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Spillover in higher-order moments across carbon and energy markets: A portfolio view

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Abstract

Motivated by the occurrence of extreme events and nonnormality of returns, we examine the spillovers among the conditional volatility, skewness and (excess) kurtosis of European Union allowances (EUA), Brent oil, natural gas, coal, electricity and clean energy markets. The jointly estimated spillover index in the system of the three higher-order moments is notably high, exceeding the spillover index estimated for each individual moment separately. This suggests that spillovers across moments in the carbon-energy system are important for the sake of completeness of the spillover analysis, and should not be ignored. The performance of the portfolio improves after considering higher-order moments.

KEYWORDS

carbon and energy assets, COVID-19 outbreak, EU ETS, spillovers of higher moments, war in Ukraine

JEL CLASSIFICATION

C10, O13, Q40

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1 | INTRODUCTION

Launched in 2005, the European Union (EU) Emissions Trading System (ETS) is the leading and largest carbon market. It represents an effective tool to fight climate change by reducing greenhouse gas emissions. This is done through motivating EU electricity and energy-intensive industries to reduce their dependence on brown (i.e., fossil) energy sources to the detriments of green (i.e., renewable) energy sources, which has initiated a significant channel of information flow between carbon prices in the EU ETS and the price of energy assets. In fact, decreasing brown energy prices make them more appealing for consumption by energy-intensive industries, which leads to more demand and potentially higher carbon prices. This in turn will urge energy-intensive industries to develop cheaper ways to generate green energy, leading to a decrease in the prices of green energy and thus influencing the prices of other energy assets (Ji et al., 2018).

Notably, extreme events and crisis periods can influence the dynamic relationship between carbon and energy markets by affecting their individual market prices. For example, in the GFC and during the period June 2008–February 2009, crude oil and natural gas (NG) prices dropped from around \$134 and \$12.65 to \$39 and \$4.50, respectively. During the oil price collapse of June 2014–January 2015, crude oil prices declined from \$108 to \$44.08. Under the peak of the COVID-19, Brent fell to \$9.12 on April 21, 2020, and WTI oil prices dropped for the first time to \$-36.98. During the ongoing war in Ukraine, crude oil prices spiked to around \$139 and prices of other energy commodities such as NG and electricity spiked too. However, carbon emissions prices crashed, as they dropped by more than 58% over the period February 23, 2020–March 2, 2022, after experiencing a boom year in 2021 during which they tripled.[1] Importantly, such extreme events have the power of not only increasing volatility[2] and affecting volatility spillovers across carbon and energy markets (see Ji et al., 2018; Uddin et al., 2018; Wang & Guo, 2018; Zhang & Sun, 2016) but also shaking skewness away from zero and building up high and excess kurtosis and thus inducing spillover effects in skewness and kurtosis too. The foundation of potential higher-order moment-dependent spillovers between carbon and energy markets emerges from the large deviation of the return of these assets from the normal distribution, driven by extreme events[3] and market conditions. In this regard, previous studies show that the return distribution of energy assets is far from being normal[4] (Bouri, 2023; Fernandez-Perez et al., 2018; Huang et al., 2021; Zhang, Jin, et al., 2022), which makes limiting the spillover analysis to the volatility only too restrictive because information flow can be transmitted via skewness and kurtosis (see Bouri, 2023; Bouri et al., 2021, 2023; Dai et al., 2021; Zhang, Jin, et al., 2022). In fact, Table 1 confirms the nonnormality of the return distribution of

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[1]https://www.cnbc.com/2022/03/10/ukraine-invasion-crashes-carbon-credit-prices.html.

[2]For example, the crude oil implied volatility (OVX) index reached a historic intraday peak of 325.15 under the severity of the pandemic in April 2020.

[3]'Extreme events' can be regarded as extreme shocks to the energy markets, such as (1) the sharp price decline around the period mid-2014 to late 2015 resulting from the price war between Saudi Arabia and Russia; (2) the COVID-19 pandemic shock which has led to a recession and thus to an unprecedented decline in crude oil prices, accentuated by the price war between Saudi Arabia and Russia; (3) the Russia-Ukraine conflict which has intensified geopolitical risk and led to a sharp increase in energy commodities, notably crude oil and natural gas. Accordingly, these extreme events are heterogeneous in nature and their implications on the energy prices were mixed, which enriches our sample period and empirical analysis.

[4]Cont (2001) shows that the return distributions of many financial assets are not normally distributed and exhibit stylised facts such as tail properties and extreme fluctuations, invalidating many of the common statistical approaches applied to examine financial data series.

TABLE 1 Measures of spillovers.

This table reports the various measures of spillovers adopted in this paper based on the generalised forecast error variance decomposition of TVP-VAR model.

Name and abbreviation	Explanation	Formula
The total spillover index (TSI)	Measures the system-wide spillover across the six indices	$TSI_t = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(H)}$
The total directional spillover to others (TO)	Measures the total directional spillover of index i to all other indices.	$C_{\blacksquare \leftarrow i,t}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji,t}^{g}(H)} \times 100$
The total directional spillover from others (FROM)	Measures the total directional spillover of all indices to index i.	$C_{i \leftarrow \blacksquare,t}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(H)} \times 100$
The net total directional spillover (NET)	Measures the impact index i has on the analysed system	$C_{i,t}(H) = TO - FROM$

both energy commodities and EU carbon allowances. Surprisingly, the academic literature limits the spillover analysis between those markets to return and volatility only (e.g., Ji et al., 2018; Tan et al., 2021; Uddin et al., 2018; Zhang & Sun, 2016; Zhou et al., 2022), despite undisputable evidence on the deviation of their return distributions from normality and their susceptivity to extreme events and crisis periods.

Accordingly, the related literature lacks a detailed analysis on the spillover effect in higher-order moments between carbon and energy markets, especially one with a time-varying setting allowing for examining various instability and crisis periods, and the portfolio implications.

In this paper, we extend the above line of research by examining the connectedness effects between carbon allowances (European Union allowances, EUA) and various energy markets (Brent crude oil, NG, coal, and electricity and clean energy)[5] via their conditional volatility (CV), conditional skewness (CS) and conditional (excess) kurtosis jointly in the same system and in a time-varying setting. We also evaluate the performance of the portfolio that accounts for the joint spillover of the three higher-order moments' connectedness and compare it to that of the portfolio involving volatility connectedness, skewness connectedness and kurtosis connectedness separately, which has not been examined before in the related literature (e.g., Bouri et al., 2021; Dai et al., 2021; Zhang, Jin, et al., 2022). The sample covers the period July 19, 2006 to March 30, 2023, which comprises various turbulent periods such as the GFC, the oil price collapse of mid-2014 to January 2015, the COVID-19 outbreak, and the ongoing war in Ukraine, thus extending the sample of Dai et al. (2021) which is limited to January 03, 2013–November 01, 2019, covering Phase III of the EU ETS only, and does not include electricity and clean energy stock indices. Such a dynamic and rich analysis allows us to assess whether crude oil, NG or coal is a dominant player in the energy market to affect the volatility and higher-order moments of the carbon market and under which time periods. It also helps us examine whether the volatility and higher-order moments of clean energy and electricity are affected by the volatility and higher-order moments of carbon prices. Importantly, we extend the spillover analysis by considering the combined system of the three moments and make inferences on whether the volatility, skewness and kurtosis of the

[5]The choice of these markets is motivated by previous studies (e.g., Ji et al., 2018).

carbon and energy markets are interrelated, that is, experience significant dependency on cross-moments and time, and whether their inclusion in the portfolio construction will lead to an improvement in the portfolio performance.

Our main analysis shows the following results. First, the spillovers in the carbon-energy system for each of the three moments differ across time and intensity, especially during crisis periods. For example, the spillover effect in CV is comparable to that of skewness, and the latter presents a large spike during the war in Ukraine. Second, for CV, NG, coal, electricity and EUA are major net transmitters, whereas coal, Brent and clean energy are net receivers. For CS, electricity is a large net transmitter, whereas coal is a large net receiver. Moreover, NG (coal) is the major net transmitter (receiver) of conditional (excess) kurtosis. Third, the level of the total spillovers index (TSI)[6] estimated jointly in the system of the three conditional moments is much higher than the TSI estimated for each conditional moment separately, which highlights the significant spillovers across the CV, skewness and (excess) kurtosis of the six indices, and supports the joint estimation of spillovers in the three moments within the same system of spillovers. This is also notable when examining the time evolution of the spillover contributions of each conditional moment [volatility, skewness and (excess) kurtosis], which seem to exhibit a slight uptrend and some peaks around the COVID-19 outbreak. Fourth, the portfolio analysis shows that accounting for higher moments improves the portfolio's performance.

