillovers. Then, we introduce the GARCH-MIDAS model in detail.

Drawing on the ideas of Engle and Rangel (2008), it is assumed that the unpredictable returns of financial assets are calculated as:

$$r_{i,t} - \mu = \sqrt{\tau_t \times g_{i,t}}\varepsilon_{i,t} \tag{9}$$

where $r_{i,t}$ is the logarithmic return on day i of month t, μ is the conditional mean, $\varepsilon_{i,t}$ obeys the standard normal distribution, τ_t is the function explained by the low-frequency explanatory variable X. If τ_t depends only on the lagged values of the explanatory variables, then the conditional variance of the daily return is $\sigma_{i,t}^2 = g_{i,t}\tau_t$. $g_{i,t}$ obeys the GARCH process and is the short-term component of volatility, which can be called daily clustering volatility. τ_t is the long-term component, whose value is consistent in a month or several months and only changes on low-frequency cycles. To improve estimation accuracy by considering information asymmetry in the market, we use GJR-GARCH (1,1) model to represent $g_{i,t}$.

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma 1_{\{\varepsilon_{i-1,t}\}<0}\right)\frac{\varepsilon_{i-1,t}^2}{\tau_t} + \beta g_{i-1,t} \tag{10}$$

where α>0, β>0, α+β<1, and γ are asymmetric coefficients. The long-term component of volatility is:

$$\tau_t = c + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{11}$$

where k is the number of lag periods of the explanatory variable. This linear equation requires c>0, $\tau_t > 0$, and the equation is only valid when the explanatory variable X_{t-k} is non-negative. If we do not restrict the value of variable X_{t-k} as positive, then the long-run component can be expressed as the following equation.

$$log\tau_t = c + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, X_{t-k} \tag{12}$$

$$\varphi_k(\omega_1,\ \omega_2) = \frac{[k/(K+1)]^{\omega_1 - 1} \cdot [1-k/(K+1)]^{\omega_2 - 1}}{\sum_{j=1}^{K} [m/(K+1)]^{\omega_1 - 1} \cdot [1-j/(K+1)]^{\omega_2 - 1}}. \tag{13}$$

This paper draws on the method of Conrad and Kleen (2020) and uses the unrestricted beta method to calculate φ_k, which assumes $\omega_1 = 1$, and $\omega_1 \geq 1$, $\omega_2 \geq 1$.

One-factor GARCH-MIDAS means we set X as geopolitical risk indices or average realized volatility RV. We assume 22 days in a month and monthly RV can be expressed as $RV = \sqrt{\frac{1}{22}\sum_{j=0}^{21} r_{i-j,t}^2}$. Then the long-term component can be expressed as:

$$log\tau_i = c + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{i-k}^{RW} \tag{14}$$

The two-factor GARCH-MIDAS model mainly study the long-term component of the two-factor, which means the long-term volatility component would be explained by two variables. We set RV and GPR indices as two explanatory variables, then the long-run component of volatility can be expressed as the following equation.

$$log\tau_i = c + \theta_1 \sum_{k1=1}^{K} \varphi_{k1}(\omega_{11}, \omega_{12})\, RV_{i-k1} + \theta_2 \sum_{k2=1}^{K} \varphi_{k2}(\omega_{21}, \omega_{22})\, GPRs_{i-k2} \tag{15}$$

where $GPRs$ represents indices *GPR, GPRT, GPRA.*

3.2. Data

This study investigates the impact of geopolitical risks on higher-order moments of risk spillover among seven carbon, energy, and clean energy markets. The data information, sources, and frequency are reported in Table 1. To capture the information on geopolitical risk, we apply monthly GPR indices constructed by Caldara and Iacoviello (2022) using news-based measurement. The GPR index represents the threat, realisation, and escalation of adverse events associated with tensions across global countries, while GPRT and GPRA indices show the threats of future adverse events and the realisation of adverse events related to wars, terrorism, and other global tensions, respectively. Moreover, we take carbon, crude oil, heating oil, natural gas, coal, electricity, and clean energy prices to estimate high-order moments, including volatility, skewness, and kurtosis. Notably, we study the oil market in depth using two products: crude oil futures and heating oil futures. Specifically, the performance of the clean energy market is represented by the S&P Global Clean Energy Index, measuring the performance of companies in the clean energy businesses. Since the European Union Emission Trading System becomes mature from Phase III starting from 2013, our sample spans January 2, 2013 to March 19, 2024. Five days of April 20, 2020, July 11, 2022, July 18, 2022, August 8, 2022, October 9, 2023, and October 16, 2023 are deleted to avoid singular values. We calculate the returns of the 7 products using $100 \times (P_t - P_{t-1})/P_{t-1}$ with a total of 2721 observations for each data series.

Table 1

Data information.

Indices	Information	Sources	Frequency
GPR/GPRT/GPRA	Caldara and Iacoviello (2022) GPR index GPRT proxies for threats GPRA proxies for acts	https://www.matteoiacoviello.com/gpr.htm	Monthly
EUA	EUA futures contracts traded on the Intercontinental Exchange (ICE) Futures price	Bloomberg	Daily
crude_oil	WTIF: NYMEX WTI Crude oil futures price	Bloomberg	Daily
heating_oil	NY Harbor ULSD Futures price	Bloomberg	Daily
natural_gas	Price for UK Natural Gas Futures of NBP (National Balancing Point)	Bloomberg	Daily
ICE_coal	The ICE Futures Rotterdam Coal Year Futures price	Bloomberg	Daily
electricity	Nord Pool electricity futures price	Bloomberg	Daily

clean_energy	S&P global clean energy index	Bloomberg	Daily

The summary statistics of sample returns are reported in Table 2. From the return minimums, median, 3rd quantile, maximum, and standard deviation, it is apparent that the crude oil market has the highest returns dispersion, followed by the electricity market. The skewness value shows natural gas, ICE coal, and electricity markets have positive deviations, while others have negative deviations. The kurtosis results for sample returns also show all markets have asymmetric features. Most importantly, Jarque and Bera (JB), and Augmented Dickey-Fuller (ADF) results for all series reject the null hypothesis at the 1% significance level, implying that all series are not normally distributed and stationary. The results of the ARCH-LM test for the return sample indicate that our data series are suitable for utilising the GJRSK model.

Table 2

Summary statistics

	EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy
Min.	-35.26	-126.60	-21.93	-29.95	-31.38	-187.92	-11.75
1st Qu.	-1.45	-1.19	-1.04	-1.68	-0.88	-7.68	-0.72
Median	0.10	0.11	0.08	0.00	-0.02	-0.90	0.05
Mean	0.13	0.00	0.02	0.20	0.03	4.20	0.03
3rd Qu.	1.77	1.27	1.16	1.82	0.90	6.72	0.76
Max.	27.19	37.66	13.15	50.93	37.40	859.22	11.66
skewness	-0.25	-14.05	-0.61	1.55	1.07	8.11	-0.13
kurtosis	10.88	505.92	9.58	14.68	39.49	103.86	7.17
Standard Deviation	3.25	3.71	2.32	5.06	2.52	47.51	1.49
JB test	13508.88	29151063.32	10582.02	25586.89	177592.72	1254672.70	5856.84
JB P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ADF test	-15.54	-14.69	-14.13	-14.44	-15.79	-13.36	-12.28
ADF P value	0.01	0.01	0.01	0.01	0.01	0.01	0.01
LM (10) test	142.41	47.97	311.96	380.10	1470.07	73.52	579.34
LM P value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: The sample minimums (Min.), 1st Qu. (first quartile), medians, means, 3rd Qu. (third quartile), maximums (Max.), skewness, kurtosis, standard deviations (Std. Dev), Jarque-Bera (J-B) tests which is the normality test of Jarque and Bera, Augmented Dickey-Fuller (ADF) tests which is the unit root test of Dickey and Fuller and ARCH-LM test for the ARCH effect for up to the 10th order of the twelve returns series of carbon, energy and clean energy markets.

Fig. 1. displays the heatmap of the pairwise correlation between pairs of assets of carbon and energy markets. We find a relatively high correlation between crude oil and heating oil markets because they belong to the more generic oil market, followed by the correlation between natural gas and ICE coal. The correlation between other pairs is low, implying that our data series are appropriate for the estimation.

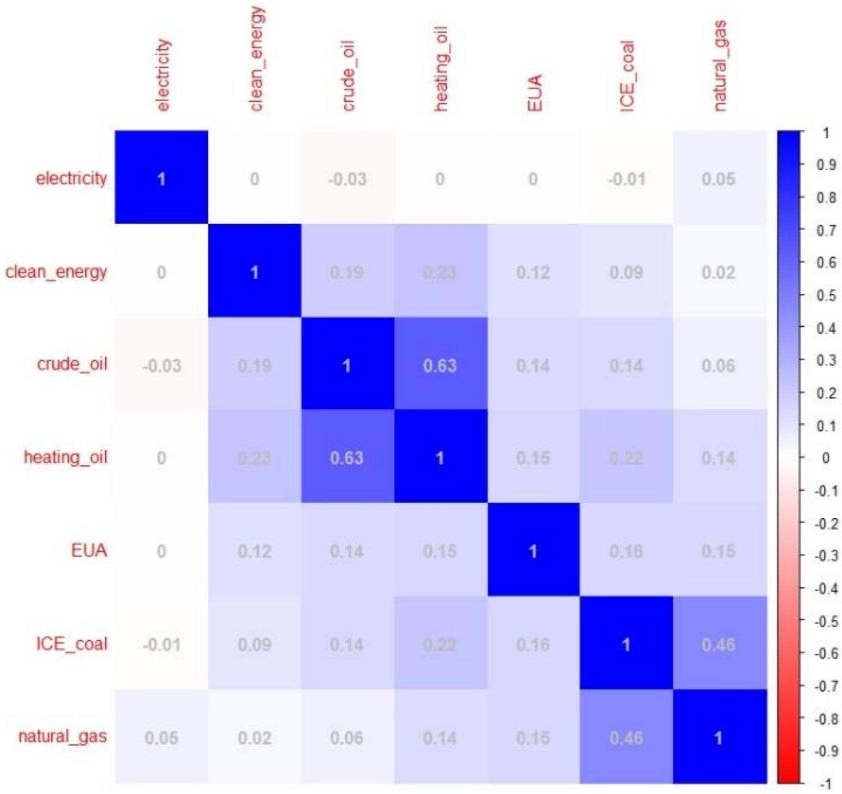


Fig. 1. Heat map of pairwise correlations of each market's returns. The numbers represent the pairwise correlation between pairs of assets, and the darker colour represents a stronger correlation.

4. Empirical results

4.1. Static spillover effects

4.1.1. Static volatility spillover based on Diebold and Yilmaz (2014)

This sub-section presents the computed static volatility spillover following Diebold and Yilmaz (DY, 2014). Static spillover refers to the fact that we estimated an average single parameter for the full sample period. Table 3 shows that the total volatility connectedness index (TCI) for the system is 21.59%. Natural gas emerges as the dominant transmitter of volatility spillovers, contributing 8.33% to other markets while heating oil is the largest receiver, absorbing 8.28% from the other six markets. It is also worth noting that the carbon market has the highest spillover to the clean energy market.

Table 3

Static variance spillovers using the DY model (%)

	EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy	FROM
EUA	91.73	0.88	0.90	0.22	1.08	0.05	5.14	1.18
crude_oil	0.23	78.97	13.32	0.20	0.02	0.00	7.25	3.00
heating_oil	0.73	8.91	42.07	13.83	14.79	0.03	19.64	8.28
natural_gas	0.16	0.56	0.61	93.33	3.20	0.02	2.12	0.95
ICE_coal	0.99	0.54	0.83	41.49	54.79	0.11	1.25	6.46
electricity	0.07	0.01	0.01	2.02	0.12	97.69	0.08	0.33
clean_energy	0.79	0.28	7.87	0.57	0.17	0.00	90.32	1.38
TO	0.42	1.60	3.36	8.33	2.77	0.03	5.07	21.59

Note: The table presents the static spillover connectedness based on the DY method. We provide the total spillover index (denoted by the term "TCI"), the directional spillover received (denoted by "FROM"), and transmitted (denoted by "TO") by each market.

4.1.2. Frequency volatility spillover based on Baruník and Křehlík (2018)model

Frequency volatility spillover will reveal the discrepancies between the short and long term. In the frequency domain framework, we have taken two distinct timescales into consideration: the high frequency, ranging from 1 to 22 days, and the low frequency, encompassing durations greater than 22 days. In the short run, the heating oil market stands out as the principal transmitter of volatility, while the crude oil market assumes the role of the primary receiver.
The total volatility spillover indices at high-frequency and low-frequency bands are 1.89% and 19.4%, respectively. Clearly, the magnitude of volatility spillovers in the short run, or say, high frequency, is comparatively lower than the long run. In the long run, the natural gas market stands out as the principal transmitter of volatility, while the heating-oil market assumes the role of the primary receiver. Clean energy appears to be the second largest transmitter. The results of skewness and kurtosis implied in the DY and BK models are presented in Supplementary information Table 2 and 3.

Table 4

Static variance spillovers using the BK model (%)

	EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy	FROM
Panel A: Frequency 1 (High frequency): 1day to 22 days								
EUA	21.64	0.05	0.07	0.01	0.10	0.01	0.19	0.06
crude_oil	0.04	51.60	7.30	0.01	0.00	0.00	0.11	1.06
heating_oil	0.13	2.51	13.26	0.11	0.43	0.00	0.12	0.47
natural_gas	0.04	0.01	0.11	2.86	0.33	0.00	0.01	0.07
ICE_coal	0.14	0.01	0.19	0.60	7.74	0.01	0.02	0.14
electricity	0.01	0.00	0.01	0.17	0.03	88.82	0.04	0.04
clean_energy	0.15	0.07	0.02	0.01	0.01	0.00	3.44	0.04
to_ABS	0.07	0.38	1.10	0.13	0.13	0.00	0.07	1.89
Panel B: Frequency 2 (Low frequency): 22 days to infinity								
EUA	70.09	0.83	0.82	0.21	0.98	0.04	4.95	1.12
crude_oil	0.19	27.37	6.03	0.19	0.02	0.00	7.14	1.94
heating_oil	0.59	6.40	28.81	13.72	14.36	0.03	19.51	7.80
natural_gas	0.13	0.55	0.50	90.47	2.86	0.02	2.10	0.88
ICE_coal	0.84	0.53	0.64	40.89	47.05	0.10	1.24	6.32
electricity	0.06	0.01	0.01	1.86	0.08	8.88	0.04	0.29
clean_energy	0.65	0.21	7.85	0.56	0.15	0.00	86.88	1.34
to_ABS	0.35	1.22	2.26	8.20	2.64	0.03	5.00	19.70

Note: The table presents the static spillover connectedness based on the BK model. We provide the total spillover index (denoted by the term "TCI"), the directional spillover received (denoted by "FROM"), and transmitted (denoted by "TO_ABS") by each market.

4.2. Dynamic Spillover effects (Time-frequency risk spillover)

The static spillover index has a significant limitation due to its assumption that the relationships between volatility, skewness, and kurtosis of carbon and energy markets are constant over time. However, economic and financial events occurred during the sample period may have impacted the interdependence among these markets.

Fig. 2 displays the dynamics of the total volatility, skewness, and kurtosis spillover indices, which are derived using a rolling window of 200 days. This entails us to compute these indexes for 2552 different time periods, spanning from January 2013 to March 2024. Robustness test using rolling window of 150 and 250 days are presented in the Supplementary information Fig.4.

The spillover index experienced a spike after significant events such as Russia-Ukrain 2014, the outbreak of the COVID-19 epidemic in 2020, and the Israel-Hamas war in 2022. Skewness and kurtosis spillovers exhibit higher sensitivity to market information compared to volatility. We find that during extreme event shocks, there is evidence of financial risk contagion, which amplifies spillovers across carbon and energy markets. This aligns with the conclusions of prior studies. Compared to volatility, skewness and kurtosis spillovers are more sensitive to market information. Volatility spillover effect in the high-frequency band is always higher than in the low-frequency band. However, the higher skewness and kurtosis spillover effects at short-term suggest that short-term shocks play a significant role in driving the total skewness and kurtosis spillover effects across markets.

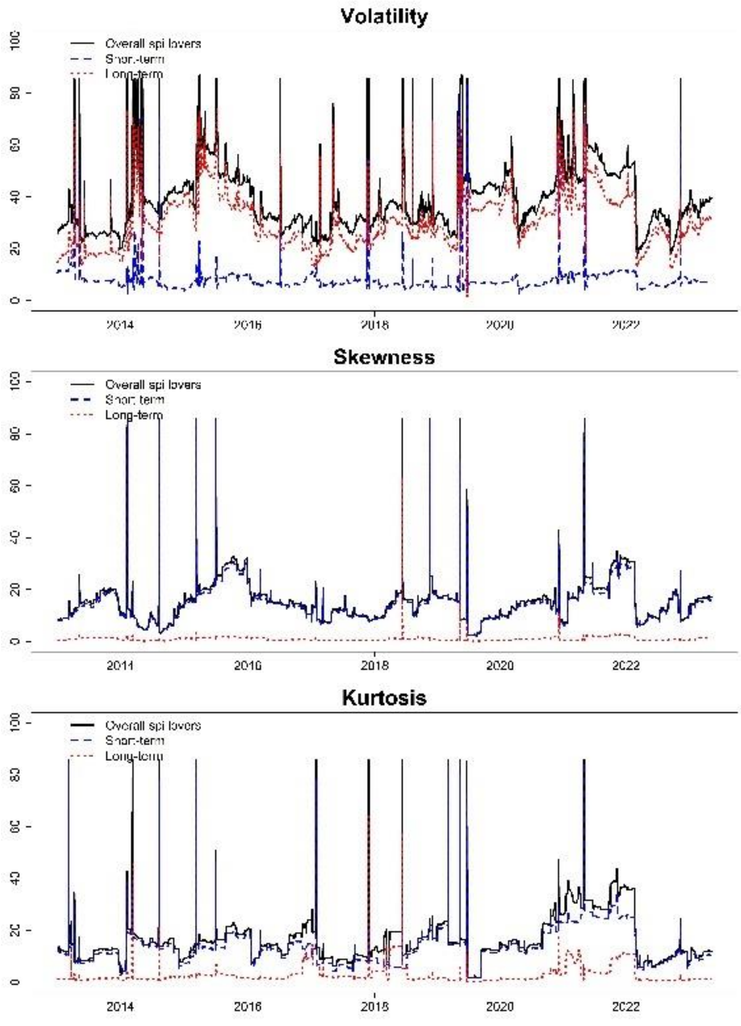


Fig. 2. Dynamic overall spillovers of carbon, energy and metals markets. The top panels "Overall spillovers" is the dynamic total spillover index of the DY model. "Short-term" and "Long-term" is the dynamic frequency connectedness on the band:3.14 to 0.14 and 0.14 to of BK model, respectively.