Those results nicely complement previous studies (e.g., Ji et al., 2018; Liu et al., 2023; Tan et al., 2021; Uddin et al., 2018; Zhang & Sun, 2016; Zhou et al., 2022) arguing that the return or volatility information spillovers between those markets are significant and informative, especially during crisis periods, and have important implications for portfolio and risk management (Wen et al., 2017). However, these studies have ignored the spillover in higher-order moments separately and jointly, and the portfolio implications. Compared to Ji et al. (2018), who point to the complexity of the system linking energy with carbon prices, and Liu et al. (2023), who examine the spillovers across EUA, electricity prices and traditional energy prices, we show that information flow between these markets is multifaceted and involves not only volatility but higher-order moments such as skewness and kurtosis. Accordingly, our analysis considers a broader and more comprehensive view on systemic risk in the system of EUA, Brent oil, NG, coal, electricity and clean energy markets based on spillovers in high-order moments jointly estimated in the same system of spillovers. This is in line with previous studies on the importance of skewness and kurtosis spillovers for energy and other commodity markets (Bouri, 2023; Bouri et al., 2021, 2023; Dai et al., 2021; Zhang, Jin, et al., 2022), suggesting the necessity and suitability of considering the effects of extreme events and crisis periods on the dynamics of spillovers of various moments. Compared to Dai et al. (2021), who consider the spillover effects in higher-order moments of crude oil, coal and NG across various time scales, over the period January 03, 2013–November 01, 2019, that only covers the Phase III of the EU ETS, our paper is different in several aspects. First, we use a larger data set covering not only EUA, Brent oil, NG, 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 July 19, 2006–March 30, 2023, which allows us to reflect more phases of the EU ETS market and important recent extreme

[6]The total spillover index measures the system-wide spillover across the EUA, Brent oil, natural gas, coal, electricity and clean energy markets. It is estimated for each of conditional volatility, conditional skewness and conditional (excess) kurtosis separately, and for the three conditional moments jointly in the same system of spillovers.

events such as the COVID-19 outbreak, and the Russia-Ukraine war, both of which 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. Second, 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 TSI 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 understood 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. Third, regarding the evidence showing that accounting for higher-order moments improves the portfolio's performance, we add to Dai et al. (2021) who studied spillovers in higher-order moments and conducted a mean-variance optimisation with skewness and kurtosis. In other words, Dai et al. (2021) looked on spillover and portfolio optimisation as two separate problems while adopting a mean-variance optimising analysis with skewness and kurtosis. Instead, we consider them as one in our framework for the analysis of portfolio implications. Specifically, we adopt a more convenient and realistic framework where the portfolio optimisation is done based on the results of the spillover effects in higher-order moments, while minimising the spillovers estimated for each moment separately and for the three moments jointly. This also adds to Nekhili and Bouri (2023) who show the importance of considering co-skewness and co-kurtosis in the spillover analysis and the hedging of US stock, crude oil and gold markets. Several possible courses of action and decisions for investors and policymakers can be implied from the above findings. For investors and portfolio managers, they concern risk management and portfolio decarbonisation decisions under the spectrum of higher-order moments, which allows for making more refined decisions under the presence of extreme events. Notably, if higher-order moments spillovers are ignored and the joint spillover effects are overlooked, an important amount of information can be missed from the system of spillovers between carbon and energy markets, which might result in making limited portfolio and risk management decisions. In fact, our portfolio analysis shows that the performance of the portfolio improves after considering higher moments, which should be useful and relevant for portfolio managers and risk managers seeking to improve the performance of their portfolios. For policymakers, the implications concern the design of policies for the benefits of market cohesion and stability, especially under extreme events during which crash risk contagion can manifest and hit hard, requiring special care and more timely warning signal and attention.

The rest of the paper is organised as follows. Section 2 reviews the related literature on the spillovers between carbon and energy assets. Section 3 provides the econometric models and Section 4 describes the data set. Section 5 reports the empirical results and discusses the findings. Section 6 provides the portfolio implications. Section 7 offers the main conclusion and policy implications.

2 | RELATED STUDIES AND FORMULATED HYPOTHESES

2.1 | Related studies

Since the formation of the European Union Emission Trading System (EU ETS) in 2005, the carbon market has been gaining more attention among researchers and practitioners as a significant tool for risk management (see, among others, Subramaniam et al., 2015). In parallel, the energy markets not only have an impact on the global economy and financial markets, but also influence political stability and are often subject to extreme events related to terrorism, global economic recessions and geopolitical conflicts (Sahir & Qureshi, 2007). Such extreme events have severe and medium-term impacts on energy markets and could lead to structure breakpoints in energy markets, the impacts of which may last for several years (Zhang et al., 2009). Besides, oil returns matter for the returns of clean energy stocks (Geng et al., 2021). The energy and financial markets are related (Bouri et al., 2021; Ding et al., 2022; Sadorsky, 2012; Saeed et al., 2021; Tan et al., 2020) and previous studies show that both carbon and energy assets have strong financial attributes (Medina & Pardo, 2013) and are interrelated.

Earlier studies considered the impact of energy commodities returns on EUA returns and apply cointegration or Granger causality tests. Mansanet-Bataller et al. (2007) find evidence of a positive impact of crude oil and NG. Alberola et al. (2008) confirm the positive effect of NG returns but report a negative impact of coal returns on EUA returns. Furthermore, Keppler and Mansanet-Bataller (2010) consider the feedback effect from EUA to various energy assets. Chevallier (2011) highlights the sensitivity of the carbon market to various shocks covering macroeconomics, finance and commodities. Later studies (Chevallier et al., 2019; Dutta et al., 2018; Hammoudeh et al., 2014; Ji et al., 2018; Tan et al., 2021; Yu et al., 2015; Zhang & Sun, 2016; Zhou et al., 2022) apply more sophisticated models and show a significant relationship between the returns and volatility of carbon and various energy assets, which seems to depend on the data sample and econometric model. While the theoretical and empirical evidence on the significant relationship between these markets is well recognised, previous studies suggest that carbon and energy markets form a complex system (Ji et al., 2018).

Interestingly, the above results are indirectly drawn on the limited and unrealistic assumption that the return distributions of carbon and energy markets are normal, which is refuted in previous studies and the results of Table 1 where the returns pursue skewness and have fat tails. Therefore, understanding how carbon[7] and energy markets are interrelated via their skewness and kurtosis besides volatility is a relevant research question. Skewness quantifies the asymmetry in the distribution of asset returns; negative skewness captures asset returns with a higher likelihood of a price decrease, whereas positive skewness captures asset returns with a larger likelihood of an increase in price (Zhang, Bouri, et al., 2022). The return distribution's tail and peak characteristics are reflected by kurtosis. A fat tail in the asset return distribution, shown by high kurtosis, indicates a significant likelihood of extreme return values. Previous studies demonstrate that skewness can be utilised as an alternative for tail risk (e.g., Bevilacqua & Tunaru, 2021) or crash risk (e.g., Bakshi et al., 2003) and its importance for risk management and portfolio implications is well recognised. In fact, several studies (Bali et al., 2008; Christoffersen et al., 2021; Harvey et al., 2010; Langlois, 2020) argue that higher-order moments information is the main risk that market participants such as traders, investors and policymakers encounter and it represents the primary source of systemic risk that must be taken into consideration.[8] Other studies highlight the importance of higher-order moments for portfolio analysis (see, Harvey et al., 2010; Kim et al., 2014). Therefore, the spillovers in higher

[7]Carbon prices exhibit instability during crisis periods (Ahonen et al., 2022).

[8]Green et al. (2018) and Fernandez-Perez et al. (2018) argue that the skewness factor illustrates the cross-section of commodity futures returns beyond exposures to standard risk premia.

moments in different markets have been examined, while considering stock markets (Finta & Aboura, 2020; He & Hamori, 2021) and commodity markets (Bonato et al., 2020; Bouri, 2023; Bouri et al., 2021, 2023; Zhang, Jin, et al., 2022). Additionally, higher-order moments are significant in asset pricing (Boudt et al., 2020; He & Hamori, 2021), and have implications for the forecasting of Value-at-Risk (VAR) (Wang et al., 2022).[9] Carnero et al. (2023) focus on the skewness of energy returns and highlight its implications for tail risk.

Hence, studying higher-order moments could be highly informative for investigating asymmetric or fat-tail risk associated to extreme, upside (downside) risk under bullish and bearish market conditions (Amaya et al., 2015; Bouri, 2023; Bouri et al., 2021, 2023; Finta & Aboura, 2020; He & Hamori, 2021; Zhang, Jin, et al., 2022; Zhang, Bouri, et al., 2022). In addition, Yu et al. (2015) show that there is a growing interest in the non-Gaussian behaviour on carbon and energy markets which indicates that return-/volatility-based analysis could be insufficient to understand the underlying risk spillover between the carbon and energy markets. Therefore, our current study somewhat examines the interaction of volatility, return asymmetry and fat tailedness between carbon and various energy markets in a time-varying setting. Notably, it provides evidence regarding the performance of the portfolio that reflects the higher-order moments' connectedness and compares it to that of the portfolio involving volatility spillovers, skewness spillovers and (excess) kurtosis spillovers separately. This evidence of the spillover effect of the three moments jointly estimated in the same system of spillovers and the portfolio construction strategies and their performance evaluation has not been examined before in the related literature, which nicely complements Zhang, Jin, et al. (2022), Dai et al. (2021) and Nekhili and Bouri (2023).

2.2 | Formulated hypotheses

As indicated in the introduction section, the EU ETS market can be used to reduce greenhouse gas emissions, by motivating electricity and energy-intensive industries to diminish their dependence on brown (i.e., fossil) energy sources to the detriments of green (i.e., renewable) energy sources. This has initiated a significant channel of information flow between EUA and energy markets. In this regard, decreasing brown energy prices make them more appealing for consumption by energy-intensive industries, which leads to more demand and potentially higher EUA prices. This in turn will urge energy-intensive industries to develop cheaper ways to generate green energy, leading to a decrease in the prices of green energy, and thus influences the prices of other energy assets (Ji et al., 2018).

The discussion on potential risk transmission in the system of EUA, Brent oil, NG, coal, electricity and clean energy markets via their CV, skewness and (excess) kurtosis is founded on the basis of the interactions across these higher-order moments, mostly driven by the occurrence of extreme events and large deviation of returns from the normal distribution. Thus, we argue that extreme events have the power of not only increasing volatility and affecting volatility spillovers across EUA and energy markets (see Ji et al., 2018; Uddin et al., 2018; Wang & Guo, 2018; Zhang & Sun, 2016) but also pushing skewness away from zero and building up high and excess kurtosis and thus inducing spillover effects in skewness and kurtosis too (Dai

[9]For a review of the literature on higher-order conditional moments, see Soltyk and Chan (2023).

et al., 2021). Notably, the spillover effects of the three higher-order moments jointly estimated within the same system are significant and should not be underestimated.

Accordingly, we formulate the following hypotheses:

H1. There is a significant spillover effect across the conditional volatility of EUA and energy markets;

H2. There is a significant spillover effect across the conditional skewness of EUA and energy markets;

H3. There is a significant spillover effect across the conditional (excess) kurtosis of EUA and energy markets;

H4. The spillover effect estimated jointly in the system of the three higher-order moments is high, exceeding the spillover effect estimated for each conditional higher-order moment separately. H4 reflects the importance of cross higher-order moment spillovers in the carbon-energy system and, for the sake of completeness of the spillover analysis, they should not be ignored.