In order to gain a better understanding of the way in which carbon and energy markets are affected by each other, we conduct an analysis of the net directional spillover in each market. This analysis helps us to understand how spillovers flow and the strength of these flows amongst these markets over time. "Net directional spillovers" is the aggregate net volatility directional spillovers of the DY model. "Short-term" and "Long-term" are the net volatility directional spillover in the short and long-term horizons of BK model, respectively. A positive net spillover index indicates the transmission of shocks from the market to other markets, whereas a negative net spillover index suggests the reception of shocks from other markets. It is evident that the net volatility spillovers demonstrate significant variability over time. Electricity and clean energy act as net contributors of shocks in the last few years.

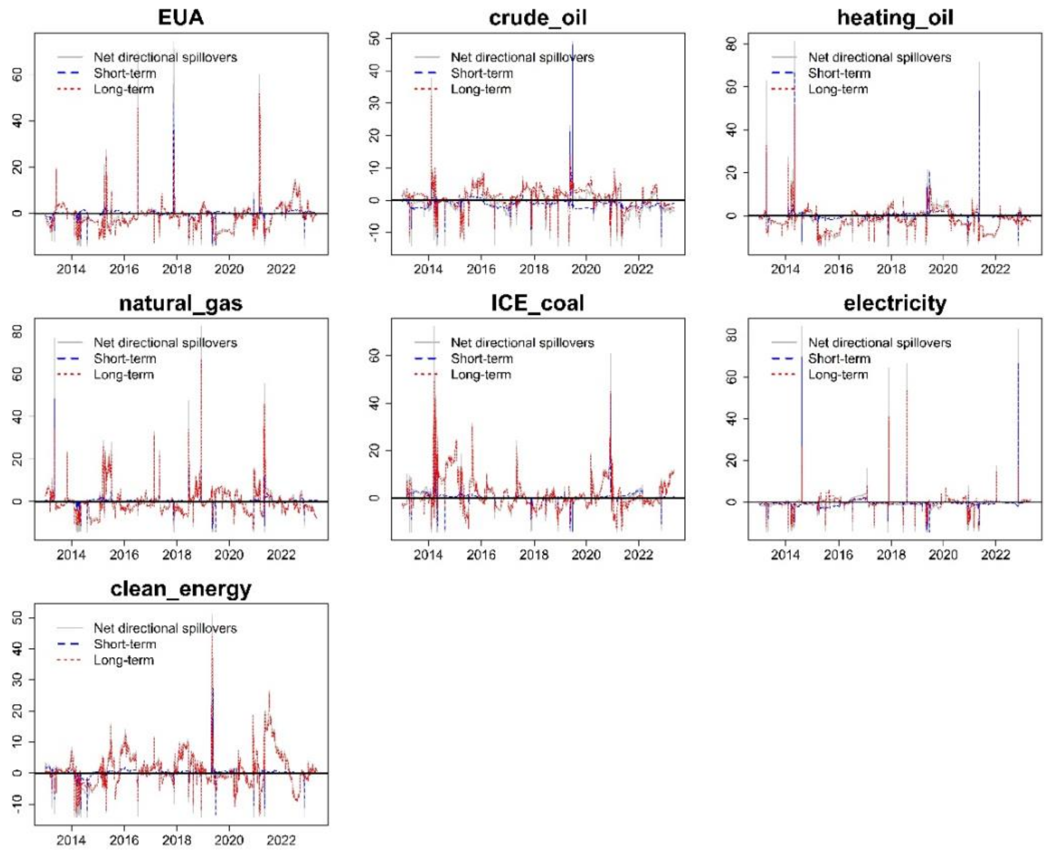


Fig. 3. Dynamic net volatility directional spillovers. The black horizontal line represents y = 0. "Net directional spillovers" is the aggregate net volatility directional spillovers of the DY model. "Short-term" and "Long-term" is the net volatility directional spillover in the short and long-term horizons of BK model, respectively. The top panels represent each market.

4.3. Net pairwise directional connectedness

The purpose of this exercise is to emphasize the significance and influence of individual markets in the network structure as a whole. Each market is represented by a node, and the thickness of the edge indicates the extent of pairwise directional connectedness. The arrows that point from market i to j indicate net spillovers, which means that the contribution of market i to market j is more significant than that of market j to market i. EUA, Heating oil are the primary volatility transmitters, while coal, clean energy are the major volatility recipients. In a skewness connectedness network, clean energy undergoes a role transformation and becomes a net transmitter in long-run. In the kurtosis spillover network, carbon market becomes the main receiver and clean energy as a net transmitter to other markets.

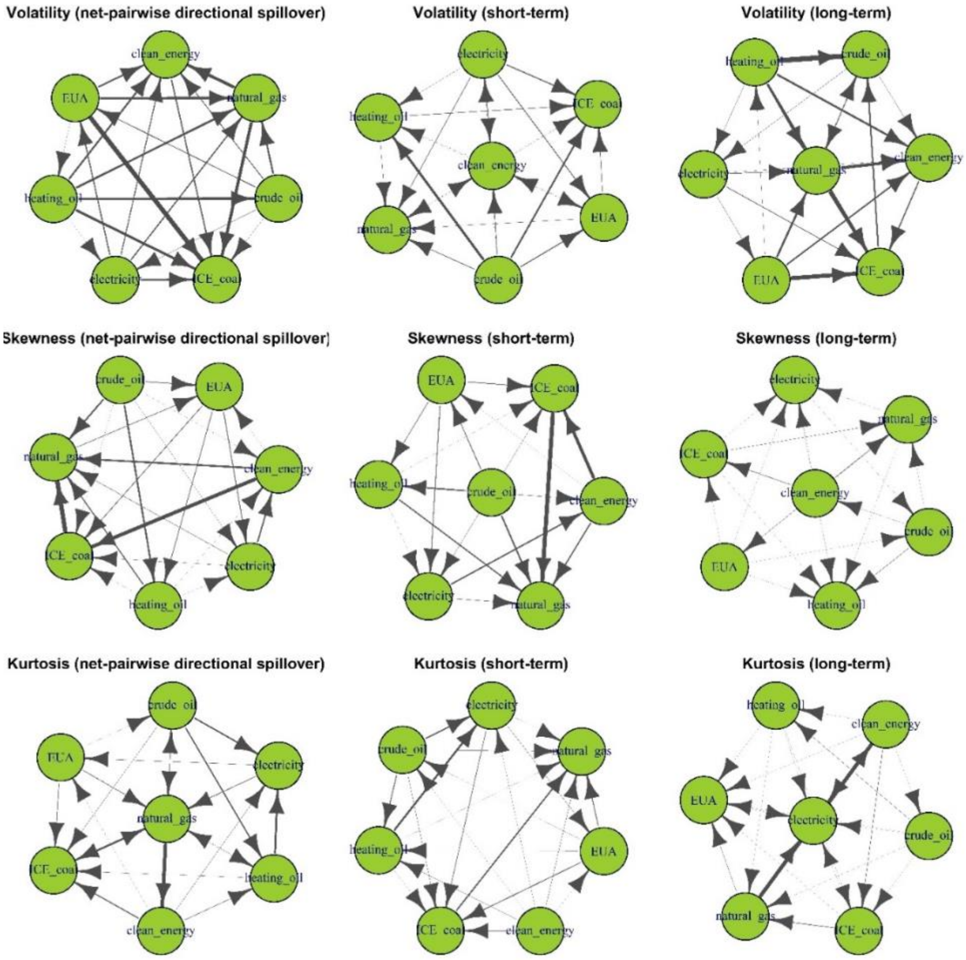


Fig. 4. Net-pairwise directional connectedness in the full-sample period. This figure shows the 21 pairs of carbon, energy and clean energy markets. The nodes represent each market, and the thickness of the edge shows the degree of the net pairwise directional connectedness. The top panels represent the volatility, skewness and kurtosis network in different frequencies, such as "Volatility (short-term)" represents the network drawn by the net-pairwise directional volatility connectedness in the short-term horizons of BK model in the full-sample period.

To accurately quantify the net-pairwise directional connectedness, we examine the network centrality characteristics of time-frequency spillovers which are shown in the Table 5.

Table 5

Network centrality characteristics of time-frequency spillovers.

		Closeness centrality	Betweenness centrality	Eigenvector centrality
Net-pairwise spillover	Volatility	EUA	EUA	ICE_coal
	Skewness	electricity	clean_energy	ICE_coal
	Kurtosis	ICE_coal	crude_oil	EUA
Short-term	Volatility	natural_gas	EUA	crude_oil
	Skewness	natural_gas	EUA	crude_oil
	Kurtosis	electricity	crude_oil	crude_oil
Long-term	Volatility	ICE_coal	clean_energy	heating_oil
	Skewness	electricity	EUA	electricity
	Kurtosis	natural_gas	natural_gas	crude_oil

Note: Only the markets with the greatest centrality in different cases are shown in the table. "Net-pairwise spillovers" is the aggregate net-pairwise directional spillovers of the DY model. "Short-term" and "Long-term" is the net-pairwise directional spillover in the short and long-term horizons of BK model, respectively.

4.4. The effects of geopolitical risk on the spillovers

4.4.1. The impact of geopolitical risk on the total risk spillover of carbon and energy markets

This study examines the impact of geopolitical risk on the carbon-energy market as a whole system as well as individually to unpack the intricate risk transmission mechanism. In this sub-section, we investigate the impact of the three GPR indices on the total spillover index for the carbon-energy network. Table 6 report the results where GPR indices are the single-factor as independent variables, the total spillover implied by DY and BK models. Main findings include first, the total spillover implied by DY model is not affected by any GPR index. The DY model estimate an average static spillover index for the whole sample period, thus the impact of GPR is not significant. Second, the GPR indices negatively impact long-term component of volatility of total volatility risk spillovers with high (short-term) frequency (sBK) while only GPRT and GPRA negatively impact long-term component of volatility of total volatility risk spillovers with low (long-term) frequency (lBK). This suggests that in the long term, people have expectation and awareness of geopolitical risk which inhibit the extreme risk spillover in the carbon, energy, and clean energy system.

Furthermore, from the results of one-factor and two-factors model (Tables 6 and 7), the total risk spillover effects from the BK model are more sensitive to GPR indices than risk spillovers from the DY model. Especially from the results of the two-factors model (Table 7), the combination of the information on risk spillovers and GPR indices distils the disturbance factors of the dependent variable which helps capture the information on geopolitical risk.

All GPR indices have stronger impacts on short-term (high) frequency risk spillover, it implies sBK matters in transmitting risk in long term and financial markets are easier to identify and absorb extreme risk spillover in the system of carbon, energy, and clean energy markets.

The threat of future geopolitical risk indexed by GPRT has more information than other two geopolitical risk indices in explaining long-run volatility of risk spillovers. This suggests that the risk spillovers effect will be weaken if the system of carbon-energy-clean energy has realized the threat of geopolitical risk.

Table 6

The impact of geopolitical risk on total volatility risk spillovers (using One factor GARCH-MIDAS model)

	α	β	γ	m	θ	w_1	w_2	K	LLH	BIC
GPR										
DY	0.560	0.513	-4.534	-3.559	0.024	1	6.202	12	-10851	21757
	(-)	(-)	(-)	(-)	(-)		(-)			
sBK	0.827 ***	0.441 ***	-0.592 *	10.302 ***	-0.054 ***	1	1.428 ***	12	-6739	13533
	(0.268)	(0.057)	(0.309)	(3.557)	(0.003)		(0.285)			
lBK	0.509 ***	0.445 ***	0.076	6.542 ***	-0.015	1	2.528	12	-8699	17452
	(0.071)	(0.047)	(0.103)	(2.407)	(0.012)		(3.646)			
GPRT										
DY	1.654	0.000	-1.313	11.781	-0.022	1	1.515	12	-9291	18638
	(-)	(-)	(-)	(-)	(-)		(-)			
sBK	0.558 **	0.482 ***	-0.112	9.599 *	-0.038 ***	1	1.889 ***	12	-6858	13771
	(0.226)	(0.080)	(0.274)	(5.325)	(0.003)		(0.483)			
lBK	0.545 ***	0.439 ***	0.011	8.305 ***	-0.027 ***	1	1.000	12	-8698	17452
	(0.102)	(0.073)	(0.116)	(2.189)	(0.008)		(1.298)			
GPRA										
DY	0.431 ***	0.699 ***	-0.259 ***	-4.634	-0.018	1	1.000	12	-10095	20245
	(0.067)	(0.034)	(0.087)	(20.218)	(0.025)		(2.669)			
sBK	0.600 ***	0.418 ***	-0.071	8.206 **	-0.033 ***	1	5.631 ***	12	-6815	13684
	(0.169)	(0.047)	(0.206)	(3.905)	(0.003)		(1.449)			
lBK	0.481 ***	0.476 ***	0.077	5.440 ***	-0.018 ***	1	3.758	12	-8688	17430
	(0.040)	(0.024)	(0.070)	(2.102)	(0.006)		(3.209)			

Notes: The sample period ranges from 25 October 2013 to 19 March 2024. We set w_{11} = 1 as a restricted weighting scheme for all models. The numbers in parentheses are Bollerslev-Wooldridge standard errors, and ***, **, * refer to the significance level of 1%, 5%, 10% in rejecting the null hypothesis. LLH is the result of the maximized log-likelihood function, and BIC is the Bayesian information criterion. In the first column, GPR, GPRT, and GPRA represent the GARCH-MIDAS model using GPR, GPRT, and GPRA as external risk variables, respectively, while DY, sBK, and lBK in the column represent the GARCH-MIDAS model using different volatility spillovers calculated from DY model, short-term BK model, and long-term BK model as return-level variables, respectively. The sign “(-)” in two rows means values of standard errors here are positive infinity or negative infinity, which means the significance of these coefficients is insignificant.

Table 7

The impact of geopolitical risk on total risk spillovers (using Two factors GARCH-MIDAS model)

	α	β	γ	m	θ_1	θ_2	w_{12}	w_{22}	K_1	K_2	LLH	BIC
RV												
DY	0.612 ***	0.386 ***	-0.012	15.021 ***	-0.274 ***		1.000 ***		12		-9024	18104
	(0.057)	(0.036)	(0.068)	(1.992)	(0.024)		(0.310)					
sBK	0.855 **	0.000	0.241	4.339	0.179 ***		1.000		12		-6774	13602
	(0.370)	(0.039)	(0.523)	(6.375)	(0.035)		(1.040)					
lBK	0.454 ***	0.535 ***	0.012	8.800 ***	-0.181 ***		1.000		12		-8621	17296
	(0.043)	(0.023)	(0.069)	(1.966)	(0.047)		(0.644)					
RV+GPR												
DY	0.671 ***	0.354 ***	-0.067	15.157 ***	-0.281 ***	0.004	4.431 ***	21.411	12	12	-9026	18123
	(0.072)	(0.041)	(0.099)	(2.261)	(0.025)	(0.008)	(1.605)	(136.567)				
sBK	0.501 ***	0.720 ***	-0.481 ***	10.033 ***	-0.188 ***	-0.042 ***	19.902	1.000 ***	12	12	-6757	13584
	(0.122)	(0.035)	(0.163)	(2.961)	(0.067)	(0.003)	(57.851)	(0.228)				
lBK	0.594 ***	0.404 ***	-0.030	10.190 ***	-0.105 **	-0.022 ***	1.000	1.023	12	12	-8613	17296
	(0.106)	(0.063)	(0.135)	(2.117)	(0.043)	(0.007)	(1.961)	(1.292)				
RV+GPRT												
DY	0.353	0.683	-5.461	0.432	-0.089	0.005	1.329	52.279	12	3	-10664	21398
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)				
sBK	0.502 ***	0.717 ***	-0.459 **	10.295 **	-0.218 **	-0.036 ***	15.378	1.000 ***	12	12	-6767	13603
	(0.135)	(0.040)	(0.189)	(4.883)	(0.093)	(0.003)	(32.248)	(0.342)				
lBK	0.469 ***	0.488 ***	0.075	6.301 **	-0.096 *	0.004	1.000	22.839	12	6	-8616	17303
	(0.049)	(0.030)	(0.079)	(2.695)	(0.055)	(0.013)	(1.339)	(1086.217)				
RV+GPRA												
DY	0.919 ***	0.193 ***	-0.268	14.175 ***	-0.196 ***	-0.010 ***	4.652	1.000	12	12	-9057	18184
	(0.156)	(0.066)	(0.189)	(2.343)	(0.022)	(0.004)	(3.258)	(1.138)				
sBK	0.627 **	0.442 ***	-0.202	5.656 **	0.124 ***	-0.023 ***	1.000	8.796 ***	12	12	-6644	13358
	(0.253)	(0.077)	(0.272)	(2.598)	(0.041)	(0.003)	(2.622)	(2.849)				
lBK	0.472 ***	0.491 ***	0.066	4.342 *	0.037	-0.019 ***	82.890	3.519	12	12	-8601	17273
	(0.041)	(0.027)	(0.071)	(2.539)	(0.061)	(0.007)	(59318.111)	(2.951)				

Notes: The sample period ranges from 25 November 2013 to 19 March 2024. We set w_{11} = 1 and w_{21} = 1 as a restricted weighting scheme for all models. The numbers in parentheses are Bollerslev-Wooldridge standard errors, and ***, **, * refer to the significance level of 1%, 5%, 10% in rejecting the null hypothesis. LLH is the result of the maximized log-likelihood function, and BIC is the Bayesian information criterion. In the first column, RV, RV+GPR, RV+GPRT, and RV+GPRA represent the GARCH-MIDAS model using one factor: average realized volatility, and two factors of average realized volatility and GPR, GPRT, and GPRA as external risk variables, respectively, while DY, sBK, and lBK in the column represent the GARCH-MIDAS model using different volatility spillovers calculated from DY model, short-term BK model, and long-term BK model as return-level variables, respectively. The sign “(-)” in two rows means values of standard errors here are positive infinity or negative infinity, which means the significance of these coefficients is insignificant.

4.4.2. The impact of geopolitical risk on net risk spillover across carbon and energy markets

From the six column θ of the results of one-factor and two-factors GARCH-MIDAS model (Tables 8 and 9), all three geopolitical risk indices significantly influence the long-run volatility of the net risk spillover of clean energy market. GPRA positively impacts it while GPRT affects it negatively with estimated coefficients of GPRT in two tables are larger than other geopolitical risk indices. The results imply that the threat of geopolitical risk matters, and particularly among geopolitical risk in reducing the long-run volatility of the net risk spillover of clean energy market. We observe that geopolitical risk indices significantly and negatively impact the long-term volatility of net risk spillover of EUA market with the most degree, followed by crude oil and electricity markets.