3 | METHODOLOGY

First, we obtain higher-order conditional higher-order moments, namely CV, skewness and (excess) kurtosis based on the ACD model of Hansen (1994). Second, we analyse dynamic spillover effects in higher-order moments between EUA and energy markets by applying a variance decomposition in a vector autoregressive (VAR) system. This is done for each conditional higher-order moment separately and for the three conditional higher-order moments jointly within the same VAR system. Third, we assess the contribution of each higher-order moment to the TSI jointly estimated for the three higher-moments.

3.1 | The autoregressive conditional density (ACD) model

The ability of CV models such as GARCH processes cannot be overestimated in modelling the CV of financial series, as well as commodities. However, modelling higher-order moments such as skewness and kurtosis is relevant and essential when volatility cannot fully describe the variability of returns due to the existence of extreme events and a large deviation of returns from normal distribution. This requires alternate models proficient at taking 'excess over sigma shocks', such as the ACD model of Hansen (1994). This model includes the autoregressive moving average generalised autoregressive conditional heteroscedasticity process (ARMA-GARCH) improved with supplementary parameters relating time-varying CS and kurtosis of a precise distribution $\mathfrak{D}$ as:

$$r_t = c + \sum_{j=1}^{p} \gamma_j r_{t-i} + \sum_{j=0}^{q} \theta_j \epsilon_{t-j}, \tag{1a}$$

$$\epsilon_t = \sigma_t z_t, \tag{1b}$$

$$z_t \sim \mathfrak{D}(0{,}1, \rho_t, \varsigma_t), \tag{1c}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i \, \epsilon_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2, \tag{1d}$$

$$\Phi(\rho_t) = f(\bar{\rho}_t), \tag{1e}$$

$$\Phi(\varsigma_t) = g(\bar{\varsigma}_t). \tag{1f}$$

Pertaining to the mean Equation (1a), the return on every asset is denoted by r_t. The constant term is c. The residual and white noise (with unit variance) are indicated by ϵ_t and z_t, respectively. Regarding the variance Equation (1d), the conditional variance, σ_t^2, depends on its pat value σ_{t-j}^2, a constant term, ω, and the past innovation to the variance, ϵ_{t-i}^2. To confirm its positivity, the three following conditions should be respected: $\omega > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$. Furthermore, ρ_t is the skew parameter reflecting the asymmetry of return distribution and ζ_t is the shape parameter indicating the kurtosis of the tails. $\Phi(.)$ is a transformation function, applied to the unconstrained motion dynamics of parameters ($\bar{\rho}_t$ *and* $\bar{\varsigma}_t$), making them to adhere to their distribution-specific bounds, with f and g representing their corresponding motion dynamic functions.

The skew and shape parameters differ with time within the ACD model. Along the lines of Hansen (1994), we apply first-order quadratic-type dynamics for higher-order moment parameters as follows:

$$\bar{\rho}_{\rm t} = a_0 + a_1 z_{t-1} + a_2 z_{t-1}^2 + c_1 \bar{\rho}_{\rm t-1}, \tag{2}$$

$$\bar{\zeta}_{\rm t} = b_0 + b_1 z_{t-1} + b_2 z_{t-1}^2 + d_1 \bar{\zeta}_{\rm t-1}. \tag{3}$$

We find the CV, skewness and (excess) kurtosis from the ACD model with normal inverse Gaussian (NIG) innovations, bearing in mind that the use of NIG distribution is appropriate for attaining a reasonable modelling (e.g., He & Hamori, 2021). Notably, when applying the skewed generalised error distribution for the innovations, our outcomes remain largely unchanged.

3.2 | The spillover approach

The original spillover approach of Diebold and Yılmaz (2014) is established on the generalised forecast error variance decompositions (GFEVD) calculated from a VAR model.[10] It requires the application of a rolling window to calculate spillover indices that differ across time. However, such a rolling analysis is not free of limitations because it is usually sensitive to the selection of window size and leads to a loss in the sample period to create time-varying spillover indices, which is equal to the window size. The TVP-VAR approach of spillover adopted by

[10]Several studies have relied on this powerful approach of spillovers (e.g., see Abosedra et al., 2020; Balli et al., 2019; Bouri et al., 2021, 2023; Zhang, Jin, et al., 2022).

Antonakakis et al. (2020), based on the initial work of Primiceri (2005) and Koop and Korobilis (2014), deals with these shortcomings. It depends on multivariate Kalman filters, which make it less sensitive to outliers. In this paper, we apply the TVP-VAR spillover approach that has become a progressively popular method for analysing the spillover effects through financial and macroeconomic variables.

Assume an n-variable TVP-VAR(p) method with stationary covariance, where the lag length p is chosen according to Bayesian information criterion (BIC). It has the following representation:

$$Y_t = \beta_{0,t} + \beta_{1,t} Y_{t-1} + \beta_{2,t} Y_{t-2} + \ldots + \beta_{p,t} Y_{t-p} + \varepsilon_t, \tag{4}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + vec(\beta_{t-2}) + \ldots + vec(\beta_{t-p}) + v_t, \tag{5}$$

where Y_t is an n-dimensional endogenous vector, representing the CV, skewness or (excess) kurtosis of the six indices under study. ε_t is an n-dimensional vector of i.i.d. innovations, which has an $n \times n$ dimensional variance-covariance matrix, S_t. $\beta_{0,t}$ is a vector of six intercepts. $\beta_{1,t} Y_{t-1}, \beta_{2,t} Y_{t-2}, \ldots, \beta_{p,t} Y_{t-p_t}$ are $n \times n$ lag coefficient matrices; v_t is an $n^2 \times 1$ vector of i.i.d. innovations, which has an $n^2 \times n^2$ dimensional variance-covariance matrix, V_t.

Next, the TVP-VAR model is transformed into a vector moving average representation using the Wold theorem:

$$Y_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} + \varepsilon_t. \tag{6}$$

Then, based on the unscaled GFEVD, represented in Equation (7), we calculate the scaled in Equation (8) to make sure that all indices under study explain 100% of index i's forecast error variance.

$$\theta^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} \left(e_i' A_t S_t e_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(e_i A_t S_t A_t' e_i\right)}, \tag{7}$$

$$\tilde{\theta}^g_{ij,t}(H) = \frac{\theta^g_{ij,t}(H)}{\sum_{j=1}^{N} \theta^g_{ij,t}(H)}, \tag{8}$$

$\sum_{j=1}^{k} \theta^g_{ij,t}(H) = 1, \sum_{i,j=1}^{k} \tilde{\theta}^g_{ij,t}(H) = k$. Furthermore, e_i is a vector with 1 on the ith element and 0 otherwise. As for $\tilde{\theta}^g_{ij,t}(H)$, it captures the pairwise directional spillover from index j to index i at horizon H.

Following Diebold and Yılmaz (2014), several measures of spillover are computed (see Table 1).

We apply the TVP-VAR spillover method to each moment (volatility, skewness and kurtosis) of the six indices separately within a 6-variable VAR. Furthermore, we use the TVP-VAR spillover approach on the three moments of the six indices together within the same system of spillovers, which leads to an 18-variable VAR system. In both cases, we calculate the spillover measures stated in Table 1.

3.3 | The contribution of each moment to the TSI on average and across time

After conducting the spillover analysis of the three higher-moments in the same VAR system, we explain the importance of analysing the spillover effects of volatility, skewness and kurtosis jointly by considering the contribution of each moment to the TSI index jointly estimated for the three moments (i.e., the spillover measures estimated in the 18-variable VAR system). Specifically, we calculate own volatility and cross volatility spillovers, own skewness and cross skewness spillovers, and own kurtosis and cross kurtosis spillovers. Examining the contribution (own and cross) is encouraged from the work of Fengler and Gisler (2015) in which the significance of covariance to volatility spillover is investigated.[11] Furthermore, Bouri (2023) considers the case of green energy, brown energy and technology stocks indices. In our case, own volatility spillovers are 'the sum of directional spillovers from all volatility series to all volatility series'. Cross volatility spillovers are 'the sum of directional spillovers from all volatility series to skewness and kurtosis moments'. Similarly, own skewness (kurtosis) spillovers are 'the sum of directional spillovers from all skewness (kurtosis) series to all skewness (kurtosis) series'. Cross skewness (kurtosis) spillovers represent 'the sum of directional spillovers from all skewness (kurtosis) series to all volatility series'. Notably, we examine the contribution of each moment to the TSI across time, which is new to Fengler and Gisler (2015), Bouri (2023) and Nekhili and Bouri (2023).

4 | DATA AND PRELIMINARY ANALYSIS

We use daily closing prices for six indices, namely the EUA[12] future prices, which are traded in the Intercontinental Exchange (ICE). Brent crude oil (Brent) futures prices are the ICE-Brent crude oil continuous index. NG prices are NG futures, TTFG1MON. Coal (COAL) futures prices are ICE-COAL Rotterdam continuous index. Nordic electricity prices (Electricity) are Nordpool-ENO continuous index. Notably, future prices can better reflect the market supply and demand of the EUA and energy market than spot prices due to their high trading activities. EU Renewable Energy index (Clean) reflects the performance of the clean energy sector, which comprises businesses that tend to benefit from the transition toward cleaner energy and decarbonisation. All data are collected from the Bloomberg terminal and converted to Euro. The sample period is July 19, 2006–March 30, 2023, yielding 4289 daily return observations for each series, according to the availability of data. Interestingly, the sample covers a part of EUA Phase I (2005–2007, the EUA trading phases II (2008–2012) and III (2013–2020), and the beginning of phase IV (2021–2028). Introduced in 2005, the EU ETS provides incentives to meet the goals set in the Kyoto protocol. Under this EU ETS scheme, market participants can buy or receive emissions allowances. Initially, the EU ETS was based on the 'cap and trade' principle; under the cap, market participants can trade CO_2 emission allowances freely, as determined by market forces (European Commission, 2015). The EU ETS sets a maximum cap on greenhouse gas emissions emitted by corporations and facilities, which is decreased annually with the

[11]Recently, Nekhili and Bouri (2023) consider the significance of higher-order moments and co-moments to the spillover analysis involving US stock, crude oil and gold markets.

[12]The contract size is as follows: One lot of 1000 EUAs, where each EUA is an entitlement to emit one tonne of carbon dioxide equivalent gas.

objective of carbon neutrality by the year 2050. The EU ETS has evolved from Phase I (2005–2007), which operated as a trial phase before the full adoption of the Kyoto protocol, to Phase II (2008–2012), which worked jointly with the Kyoto protocol, to Phase III (2013–2020), under which carbon emissions were set to be cut by 20%. The EU ETS is currently in Phase IV (2021–2030), and the sectors covered by this trading scheme are demanded before the end of 2030 to cut their carbon emissions by 43% compared to 2005 levels.

Furthermore, the sample period is large enough, comprising the 2008 global financial crisis (GFC), oil price crash of mid-2014 to January 2016,[13] the COVID-19 pandemic, and the war in Ukraine. As shown in Figure 1a, Brent and CLEAN exhibit a sharp decline following the GFC and a shy rebound afterwards, including the period following the peak of the pandemic, while we notice that from Q2 2020 onwards, EUA, NG, COAL and Electricity experienced a large spike that was temporarily disrupted by the war in Ukraine. The index is transformed into log-returns before being employed in the ACD model. As shown in Figure 1b, the time evolution of the log-returns exhibits large fluctuations during various crisis periods, notably during the pandemic for Brent, Clean, and Electricity, and during the war in Ukraine for Coal. From 2017, EUA prices were climbing due to tightening cap and implementation of new operationalities such as market stability reserve. During February–March 2020, EUA prices declined from around 30 euro/tCO_2 to less than 20 euro. After that, they climbed sharply to around 95 euros in early February 2022, helped by inflation and high energy prices, before recouping almost 40% of the price gains during the early days of the war in Ukraine. In contrast, several energy prices have increased due to the war in Ukraine's shock to the commodity markets. Such a decoupling of EUA from energy prices is not common and is possibly due to the adverse impact of the sanctions imposed on Russia, given that the EU relies on Russian gas to meet 40% of its gas consumption needs. The imposed sanctions limit Russian trade with the EU and freeze individuals' and companies' assets and possibly encourage EU countries to adopt more strict energy efficiency, which ultimately reduces the demand for emission allowances. A quite similar price behaviour is shown for Nordic electricity and NG futures prices.

Table 2 shows that all mean returns are positive. EUA has the only negative mean of returns. The standard deviation is reported for NG and EUA, whereas the lowest is for Coal and Clean. The skewness value is positive for Coal and Electricity but negative for the rest. Excess kurtosis is omnipresent, especially for EUA and NG, suggesting a leptokurtic distribution. Jarque–Bera statistics confirm the deviation from the normal distribution. All returns are stationary according to the results of the augmented Dickey–Fuller (ADF) and Philips–Perron (PP) tests.[14]

5 | RESULTS

In this section, we first give an overview of summary statistics of the CV, skewness, and kurtosis of the returns of EUA, Brent, NG, Coal, Electricity and Clean energy markets. Second, we present the results on the dynamic spillover effects across these markets for each moment (volatility, skewness and kurtosis) separately. Third, we focus on the dynamic spillover effects across those markets of the three moments jointly. Lastly, we examine the contribution of each moment to the TSI estimated for the three moments jointly.

[13]It was the result of a price war between Saudi Arabia and Russia.

[14]Unreported results of the Autoregressive Conditional Heteroscedasticity (ARCH) test of heteroscedasticity conducted on the squared residuals at lag 10 are found to be statistically significant for most cases, which justifies the use of a GARCH-based model.

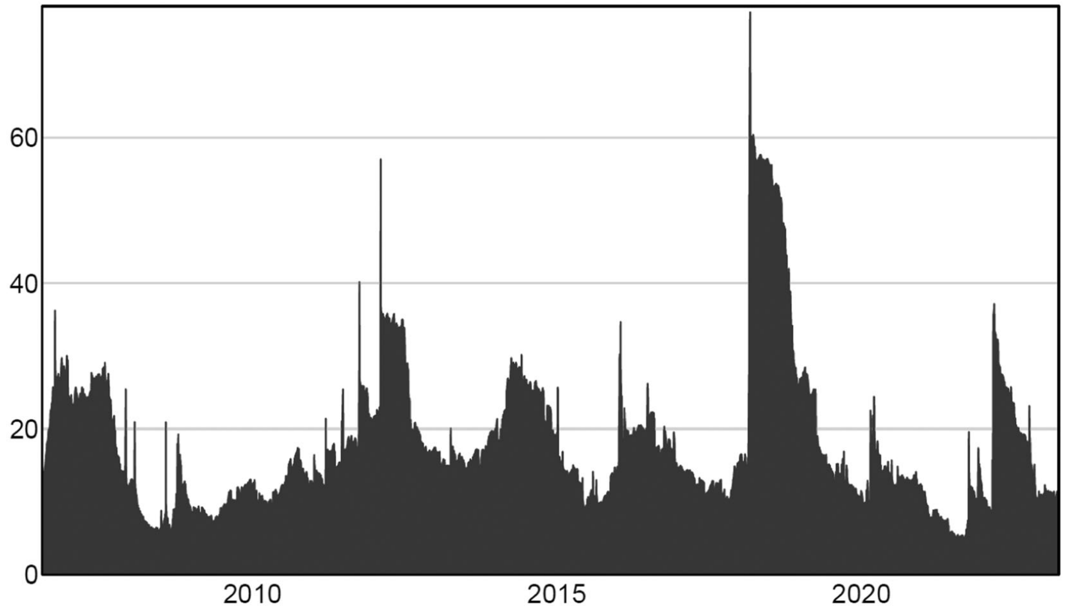

FIGURE 1 The total spillover index of conditional volatility. This figure displays the time-varying dynamics of the total conditional volatility spillover index using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 2 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion. [Color figure can be viewed at wileyonlinelibrary.com]

5.1 | Extraction of the three conditional moments

Table 3 reports summary statistics of daily CV (panel A), CS (panel B) and conditional excess kurtosis (panel C) for carbon and energy markets under study. Panel A shows that the mean values of the CV are the highest among EUA, NG and Electricity. Moving to Panel B, the mean value of skewness is positive, except for Clean energy. Regarding kurtosis, Panel C indicates that the highest mean value is for Clean energy, Brent and Coal, whereas NG has the lowest mean value. The distributions of the three moments for all series are not normally distributed, but rather show high peaks and nonzero skewness. This is evidenced in the Jarque–Bera statistics. The Augmented Dickey Fuller (ADF) and Phillips–Perron (PP) tests indicate the stationarity of the three moments of all series under study.

Table 4 shows the correlation matrix for the three-moment series. Panels A–C indicate a weak correlation between EUA and energy assets, irrespective of its statistical significance.

5.2 | Results of spillovers—Estimated for each conditional higher-order moment separately

In this section, we consider the averaged spillovers of CV, skewness and kurtosis estimated separately, which helps in understanding the information flow and transmission mechanism among carbon and energy markets.

TABLE 2 Summary statistics of daily returns.

This table reports the summary statistics of daily returns. The sample period is July 19, 2006–March 30, 2023, yielding 4289 daily return observations. Jarque–Bera tests the normality for the distribution of the series. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test the stationarity of the series, conducted with an intercept based on a lag length selected according to SIC. *** indicates statistical significance at the 1% level.

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	ADF	PP
EUA	−0.1160	109.8612	−138.6294	5.6966	−1.9533	225.7115	8,866,731***	−11.846***	−83.428***
Brent	0.0046	19.6328	−28.5255	2.3548	−0.6977	17.6358	38,628.5***	−66.934***	−66.938***
NG	0.0175	141.7066	−152.9673	6.5938	−0.6943	141.8244	3,444,452***	−44.157***	−76.878***
Coal	0.0313	32.6222	−21.0195	1.6512	1.7859	69.0401	781,679.4***	−27.154***	−60.376***
Electricity	0.0089	76.1355	−51.4548	5.1276	1.7005	31.4055	146,261.8***	−61.008***	−60.857***
Clean	0.0109	14.5893	−14.9896	1.9062	−0.4156	9.7225	8199.74***	−62.159***	−62.091***

TABLE 3 Summary statistics of daily conditional volatility, skewness and (excess) kurtosis.

This table reports the summary statistics of daily conditional volatility, skewness and (excess) kurtosis. The sample period is July 20, 2006–March 30, 2023, yielding 4288 daily observations. Jarque–Bera tests the normality for the distribution of the series. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test the stationarity of the series, conducted with an intercept based on a lag length selected according to SIC. *** indicates statistical significance at the 1% level.

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP
Panel A: Conditional volatility									
EUA	10.898	46.311	10.212	2.030	7.446	78.066	1,046,155.0***	−6.928***	−9.502***
Brent	2.029	16.688	0.834	1.195	3.860	28.531	127,079.3***	−8.039***	−14.467***
NG	6.522	40.456	6.281	1.055	18.431	463.006	3,804,0783***	−20.934***	−19.179***
Coal	1.644	9.607	1.571	0.271	14.910	328.845	19,124,296***	−18.843***	−18.762***
Electricity	5.120	23.676	4.536	1.112	5.863	57.543	55,5961.5***	−5.670***	−20.993***
Clean	1.879	4.544	1.608	0.320	4.293	27.830	123,298.0***	−5.009***	−5.134***
Panel B: Skewness									
EUA	0.422	9.486	−0.142	0.964	3.966	24.962	97,395.2***	−18.470***	−24.255***
Brent	3.727	9.485	1.284	0.747	2.555	12.237	19,904.9***	−39.999***	−58.342***
NG	0.642	9.487	−0.362	1.269	4.136	23.296	85,801.9***	−12.963***	−43.600***
Coal	1.321	9.486	−0.678	2.419	1.926	5.980	4236.0***	−6.301***	−26.680***
Electricity	0.573	9.487	−0.425	1.380	2.859	12.614	22,348.8***	−5.780***	−41.558***
Clean	−4.273	−2.661	−9.486	1.236	−1.857	6.364	4484.6***	−18.012***	−56.038***

(Continues)

TABLE 3 (Continued)

	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP
Panel C: Kurtosis									
EUA	30.975	149.990	7.199	7.022	9.831	125.381	2,744,350.0***	−10.068***	−38.550***
Brent	46.790	149.988	9.283	9.828	3.750	24.426	92052.4***	−45.703***	−57.808***
NG	6.932	149.999	3.300	14.998	6.933	56.333	542,430.0***	−11.907***	−51.044***
Coal	40.130	149.997	30.000	25.142	3.093	11.935	21,096.2***	−7.094***	−32.939***
Electricity	13.198	149.993	8.428	11.938	6.298	52.782	47,1023.2***	−7.053***	−47.361***
Clean	56.383	149.987	37.038	18.082	2.557	10.209	13,954.7***	−18.145***	−56.987***

TABLE 4 Correlation matrix for the higher-order conditional moment series.