Table 8

The impact of geopolitical risk on net risk spillovers (using One factor GARCH-MIDAS model)

	α	β	γ	m	θ	w_1	w_2	K	LLH	BIC
GPR										
EUA	0.975 ***	0.176 ***	-0.327 *	12.290 **	-0.072 ***	1	3.716 *	12	-6810	13674
	(0.100)	(0.047)	(0.197)	(4.859)	(0.008)		(1.993)			
crude oil	0.596 ***	0.244 ***	0.308 ***	8.453 *	-0.038 ***	1	1.000	12	-5904	11862
	(0.066)	(0.040)	(0.114)	(4.329)	(0.007)		(0.852)			
heating oil	0.609 ***	0.417 ***	-0.064	3.837	-0.005	1	65.880	12	-6503	13061
	(0.058)	(0.039)	(0.072)	(2.983)	(0.005)		(4417.949)			
natural gas	0.433 ***	0.626 ***	-0.125 **	6.465	-0.024 *	1	1.000	12	-6933	13921
	(0.056)	(0.026)	(0.060)	(4.433)	(0.013)		(1.276)			
ICE coal	0.554 ***	0.433 ***	0.000	6.983 ***	-0.031 ***	1	1.000 *	12	-6983	14021
	(0.081)	(0.026)	(0.105)	(1.625)	(0.005)		(0.586)			
electricity	1.127 ***	0.120	-0.514	11.172	-0.050 ***	1	1.000	12	-6284	12622
	(0.268)	(0.187)	(0.344)	(12.090)	(0.005)		(1.367)			
clean energy	0.693 ***	0.343 ***	-0.098	6.381 ***	-0.025 ***	1	1.000 *	12	-6554	13163
	(0.095)	(0.040)	(0.138)	(2.230)	(0.005)		(0.549)			
GPRT										
EUA	0.876 ***	0.204 ***	-0.190	10.299 *	-0.047 ***	1	3.825	12	-6875	13805
	(0.135)	(0.078)	(0.336)	(6.228)	(0.007)		(3.253)			
crude oil	0.717 ***	0.314 ***	-0.076	8.653 **	-0.041 ***	1	1.000	12	-5869	11793
	(0.118)	(0.077)	(0.125)	(3.968)	(0.005)		(0.910)			
heating oil	0.610 ***	0.418 ***	-0.066	3.538	-0.003	1	1.000	12	-6505	13064
	(0.054)	(0.042)	(0.062)	(3.061)	(0.011)		(23.805)			
natural gas	0.448 ***	0.601 ***	-0.106 *	6.114	-0.017	1	1.000	12	-6937	13930
	(0.053)	(0.026)	(0.062)	(4.929)	(0.011)		(1.306)			
ICE coal	0.524 ***	0.473 ***	-0.030	6.806 ***	-0.028 ***	1	1.000 **	12	-6971	13997
	(0.070)	(0.022)	(0.086)	(1.361)	(0.004)		(0.504)			

electricity	0.675 ***	0.000	0.551	7.572	-0.023 ***	1	1.000	12	-6499	13053
	(0.166)	(0.035)	(1.951)	(17.338)	(0.003)		(2.084)			
clean energy	0.648 ***	0.345 ***	-0.032	6.577 ***	-0.031 ***	1	1.000 ***	12	-6522	13099
	(0.083)	(0.032)	(0.108)	(1.515)	(0.003)		(0.354)			
GPRA										
EUA	0.504 ***	0.600 ***	-0.215 ***	0.066	0.009	1	5.347	12	-7092	14239
	(0.037)	(0.027)	(0.072)	(3.946)	(0.015)		(12.440)			
crude oil	0.782 ***	0.153 **	0.113	4.669	0.003	1	2.005	12	-5927	11909
	(0.103)	(0.073)	(0.161)	(4.518)	(0.004)		(9.906)			
heating oil	0.616 ***	0.416 ***	-0.076	3.827	-0.006 ***	1	74.102	12	-6499	13054
	(0.059)	(0.039)	(0.074)	(2.906)	(0.002)		(3568.292)			
natural gas	0.470 ***	0.577 ***	-0.102	5.640	-0.016 *	1	2.079	12	-6931	13917
	(0.057)	(0.028)	(0.070)	(4.374)	(0.009)		(3.153)			
ICE coal	0.530 ***	0.463 ***	-0.016	4.699 ***	-0.012 **	1	1.000	12	-7001	14058
	(0.083)	(0.026)	(0.121)	(1.759)	(0.005)		(1.319)			
electricity	0.938 ***	0.353 ***	-0.602 **	8.863	-0.041 ***	1	1.000	12	-6207	12469
	(0.174)	(0.129)	(0.283)	(7.969)	(0.005)		(0.703)			
clean energy	0.737 ***	0.304 ***	-0.096	3.436	0.007 ***	1	15.178	12	-6562	13179
	(0.096)	(0.038)	(0.140)	(2.748)	(0.002)		(18.372)			

Notes: The sample period ranges from 25 October 2013 to 19 March 2024. We set w_{11} = 1 as a restricted weighting scheme for all models. The numbers in parentheses are Bollerslev-Wooldridge standard errors, and ***, **, * refer to the significance level of 1%, 5%, 10% in rejecting the null hypothesis. LLH is the result of the maximized log-likelihood function, and BIC is the Bayesian information criterion. In the first column, GPR, GPRT, and GPRA represent the GARCH-MIDAS model using GPR, GPRT, and GPRA as external risk variables, respectively, while EUA, crude_oil, heating_oil, natural_gas, ICE_coal, electricity, and clean_energy in the column represent the GARCH-MIDAS model using net spillovers across EUA, crude oil, heating oil, natural gas, coal, electricity, and clean energy markets as return-level variables, respectively.

To further perform our investigation, we employ the two explanatory components or two factors in the GARCH-MIDAS models with average realized return volatility as the key variable plus one of the other three variables - GPR, GPRT, GPRA, separately to see whether there is a complementary effect in interpreting average realized return volatility.

In Table 9, we have both statistically significant positive and negative θ_1s for all models indicating that the realized volatility has positive and negative effect on average realized return volatility. θ_2s are negative for all explanatory variables except for the clean energy market, which suggests that a varied response from this market when faced with geopolitical risk. Comparing with Table 8 when an one-factor model is estimated, the result difference for clean energy is rather apparent. In the one-factor model where estimated θs of clean energy are mostly negative, their direction of effect has changed to positive. For the value of θ_2, all variables have smaller value of θ_2 than θ_1 in the one-factor models which shows that the variables have complementary relation with average realized return volatility.

Table 9

The impact of geopolitical risk on net risk spillovers (using Two factors GARCH-MIDAS model)