This table reports the correlation matrix for the higher–order conditional moment series. The sample period is July 20, 2006–March 30, 2023. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively. *p*-Values are given in brackets.

	EUA	Brent	NG	Coal	Electricity	Clean
Panel A: Conditional volatility						
EUA	1.000					
Brent	0.010	1.000				
	[0.520]					
NG	0.037**	0.038**	1.000			
	[0.014]	[0.013]				
Coal	0.006	0.209***	0.166***	1.000		
	[0.683]	[0.000]	[0.000]			
Electricity	−0.033**	0.139***	0.095***	0.162***	1.000	
	[0.032]	[0.000]	[0.000]	[0.000]		
Clean	0.065***	0.499***	0.032**	0.289***	0.059***	1.000
	[0.000]	[0.000]	[0.034]	[0.000]	[0.000]	
Panel B: Skewness						
EUA	1.000					
Brent	0.002	1.000				
	[0.888]					
NG	0.065***	0.005	1.000			
	[0.000]	[0.747]				
Coal	0.009	0.090***	0.159***	1.000		
	[0.554]	[0.000]	[0.000]			
Electricity	0.030*	0.050***	0.148***	0.192***	1.000	
	[0.051]	[0.001]	[0.000]	[0.000]		
Clean	−0.032**	−0.042***	−0.028*	−0.136***	−0.051***	1.000
	[0.034]	[0.007]	[0.062]	[0.000]	[0.001]	
Panel C: Kurtosis						
EUA	1.000					
Brent	−0.013	1.000				
	[0.381]					
NG	0.018	0.010	1.000			
	[0.238]	[0.501]				
Coal	−0.015	0.074***	0.124***	1.000		

(Continues)

TABLE 4 (Continued)

	EUA	Brent	NG	Coal	Electricity	Clean
	[0.316]	[0.000]	[0.000]			
Electricity	−0.004	0.028*	0.116***	0.092***	1.000	
	[0.816]	[0.064]	[0.000]	[0.000]		
Clean	0.025*	0.054***	0.015	0.144***	0.026*	1.000
	[0.096]	[0.000]	[0.312]	[0.000]	[0.093]	

TABLE 5 Averaged spillover of conditional volatility.

This table reports the directional conditional volatility connectedness computed using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 2 (based on the SIC criterion) and the forecasting range adopted for GFEVD is 10 days. Abbreviations: EUA, European Union Allowances; GFEVD, generalised forecast error variance decompositions; NG, Natural Gas.

	EUA	Brent	NG	Coal	Electricity	Clean	FROM others
EUA	87.07	2.04	4.03	1.86	1.84	3.16	12.93
Brent	4.81	77.48	3.87	5.89	3.84	4.12	22.52
NG	3.62	1.93	86.02	4.34	2.85	1.23	13.98
Coal	2.27	3.42	7.47	77.28	5.29	4.27	22.72
Electricity	3.67	2.39	5.41	3.64	83.34	1.54	16.67
Clean Energy	3.14	3.17	3.7	4.58	3.12	82.28	17.72
TO others	17.51	12.96	24.48	20.31	16.94	14.32	
Inc. own	104.58	90.44	110.5	97.59	100.28	96.6	TCI = 17.75
NET	4.58	−9.56	10.5	−2.41	0.28	−3.4	

5.2.1 | Spillovers of CV

Table 5 presents the averaged spillover matrix of CV for EUA, Brent, NG, Coal, Electricity and Clean markets. The main diagonal provides its own CV shares of volatility shocks, whereas off-diagonal elements indicate the interactions across CV. Overall, own CV spillovers are high for all cases, varying from 87.07% for EUA to 77.28% for Brent. This suggests their pairwise volatility spillovers are relatively low. The average TSI in the system of CV reaches 17.75%. Interestingly, among the data we analysed, NG stands out as the market that exhibits the highest degree of volatility transmission, representing 24.48% of the overall spillover effects. Coal, on the other hand, demonstrates the highest susceptibility to changes in other markets, as 22.72% of its CV is significantly influenced by them. The NG and Coal markets exhibit a relatively noteworthy cross-spillover of volatility, where 7.47% of the volatility shock is transmitted from NG to Coal. Additionally, Coal receives 4.34% of its CV from NG. Upon analysing both the 'From' and 'To' metrics for each market, it becomes clear that Coal, Brent oil and Clean Energy are the primary receivers of volatility shocks, whereas NG, Coal and EUA are the main transmitters of volatility shocks to other markets. Taken together, NG and EUA are the largest net transmitters of volatility shocks, whereas Brent and Clean are the largest net receivers of volatility shocks. These findings emphasise the crucial role that these marketplaces play in connecting and enabling the spread of volatility information within the system. Thus, H1 is accepted. The consumption trends in Coal, Brent, Clean Energy and EUA are significantly impacted by the transition from conventional fossil fuels to sustainable alternatives, as evidenced by Papageorgiou et al. (2017) and Cao et al. (2021). However, it is important to mention that 12.93% of the CV in the EUA market can be attributed to the volatility in the other five markets. Out of these contributions, NG has the highest significance, at 4.03% of the total. Clean Energy is next at 3.16%, followed by Brent at 2.04%, Coal at 1.86% and Electricity at 1.84%. This phenomenon can be ascribed to the industries that fall under the EUA allowances and possess the ability to change the type of fuels used in their production methods, as elucidated by Creti et al. (2012). The green transition has led to a notable shift in fuel preferences, with NG being favoured over coal for power generation, as observed by Pettersson et al. (2012). These findings highlight the significance of examining the volatility interdependence relationship between energy markets, especially while shifting from traditional to renewable energy sources.

Figure 1 shows the TSI of CV over the sample period. The fluctuations in the TSI range from 5% to 80% and are observed at various peaks. During the 2008 GFC, the volatility spillover effect was observed across all carbon and energy assets, and the spillover index continued to be high for the next year. The remaining time periods show that volatility spillovers between markets increased quite substantially. During 2014, crude oil went into a low-price regime following the oil price war between Saudi Arabia and Russia. In 2018, the international benchmark Brent crude oil decreased by around 20%, reflecting the fear about shortage of crude oil. In 2020 and onwards, energy prices fell in response to concerns about the rapid increase of COVID-19 and a decrease in global demand following the resulting economic recession. Furthermore, we notice a small spike in the spillover effect around the war in Ukraine. Overall, our results indicate that volatility risks are linked with carbon and energy assets in a time-varying manner and are affected by various crisis periods. These findings are in line with Ji et al. (2018) and Gong et al. (2021) who disclose evidence of strong volatility linkages among NG, crude oil and carbon markets.

Figure 2 shows the CV spillover from EUA to individual other markets, which depicts a large degree of change and shows high peaks in many markets around 2020. Notably, from EUA to NG and EUA to Oil exhibit jumps of over 80 and 22, respectively. Previous studies such as Ghorbel and Jeribi (2021) and Tiwari et al. (2022) also illustrate the importance of systematic risk spillovers during extreme market movements and the results explain a prominent level of dynamic co-movement between energy and financial markets, reflecting the contagion effect of the COVID-19 pandemic. This is in line with the study of Ding et al. (2022) who found that the COVID-19 pandemic has led to a rise in cross-market risk contagion in the long term and that the carbon market endures larger input risks Conversely, a small spike in the spillover effect around the war in Ukraine can also be observed in CV spillover from EUA to individual others.

Figure 3 plots the CV spillover to EUA from individual other markets. There is a spillover of volatility from the NG, coal and clean energy markets to the European Union Allowances (EUA), indicating that changes in these markets have significantly influenced the CV of EUA. In addition, there is a significant observation of sharp increases in volatility spillover in 2004, particularly in the oil, coal and electricity markets. The presence of these spikes may suggest periods of increased market volatility or notable events occurring within these markets, which could have potential implications for the EUA and other interconnected markets. Previous

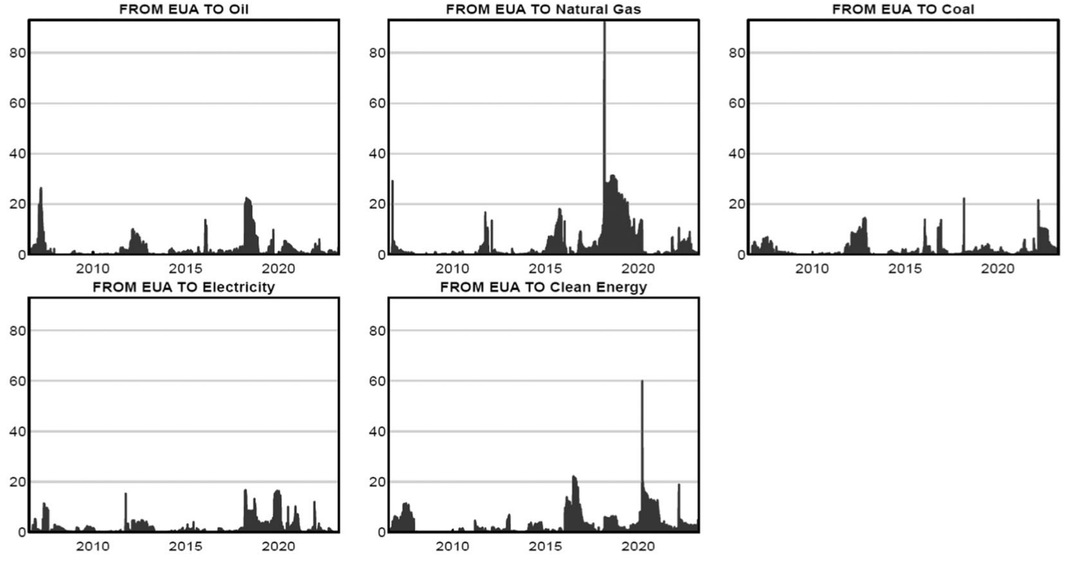

FIGURE 2 Conditional volatility spillover FROM European Union allowances (EUA) to individual other markets. These figures show the time-varying dynamics of conditional volatility spillover from carbon assets (EUA) to other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 2 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