	α	β	γ	m	θ_1	θ_2	w_{12}	w_{22}	K_1	K_2	LLH	BIC
RV												
EUA	0.777 ***	0.358 ***	-0.290	5.488	-0.109 *		1.000		12		-6874	13803
	(0.146)	(0.110)	(0.352)	(7.116)	(0.061)		(5.426)					
crude oil	0.844 ***	0.000	0.304	5.573	0.179 ***		2.034		12		-5882	11818
	(0.147)	(0.019)	(0.282)	(8.368)	(0.048)		(3.705)					
heating oil	0.583 ***	0.442 ***	-0.060	3.554	-0.082		1.000		12		-6476	13007
	(0.049)	(0.040)	(0.059)	(3.461)	(0.234)		(4.587)					
natural gas	0.404 ***	0.635 ***	-0.084	4.798	-0.173		1.000		12		-6845	13745
	(0.047)	(0.036)	(0.069)	(4.316)	(0.142)		(2.076)					
ICE coal	0.871 ***	0.092 ***	0.044	3.933	0.159 ***		1.568		12		-6889	13832
	(0.113)	(0.034)	(0.171)	(2.455)	(0.017)		(1.574)					
electricity	1.088 ***	0.198	-0.598	6.447	-0.163		1.572		22		-6505	13065
	(0.393)	(0.180)	(1.006)	(13.127)	(0.114)		(1.271)					
clean energy	0.814 ***	0.239 ***	-0.136	3.147	0.266 ***		1.802		12		-6489	13033
	(0.122)	(0.042)	(0.169)	(2.368)	(0.035)		(1.860)					
RV+GPR												
EUA	0.810 ***	0.188 ***	-0.013	13.301 ***	-0.233 ***	-0.074 ***	1.000	3.485 **	12	12	-6698	13466
	(0.066)	(0.039)	(0.149)	(4.884)	(0.081)	(0.009)	(1.681)	(1.569)				
crude oil	0.674 ***	0.296 ***	0.051	8.462 **	-0.459 ***	-0.033 ***	8.073	1.000	12	12	-5844	11758
	(0.110)	(0.045)	(0.172)	(4.082)	(0.148)	(0.008)	(12.711)	(1.149)				
heating oil	0.516 ***	0.497 ***	-0.034	4.066	-0.106	-0.005	1.000	43.702	12	6	-6477	13023
	(0.057)	(0.040)	(0.079)	(3.188)	(0.207)	(0.005)	(3.864)	(22257.702)				
natural gas	0.411 ***	0.623 ***	-0.074	5.905	-0.145	-0.013	1.000	1.000	12	12	-6840	13750
	(0.064)	(0.048)	(0.074)	(5.014)	(0.165)	(0.010)	(2.782)	(2.471)				
ICE coal	0.755 ***	0.181 ***	0.071	5.093 ***	0.159 ***	-0.019 ***	1.583	1.000	12	12	-6879	13828
	(0.109)	(0.046)	(0.148)	(1.609)	(0.014)	(0.004)	(1.557)	(1.117)				
electricity	0.570 ***	0.494 **	-0.167	10.852 *	-0.299 ***	-0.053 ***	1.000	1.000	12	12	-6230	12530
	(0.109)	(0.218)	(0.281)	(5.917)	(0.096)	(0.009)	(0.872)	(1.421)				
clean energy	0.838 ***	0.215 ***	-0.132	2.489	0.272 ***	0.007 ***	1.568	28.842	12	12	-6485	13041
	(0.123)	(0.047)	(0.173)	(2.549)	(0.039)	(0.002)	(1.671)	(53.012)				
RV+GPRT												
EUA	0.880 ***	0.355 ***	-0.491	5.935	-0.079	-0.004	1.000	2.294	12	12	-6880	13831
	(0.161)	(0.109)	(0.333)	(6.613)	(0.055)	(0.004)	(7.582)	(38.483)				
crude oil	0.441 ***	0.489 ***	0.123	7.933 ***	-0.375 ***	-0.034 ***	5.453	1.000	12	12	-5821	11712
	(0.112)	(0.075)	(0.133)	(2.875)	(0.128)	(0.006)	(9.978)	(0.727)				
heating oil	0.495 ***	0.504 ***	-0.006	3.271	-0.122	0.002	1.000	42.695	12	12	-6479	13029
	(0.049)	(0.040)	(0.069)	(3.403)	(0.206)	(0.009)	(3.047)	(4902.782)				
natural gas	0.371 ***	0.656 ***	-0.060	3.546	-0.188	0.011 ***	1.030	72.486	12	12	-6822	13715
	(0.052)	(0.035)	(0.074)	(5.031)	(0.124)	(0.004)	(1.911)	(2194.857)				
ICE coal	0.677 ***	0.279 ***	0.021	6.188 ***	0.126 ***	-0.027 ***	1.507	1.000 *	12	12	-6877	13824
	(0.099)	(0.049)	(0.123)	(1.270)	(0.013)	(0.004)	(1.964)	(0.527)				
electricity	0.796 ***	0.308	-0.342	7.160 **	-0.226 ***	-0.021 ***	1.000	1.000	12	12	-6387	12845
	(0.200)	(0.409)	(0.579)	(3.074)	(0.087)	(0.005)	(0.962)	(2.674)				
clean energy	0.705 ***	0.348 ***	-0.152	5.879 ***	0.204 ***	-0.029 ***	1.875	1.000 ***	12	12	-6455	12980
	(0.090)	(0.035)	(0.109)	(1.466)	(0.029)	(0.003)	(2.011)	(0.372)				
RV+GPRA												
EUA	0.754 ***	0.235 ***	0.001	9.682 *	-0.282 ***	-0.046 ***	1.000	2.837 **	12	12	-6754	13578
	(0.069)	(0.056)	(0.164)	(5.540)	(0.084)	(0.008)	(1.838)	(1.326)				
crude oil	0.560 ***	0.379 ***	0.110	5.538	-0.505 ***	-0.004	5.701	75.494	12	12	-5859	11787
	(0.093)	(0.058)	(0.140)	(3.506)	(0.107)	(0.005)	(7.590)	(12407.182)				
heating oil	0.550 ***	0.498 ***	-0.106	3.942	-0.075	-0.006 ***	1.000	71.116	12	12	-6476	13022
	(0.062)	(0.040)	(0.082)	(3.008)	(0.198)	(0.002)	(5.432)	(3242.189)				
natural gas	0.378 ***	0.641 ***	-0.045	5.728	-0.162	-0.012	1.000	2.510	12	12	-6835	13740
	(0.053)	(0.043)	(0.067)	(4.427)	(0.146)	(0.008)	(2.321)	(4.311)				
ICE coal	0.786 ***	0.072 **	0.266	4.781 *	0.164 ***	-0.004	1.878	1.001	12	12	-6894	13858
	(0.109)	(0.034)	(0.185)	(2.783)	(0.017)	(0.004)	(1.980)	(3.458)				
electricity	0.805 ***	0.417 ***	-0.477 **	8.949	-0.237 ***	-0.042 ***	1.000	1.000 *	12	12	-6104	12278
	(0.162)	(0.120)	(0.236)	(5.790)	(0.083)	(0.005)	(0.808)	(0.521)				
clean energy	0.844 ***	0.235 ***	-0.182	2.857	0.265 ***	0.005 ***	1.521	13.613	12	12	-6485	13040
	(0.119)	(0.044)	(0.163)	(2.592)	(0.042)	(0.002)	(1.597)	(19.499)				

Notes: The sample period ranges from 25 November 2013 to 19 March 2024. We set w_{11} = 1 and w_{21} = 1 as a restricted weighting scheme for all models. The numbers in parentheses are Bollerslev-Wooldridge standard errors, and ***, **, * refer to the significance level of 1%, 5%, 10% in rejecting the null hypothesis. LLH is the result of the maximized log-likelihood function, and BIC is the Bayesian information criterion. In the first column, RV, RV+GPR, RV+GPRT, and RV+GPRA represent the GARCH-MIDAS model using one factor: average realized volatility, and two factors of average realized volatility and GPR, GPRT, and GPRA as external risk variables, respectively, while *EUA, crude_oil, heating_oil, natural_gas, ICE_coal, electricity,* and *clean_energy* in the column represent the GARCH-MIDAS model using net spillovers across EUA, crude oil, heating oil, natural gas, coal, electricity, and clean energy markets as return-level variables, respectively.

5. Conclusions

This paper responds to Ahmed (2024)'s proposal for the investigation of risk spillover between carbon and energy markets and the estimation of volatility and higher-moments jointly moments while considering the impact of global risk factors. We agree that it is important to capture spillovers in higher-order moments in the system of spillovers between carbon and energy markets to avoid missing out on critical information on systemic risk. Failure to do so could lead to limited and distorted portfolio and risk management decisions, destroying investors' confidence in carbon, clean energy markets investments and developments. This will potentially affect portfolio decarbonisation and the decision to reductions in carbon-intensive assets investments while increasing investments in carbon-inefficient assets. Furthermore, our empirical evidence shows that the risk transmitter and receivers of the network various after considering the higher-order moments. In particular, electricity and clean energy become key players in time-frequency spillover framework. This highlights the asymmetric characteristics of the markets to geopolitical risk while stressing the danger of treating all markets homogeneously. Supported by strong and extensive empirical evidence, this paper contributes to the theoretical framework through exploring how the geopolitical risk affects the already complicated nexus in the carbon-energy network. The examination of the impact of GPR indices on the total spillover indices suggest in the long term, people have expectation and awareness of geopolitical risk which inhibit the extreme risk spillover in the carbon, energy, and clean energy system. The results from the impact of GPR on net spillover demonstrates that geopolitical risk significantly influences the long-run volatility of the net risk spillover of clean energy market. Furthermore, our findings show that GPRA positively impacts it while GPRT negatively impacts it with larger degree since estimated coefficients of GPRT are larger than other geopolitical risk indices. Specifically, our results imply that the threat of geopolitical risk plays a role in reducing the long-run volatility of the net risk spillover of clean energy market which is an important sector in achieving net-zero target but with limited research and examination. This finding serves as a signal for investments to continue their switch towards net-zero emissions. As for government regulatory bodies, our findings should provide pertinent information that helps officials to advance and expand their environmental and sustainability related policies.

Supplementary Materials

Supplementary Table 1: The parameter estimation for the GJRSK model. ***, **, and * denote 1%, 5%, and 10% level of significance, respectively.

Parameter		EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy
Mean equation	α_1	-0.03***	-0.55***	0.00	-0.01	0.04***	0.50***	0.19***
	β_0	0.17***	1.01***	0.07***	0.02	0.03**	1719.49***	0.03**
Variance equation	β_1	0.08***	0.01	0.10***	0.05***	0.04**	0.04**	0.05**
	β_2	0.04**	0.14***	0.02	0.01	0.01	0.84***	0.04***
	β_3	0.88***	0.78***	0.88***	0.94***	0.95***	0.12***	0.91***
	γ_0	-0.03*	-0.27***	-0.14***	0.03*	0.15***	0.14***	-0.03*
Skewness equation	γ_1	0.03**	-0.15***	-0.01	0.04***	-0.02	-0.69***	0.02
	γ_2	-0.03**	-0.08***	0.01	-0.07***	0.64***	0.58***	-0.02
	γ_3	-0.11***	-0.41***	-0.71***	0.36***	0.00	-0.47***	0.46***
	δ_0	3.51***	11.60***	3.37***	0.84***	1.82***	6.86***	2.16***
Kurtosis equation	δ_1	0.00	0.97***	0.00	0.00	0.00	0.16***	0.00
	δ_2	0.00	0.03*	0.00	0.00	0.00	0.84***	0.00
	δ_3	0.00	0.00	0.00	0.76***	0.47***	0.00	0.36***

Supplementary Table 2: The static skewness spillover connectedness based on the DY method and BK model (%). TCI presents the total spillover index. The directional spillover received of each market is denoted by "FROM", and transmitted is denoted by "TO" or "TO_ABS".

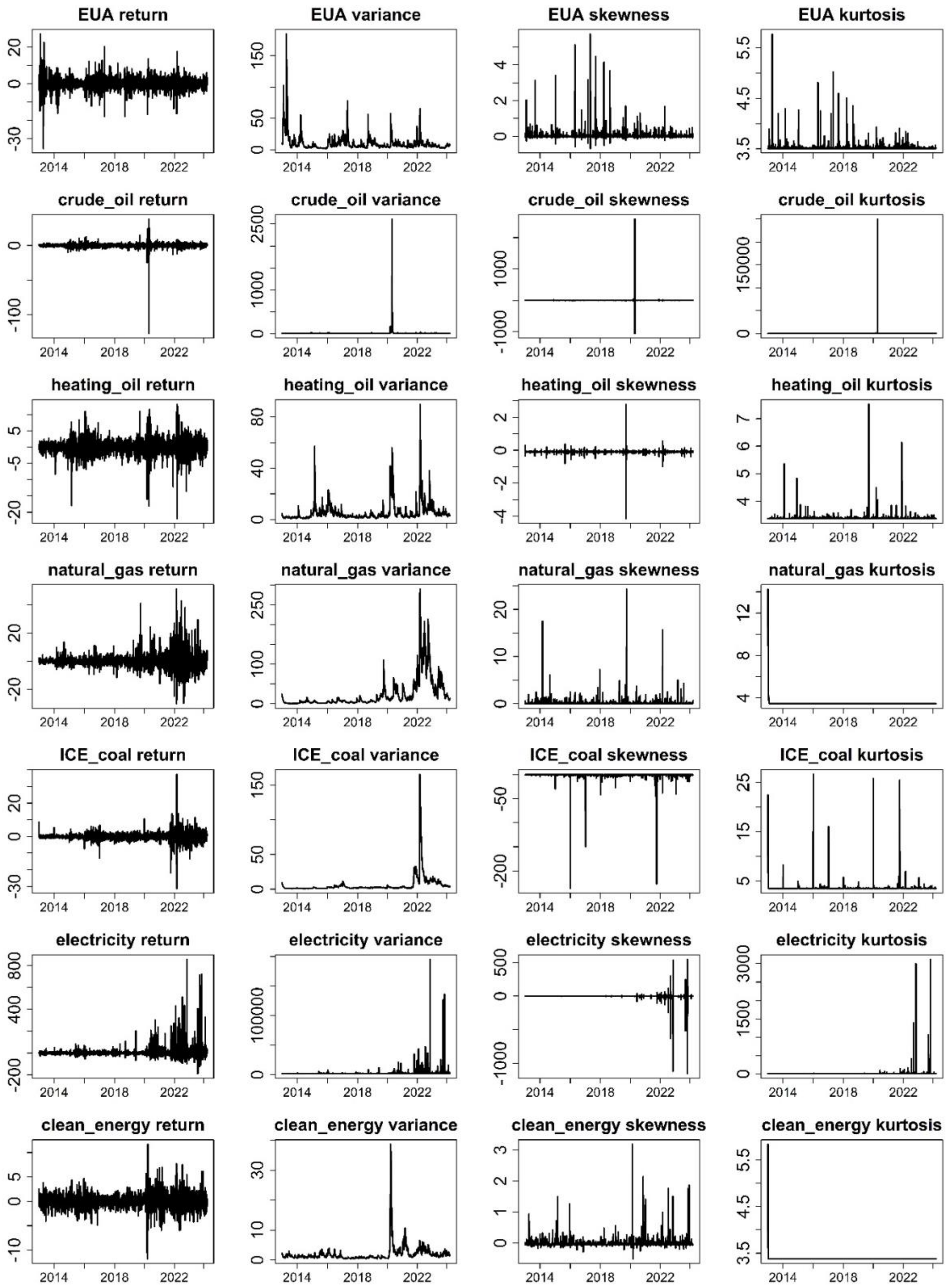
	EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy	FROM
Panel A: DY model								
EUA	99.62	0.00	0.17	0.15	0.02	0.01	0.03	0.05
crude_oil	0.01	99.97	0.02	0.00	0.00	0.00	0.01	0.00
heating_oil	0.04	0.01	99.51	0.24	0.01	0.01	0.19	0.07
natural_gas	0.21	0.00	0.06	99.59	0.01	0.01	0.12	0.06
ICE_coal	0.02	0.00	0.02	0.48	99.41	0.05	0.02	0.08
electricity	0.01	0.00	0.01	0.01	0.04	98.79	1.15	0.17
clean_energy	0.05	0.01	0.04	0.60	0.07	0.11	99.12	0.13
TO	0.05	0.00	0.05	0.21	0.02	0.03	0.22	0.57
Panel B: BK model, Frequency 1 (High Frequency): 1 day to 22 days								
EUA	95.60	0.00	0.17	0.15	0.02	0.01	0.03	0.05
crude_oil	0.01	97.88	0.02	0.00	0.00	0.00	0.00	0.00
heating_oil	0.04	0.01	98.67	0.23	0.01	0.01	0.18	0.07
natural_gas	0.18	0.00	0.06	89.17	0.01	0.00	0.11	0.05
ICE_coal	0.02	0.00	0.02	0.41	94.62	0.05	0.02	0.07
electricity	0.00	0.00	0.01	0.01	0.04	97.07	1.06	0.16
clean_energy	0.05	0.00	0.04	0.42	0.07	0.09	84.79	0.09
to_ABS	0.04	0.00	0.04	0.17	0.02	0.02	0.20	0.51
Panel C: BK model, Frequency 2 (Low frequency): 22 days to infinity								
EUA	4.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
crude_oil	0.00	2.09	0.00	0.00	0.00	0.00	0.00	0.00

heating_oil	0.00	0.00	0.84	0.01	0.00	0.00	0.00	0.00
natural_gas	0.04	0.00	0.01	10.42	0.00	0.00	0.01	0.01
ICE_coal	0.00	0.00	0.00	0.07	4.79	0.00	0.00	0.01
electricity	0.00	0.00	0.00	0.00	0.00	1.72	0.09	0.01
clean_energy	0.00	0.00	0.01	0.18	0.01	0.02	14.33	0.03
to_ABS	0.01	0.00	0.00	0.04	0.00	0.00	0.01	0.06

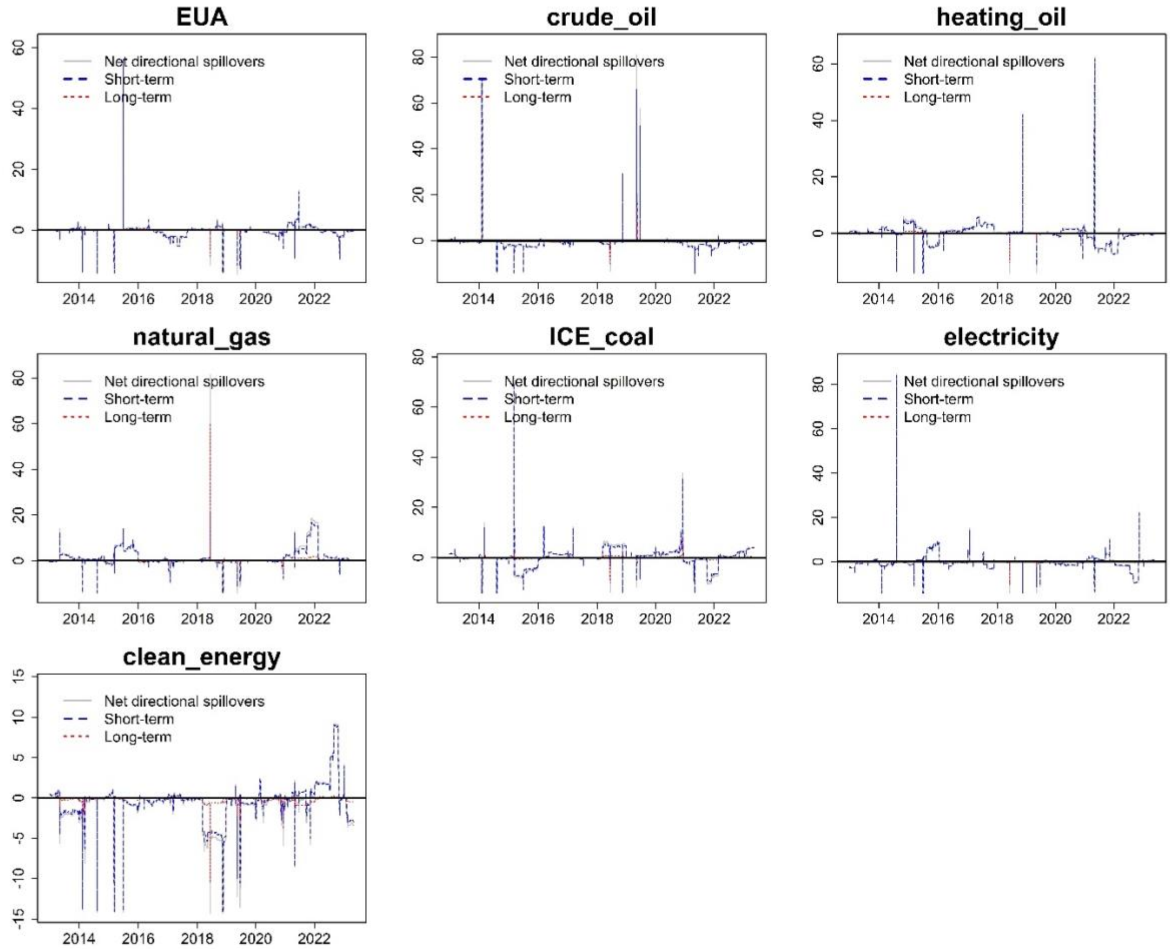
Supplementary Table 3: The static kurtosis spillover connectedness based on the DY method and BK model (%). TCI presents the total spillover index. The directional spillover received of each market is denoted by "FROM", and transmitted is denoted by "TO" or "TO_ABS".