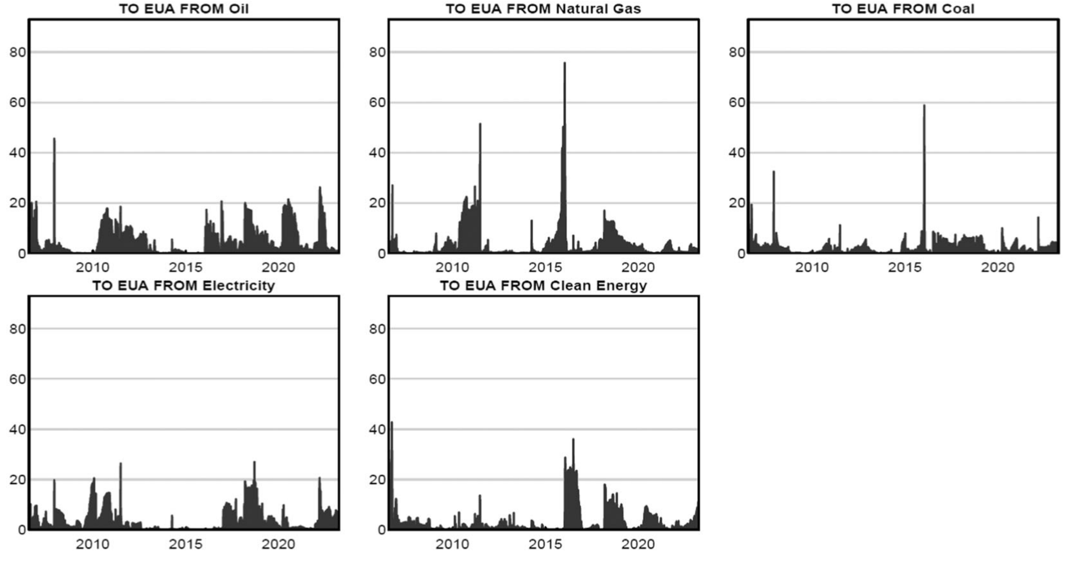

FIGURE 3 Conditional volatility spillover TO European Union allowances (EUA) from individual other markets. These figures show the time-varying dynamics of conditional volatility spillover to carbon assets (EUA) from other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 2 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

studies such as Ghorbel and Jeribi (2021) and Tiwari et al. (2022) also illustrate the importance of systematic risk spillovers during extreme market movements and the results explain a prominent level of dynamic co-movement between energy and financial markets.

5.2.2 | Spillovers of CS

The averaged spillovers matrix of CS is presented in Table 6. The average TSI of skewness is 11.81%, which is lower than that for CV. For directional spillovers, the Electricity market is the largest transmitter of skewness spillover, contributing 15.39% to others, whereas the Coal market is the largest receiver, receiving 18.04% from others. The highest skewness spillover occurs between Electricity and Coal (6.09%), followed by NG and Electricity (4.98%). We notice that Coal, NG and Electricity are the top three in terms of both contribution to and receiving from the system of skewness spillovers. However, the highest receiver of skewness spillover is Coal (18.04%) and highest transmitter of skewness spillover is Electricity (15.39%). Conversely, the lowest receiver of skewness shocks is Brent (6.41%), which is explained by the skewness of Coal (1.92%), Electricity (1.29%), NG (1.09%), Clean (1.08%) and EUA (1.03%), respectively. Overall, Coal and NG play a crucial role in the system of skewness spillovers. This finding may be due to the substitution of fossil fuels with NG and hedging strategies against inflation induced by high coal and oil prices, which is comparable to the study of Singh et al. (2019), or it may be evidence for close relationships among carbon, energy and stock, since the industrial production activities directed by the price of commodities and stock are the dominant sources of carbon emissions and the carbon price tends to have influence on the gas price by determining the fuel-switching behaviour of producers (Tan et al., 2020). The above results suggests that H2 is accepted.

TABLE 6 Averaged spillover of conditional skewness.

This table reports the directional conditional skewness connectedness computed using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for GFEVD is 10 days. Abbreviations: EUA, European Union Allowances; GFEVD, generalised forecast error variance decompositions; NG, Natural Gas.

	EUA	Brent	NG	Coal	Electricity	Clean	FROM others
EUA	92.21	0.71	1.59	2.01	1.93	1.55	7.79
Brent	1.03	93.59	1.09	1.92	1.29	1.08	6.41
NG	4.42	0.94	85.57	3.68	4	1.4	14.43
Coal	2.95	1.83	4.88	81.96	6.09	2.28	18.04
Electricity	2.54	0.98	4.98	4.25	85.75	1.49	14.25
Clean	2.01	0.95	2.32	2.59	2.07	90.06	9.94
TO others	12.96	5.4	14.86	14.45	15.39	7.8	
Inc. own	105.17	98.99	100.43	96.41	101.14	97.86	TCI = 11.81
NET	5.17	−1.01	0.43	−3.59	1.14	−2.14	

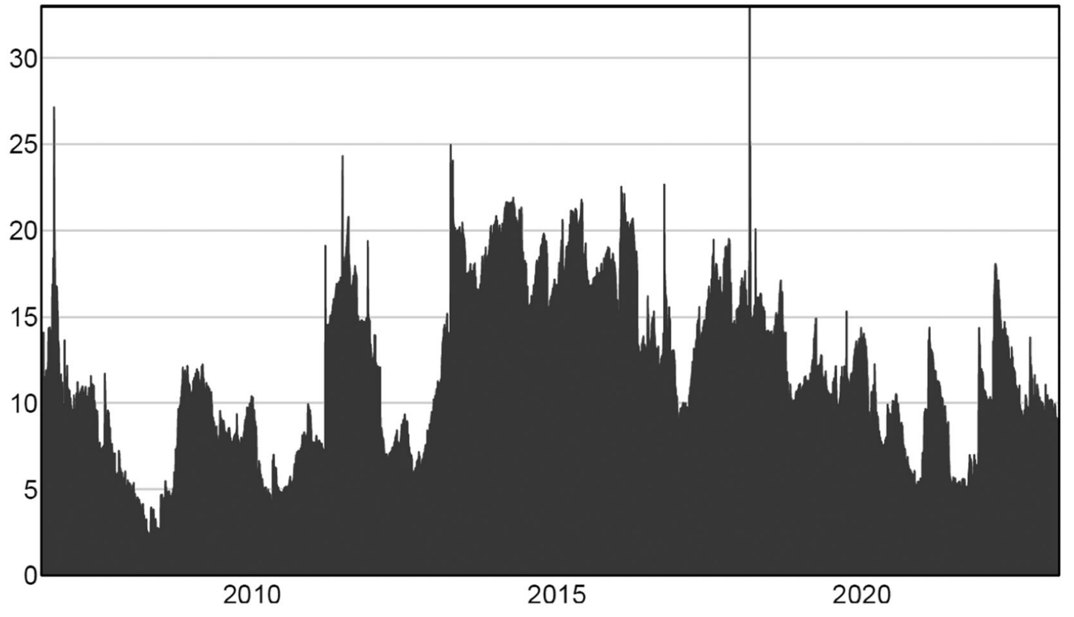

FIGURE 4 The total spillover index of conditional skewness. This figure displays the time-varying dynamics of the total conditional skewness spillover index using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

Figure 4 plots the TSI of skewness over time, ranging between 5% and 35%, which is lower in comparison with the TSI of volatility, despite occasionally rising to over 25%. Overall, three peaks can be observed, during 2010, 2017 and 2019, while, interestingly, during 2013 and 2021 the spillover slightly declined and hovered. The reason for the decline would be that market risk reduced after comprehensive interaction among markets (see Tan et al., 2020).

Figure 5 presents the evolution of the CS spillover from EUA to individual other markets, whereas Figure 6 plots the CS spillover to EUA from individual other markets. Figure 5 depicts a large degree of changes. The Coal skewness has high peaks among all others in skewness of spillovers, followed by Clean Energy, Electricity, NG and Oil. Previous studies such as Dhamija et al. (2018) also show a positive skewness and high degree of volatility co-movement between EUA market and the markets of Brent, coal and NG. Figure 6 shows the skewness spillover from each of the other individual markets to EUA. The magnitude of spillover from NG, Coal and Clean energy to EUA is larger than that from Electricity and Oil to EUA. NG had a notable spillover effect to EUA in 2012 and 2016 when the price increased quickly to 55% in 2012 and NG demand reached a record high during 2016. This shows the importance of skewness as a market crash risk measure in the financial markets, which is in line with Jian and Li (2021) and Bouri (2023) who show that skewness can spread from one market to another, particularly in times of turbulence.