	EUA	crude_oil	heating_oil	natural_gas	ICE_coal	electricity	clean_energy	FROM
Panel A: DY model								
EUA	99.53	0.00	0.00	0.05	0.39	0.00	0.03	0.07
crude_oil	0.00	98.62	1.38	0.00	0.00	0.00	0.00	0.20
heating_oil	0.01	1.36	97.69	0.00	0.00	0.00	0.93	0.33
natural_gas	0.05	0.00	0.00	99.83	0.09	0.00	0.02	0.02
ICE_coal	0.45	0.00	0.00	0.11	99.43	0.00	0.01	0.08
electricity	0.00	0.00	0.00	0.00	0.01	99.99	0.00	0.00
clean_energy	0.02	0.00	1.04	0.02	0.02	0.02	98.88	0.16
TO	0.08	0.20	0.35	0.03	0.07	0.00	0.14	0.86
Panel B: BK model, Frequency 1 (High Frequency): 1 day to 22 days								
EUA	94.59	0.00	0.00	0.04	0.38	0.00	0.02	0.06
crude_oil	0.00	93.74	1.31	0.00	0.00	0.00	0.00	0.19
heating_oil	0.01	1.30	92.85	0.00	0.00	0.00	0.88	0.31
natural_gas	0.03	0.00	0.00	66.99	0.07	0.00	0.01	0.02
ICE_coal	0.38	0.00	0.00	0.10	85.73	0.00	0.01	0.07
electricity	0.00	0.00	0.00	0.00	0.01	94.82	0.00	0.00
clean_energy	0.02	0.00	0.92	0.02	0.01	0.02	88.49	0.14
to_ABS	0.06	0.19	0.32	0.02	0.07	0.00	0.13	0.79
Panel C: BK model, Frequency 2 (Low frequency): 22 days to infinity								
EUA	4.93	0.00	0.00	0.00	0.02	0.00	0.00	0.00
crude_oil	0.00	4.88	0.07	0.00	0.00	0.00	0.00	0.01
heating_oil	0.00	0.07	4.84	0.00	0.00	0.00	0.05	0.02
natural_gas	0.02	0.00	0.00	32.84	0.03	0.00	0.01	0.01
ICE_coal	0.07	0.00	0.00	0.02	13.70	0.00	0.00	0.01
electricity	0.00	0.00	0.00	0.00	0.00	5.17	0.00	0.00
clean_energy	0.00	0.00	0.12	0.00	0.00	0.00	10.39	0.02
to_ABS	0.01	0.01	0.03	0.00	0.01	0.00	0.01	0.07

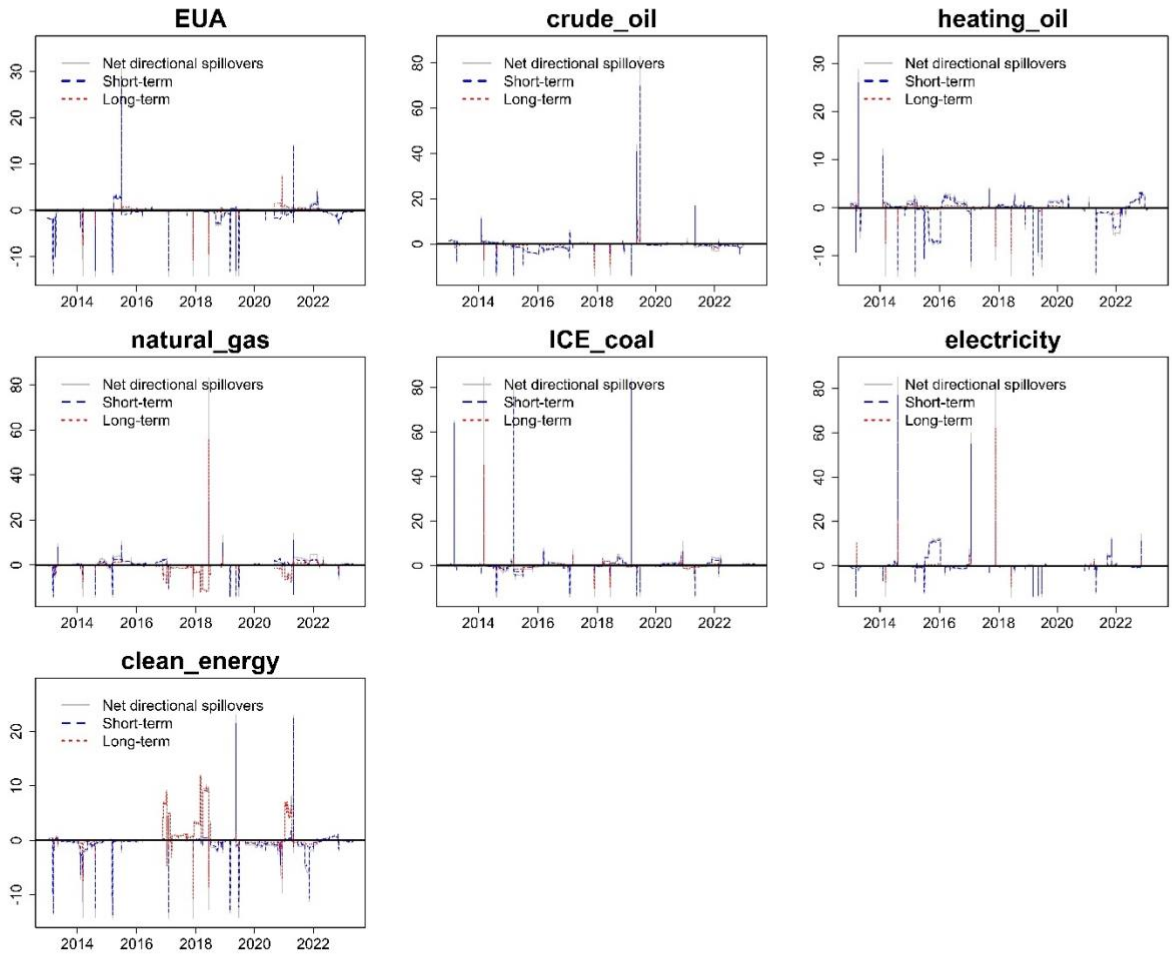
Supplementary Figure 1: The time-varying conditional return, variance, skewness and kurtosis of each market. The top panels represents the return, variance, skewness and kurtosis sequence of different markets, such as “EUA return” represents the time-varying conditional return of EUA.



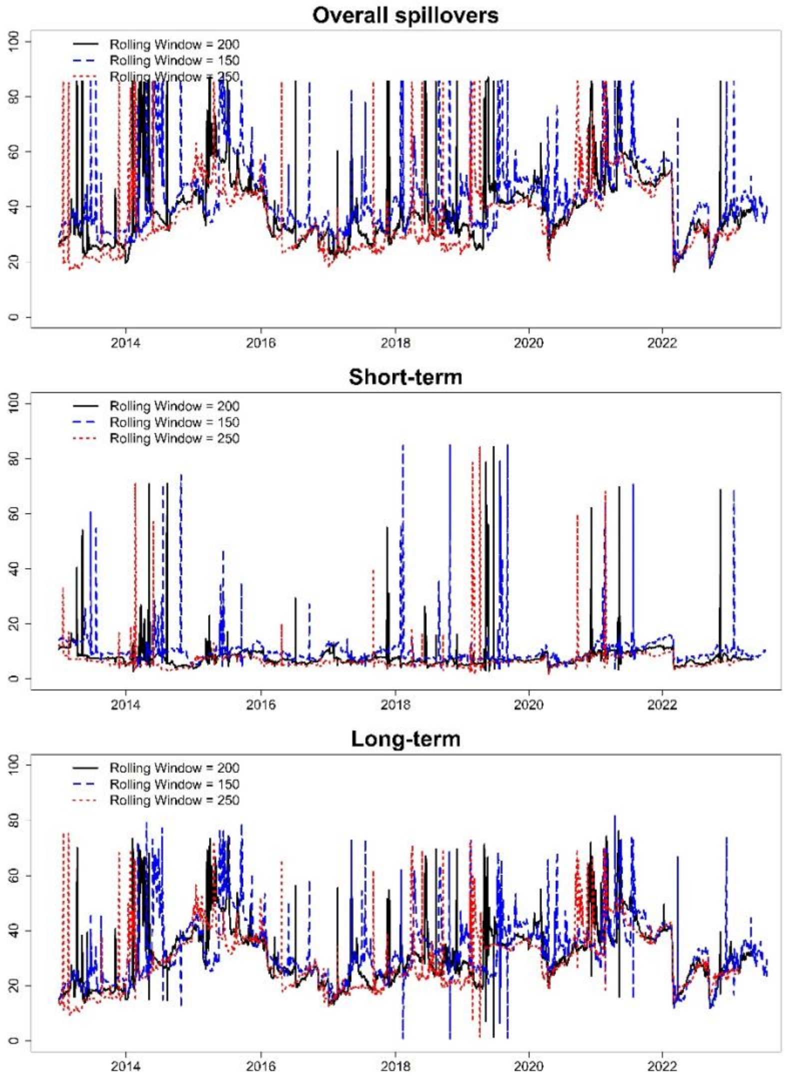
Supplementary Figure 2: Dynamic net skewness directional spillovers. The black horizontal line represents y = 0. “Net directional spillovers” is the aggregate net volatility directional spillovers of the DY model. “Short-term” and “Long-term” is the net volatility directional spillover in the short and long-term horizons of BK model, respectively. The top panels represent each market.



Supplementary Figure 3: Dynamic net kurtosis directional spillovers. The black horizontal line represents y = 0. “Net directional spillovers” is the aggregate net volatility directional spillovers of the DY model. “Short-term” and “Long-term” is the net volatility directional spillover in the short and long-term horizons of BK model, respectively. The top panels represent each market.



Supplementary Figure 4: Overall volatility spillover index using different rolling window sizes. The top panel "Overall spillovers" is the dynamic total spillover index of the DY model. "Short term" and "Long--term" is the dynamic frequency connectedness of BK model, respectively.



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