5.2.3 | Spillovers of conditional (excess) kurtosis

Table 7 presents averaged spillovers of conditional (excess) kurtosis for the six variables under study. The diagonal values in the matrix indicate self-contributions, or variations due to the

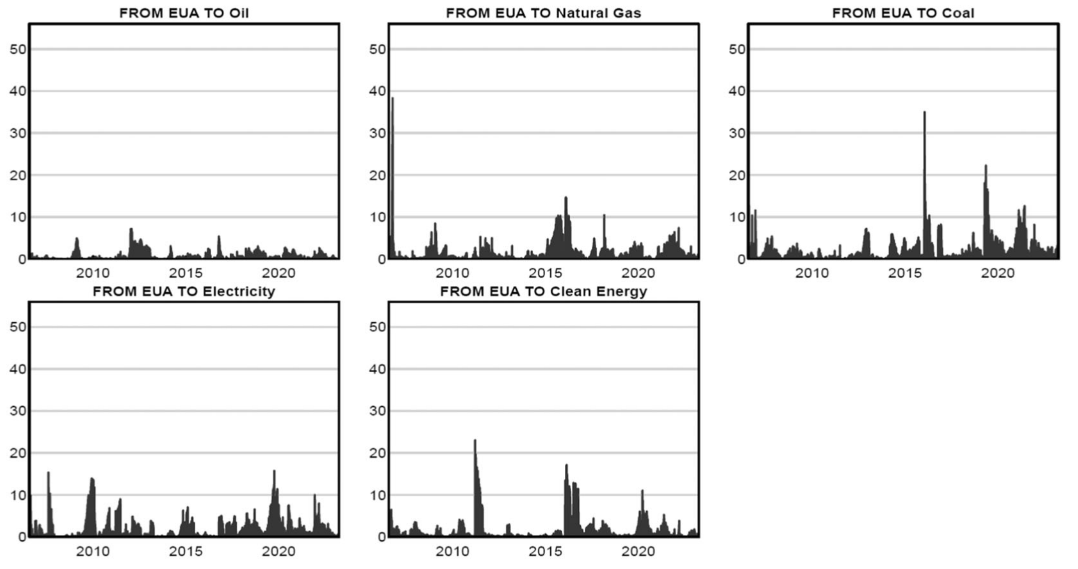

FIGURE 5 Conditional skewness spillover FROM European Union allowances (EUA) to individual other markets. These figures show the time-varying dynamics of conditional skewness spillover from carbon assets (EUA) to other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

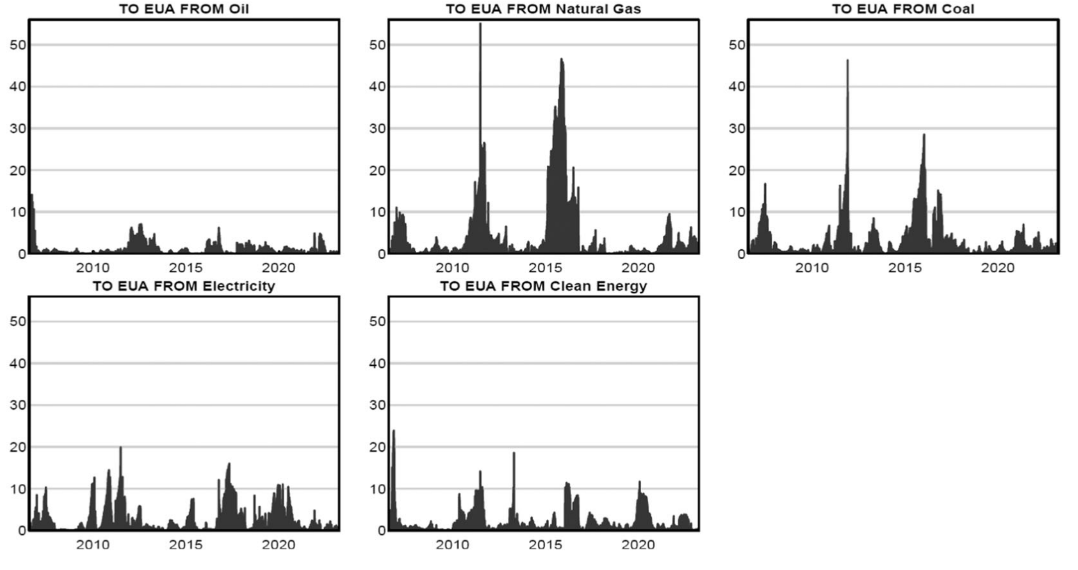

FIGURE 6 Conditional skewness spillover TO European Union allowances (EUA) from individual other markets. These figures show the time-varying dynamics of conditional skewness spillover to carbon assets (EUA) from other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

TABLE 7 Averaged spillover of conditional (excess) kurtosis.

This table reports the directional conditional (excess)kurtosis connectedness computed using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for GFEVD is 10 days. Abbreviations: EUA, European Union Allowances; GFEVD, generalised forecast error variance decompositions; NG, Natural Gas.

	EUA	Brent	NG	Coal	Electricity	Clean	FROM others
EUA	91.64	0.49	2.71	2.18	1.42	1.55	8.36
Brent	1.04	92.78	1.43	2.37	1.15	1.24	7.22
NG	5.23	0.7	85.87	3.44	4.01	0.74	14.13
Coal	4.45	1.77	8.54	77.98	4.68	2.58	22.02
Electricity	3.29	0.66	7.19	4.18	83.38	1.31	16.62
Clean	2.39	1.05	3.05	3.44	1.87	88.2	11.8
TO others	16.39	4.68	22.91	15.62	13.13	7.41	
Inc. own	108.04	97.46	108.78	93.61	96.5	95.61	TCI = 13.36
NET	8.04	−2.54	8.78	−6.39	−3.5	−4.39	

changes in each variable. Total (excess) kurtosis spillover of 13.36% in the system is due to market interactions, and the remaining 86.64% is due to market specific factors. In each case, the proportion of self-contribution is large, above 77%, but varies across markets. The Brent market has the biggest self-explanatory power, 92.78%, followed by EUA (91.64%), Clean (88.2%), NG (85.87%), Electricity (83.38%) and Coal (77.98%). Looking at the FROM others and TO others measure, we notice that Coal, Electricity and NG are top three receivers from the system and NG, EUA and Coal are the top three transmitters to the system. Interestingly, it shows that Coal and NG are among the top three for both contributions: transmitter (receiver) from the system. In other words, these markets have a critical role in connecting the system or information spillovers within the system. Specifically, 7.22% of Brent excess kurtosis variations can be explained by the five energy excess kurtoses, in which the largest contribution is made by Coal (2.37%), followed by NG (1.43%), and Clean (1.24%). Brent also contributes 1.77% of Coal variation, 1.05% of Clean variation and 0.7% of NG variation. These findings indicate that NG and Coal have a significant role in the system of kurtosis spillovers. The same as for skewness, this finding indicates that kurtosis provides additional information to investors concerned about spillover effects and interested in making more refined investment strategies and risk management inferences over strategies involving volatility alone (Bonato et al., 2020; Bouri, 2023; Zhang, Jin, et al., 2022). Accordingly, H3 is accepted.

Figure 7 shows that that the total (excess) kurtosis spillover index ranges from 3% to 64%. Particularly the spillovers are higher in 2013, 2018 and 2021. The kurtosis index captures the peak in 2018 and the results suggest that the spillover effect may be related to market risk associated with events such as the trade war between China and the US in that year. Zhang, Jin, et al. (2022) and Bouri (2023) show that the total kurtosis spillover index is sensitive to risk events and fluctuates sharply, reflecting the transmission of extreme values across markets under extreme events and thus nonnormal return distributions (Bouri et al., 2021).

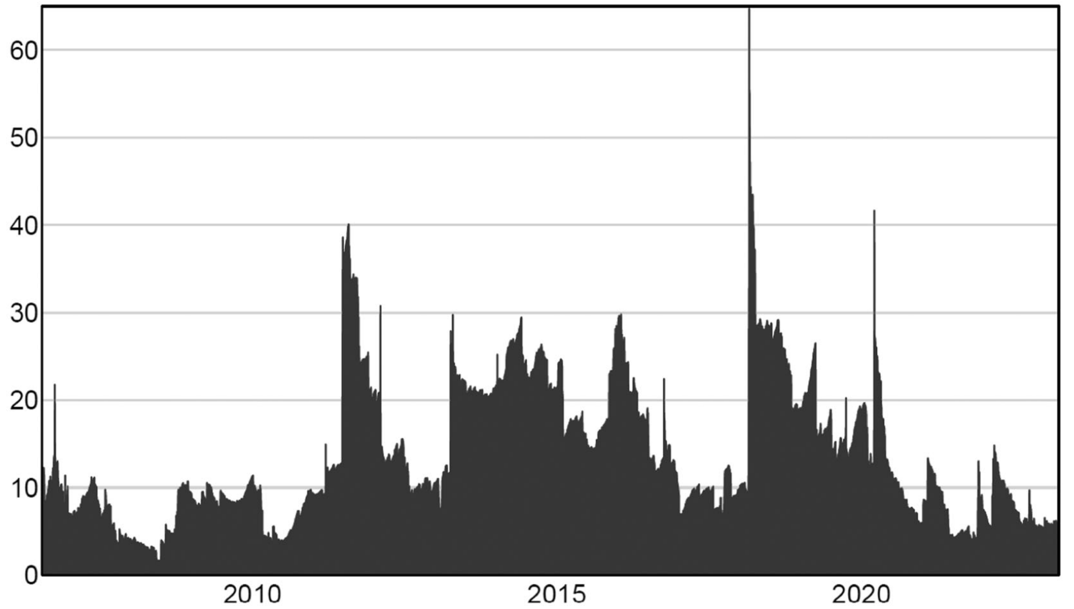

FIGURE 7 The total spillover index of conditional (excess) kurtosis. This figure displays the time-varying dynamics of the total conditional kurtosis spillover index using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

Figure 8 presents the evolution of the conditional (excess) kurtosis spillover from EUA to individual other markets, whereas Figure 9 plots the conditional (excess) kurtosis spillover to EUA from individual other markets. Both figures depict a large degree of changes. The kurtosis spillovers from EUA to NG, around 2012, 2016 and 2018, and from NG to EUA, around 2012, 2016 and 2020, have high peaks compared to the spillovers from EUA to other individual markets and from other individual markets to EUA. Ahmed and Sleem (2022) mention that the transmission of kurtosis offers valuable insights into whether and to what degree extreme events spread throughout various markets. Moreover, the magnitude of kurtosis spillover from and to EUA is larger in NG than other markets, indicating the strong ties between EUA and NG markets (see Wang & Guo, 2018). For example, NG had a notable spillover effect on EUA in 2012, 2016 and 2018 and EUA exerts a large spillover effect on NG in 2012, 2016 and around 2020 when the price of NG increased quickly by 70% in 2012 and NG demand reached a record high during 2016 and 2020. Our evidence on the persistence in the spillover effect is line with previous studies such as Kang et al. (2017), Zhang, Jin, et al. (2022), Bouri (2023) and Bouri et al. (2023) which indicate that the spillover effect is persistent during periods of economic and financial turmoil. Furthermore, the result showing that the EUA carbon market tends to receive spillovers of multifaceted risk during crisis periods and under fat-tailed return distributions concords with previous evidence highlighting the limited ability of the variance to comprehensively capture the information flow across energy markets because skewness and kurtosis spillovers often materialise when the return distribution substantially deviates from the normal (see Bouri, 2023; Bouri et al., 2021, 2023; Zhang, Jin, et al., 2022).

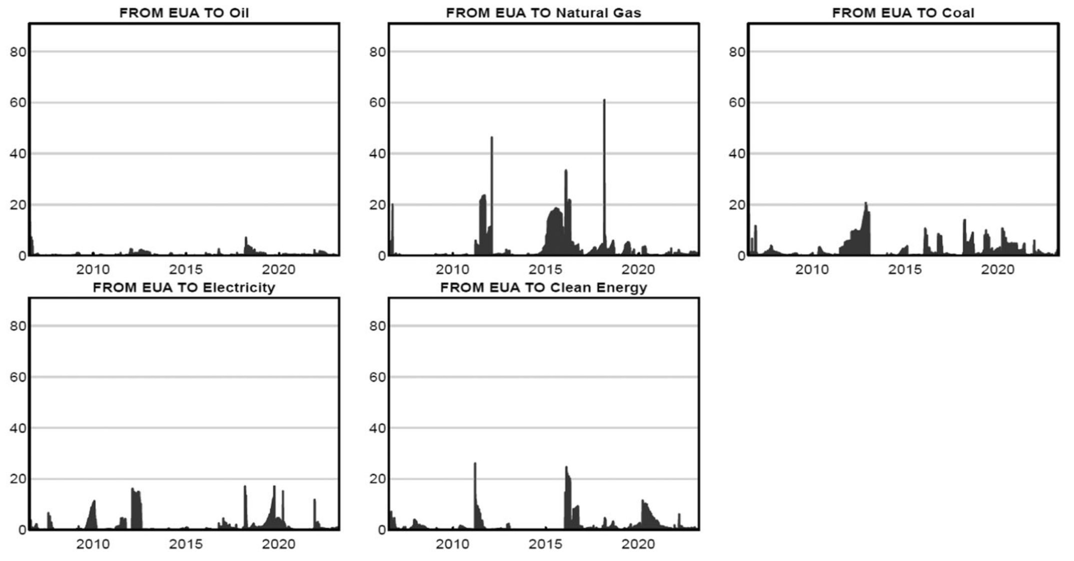

FIGURE 8 Conditional (excess) kurtosis spillover FROM European Union allowances (EUA) to individual other markets. These figures show the time-varying dynamics of conditional kurtosis spillover from carbon assets (EUA) to other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

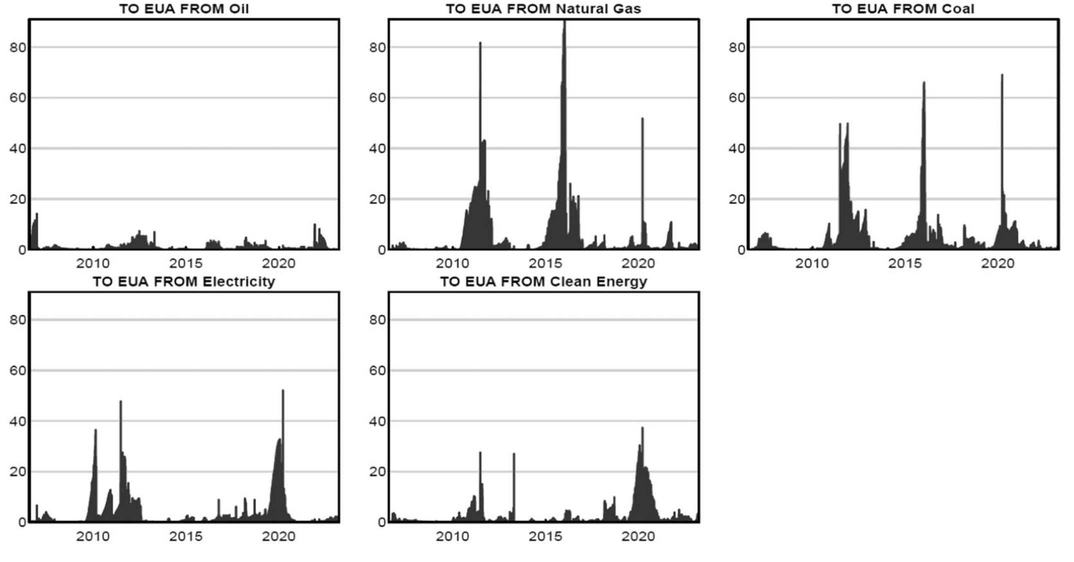

FIGURE 9 Conditional (excess) kurtosis spillover TO European Union allowances (EUA) from individual other markets. These figures show the time-varying dynamics of conditional kurtosis spillover to carbon assets (EUA) from other assets using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

5.3 | Results of spillovers—Estimated for the three conditional higher-order moments jointly

In this section, averaged spillovers of CV, skewness and kurtosis for the six markets are estimated jointly to determine the information flow and transmission mechanism among carbon and energy markets. As presented in Table 8, the total TSI reaches 64.36%, which exceeds the sum of the three indices estimated for each moment separately. Accordingly, H4 is accepted. The main diagonal elements reveal their own volatility, skewness and kurtosis spillovers but off-diagonal elements show the interactions across volatility, skewness and kurtosis spillovers. In many cases, own spillovers are not as high as the ones shown for the spillover in each conditional moment separately (see Tables 5–7). The largest does not exceed the 50% mark for volatility in NG (41.74%), Brent (36.75%), Coal (36.34%) and EUA (35.31%), and for skewness in EUA (39.47%), NG (38.11%) and Brent (35.31%), and for Kurtosis in EUA (37.79%), NG (37.53%) and Brent (35.16%). This suggests the importance of cross-moment spillovers for explaining the moments of each market under study. Accordingly, cross spillovers of moments contain useful incremental information for determining the overall spillover in the combined system of all moments jointly estimated in the same system of spillovers. Moreover, the highest pairwise spillovers, more than 30%, are from kurtosis to skewness and vice versa, which somewhat reflects the extreme return observations in the non-Gaussian (e.g., fat-tailed) distribution of EUA and other energy markets under study. For example, we notice that the transmission of Brent kurtosis to skewness in Brent is 34.36%, kurtosis in Clean to skewness in Clean is 32.49%, and kurtosis in NG to skewness in NG is 31.36%, skewness in Brent to kurtosis in Brent is 34.07%, and skewness in Clean to kurtosis in Clean is 31.78%. These significant spillover effects across moments have implications for risk management decisions to better comprehend the spillover effects estimated for the three moments jointly. Regarding the net transmitters and receivers of shocks, NG kurtosis (15.25%), Electricity volatility (5.96%), NG volatility (4.59%) are the largest net transmitters of spillovers, whereas Coal skewness (−8.65%), Brent volatility (−7.48%) and EUA volatility (−4.6%) are the largest net receivers of spillovers. Notably, the economic significance and practical implications of these large cross-spillovers across the three conditional moments of EUA and energy markets will be the subject of Section 6, where we evaluate the utility of considering spillovers in higher-order moments in the construction of portfolios containing these markets and whether they will lead to a significant improvement in the portfolio performance.

Figure 10 shows the evolution of the TSI of the three conditional moments estimated jointly in the same system of spillovers. TSI fluctuates more rapidly and significantly than the TSI of each moment estimated separately (see Figures 2, 4, and 7), specifically during extreme events, such as financial crisis, oil price fluctuations and COVID-19 outbreak. All findings indicate that the spillovers of the three moments are more sensitive to extreme events, which is generally in line with Zhang, Jin, et al. (2022), Bouri (2023) and Bouri et al. (2023) who illustrate an increase in the spillovers of three moments during crisis periods.

5.4 | Results of the contribution of each conditional moment to the TSI

In this section, we analyse the contribution of CV, CS and conditional (excess) kurtosis to the TSI on average and across time. The spillover contribution of each moment has been shown in Table 9.

TABLE 8 Averaged spillovers in the three conditional moments [volatility, skewness and (excess) kurtosis].

This table reports the average values of directional spillover among all three higher order moments using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for GFEVD is 10 days. Abbreviations: EUA, European Union Allowances; GFEVD, generalised forecast error variance decompositions; NG, Natural Gas.

	EUA vol.	Brent vol.	NG vol.	Coal vol.	Electricity vol.	Clean vol.	EUA skew	Brent skew	NG skew	Coal skew	Electricity skew	Clean skew	EUA kurtosis	Brent kurtosis	NG kurtosis	Coal kurtosis	Electricity kurtosis	Clean kurtosis	FROM others
EUA vol.	35.31	0.83	1.09	1.43	1.1	1.15	25.05	0.53	0.76	1.02	0.98	1.12	25.28	0.55	0.9	0.86	0.81	1.22	64.69
Brent vol.	1.22	36.75	1.33	2.67	1.57	2.22	1.03	19.13	1.21	1.62	1.32	1.42	1.15	20.83	1.42	2.38	1.14	1.6	63.25
NG vol.	1.72	0.93	41.74	2.38	1.1	0.59	1.26	0.53	16.04	0.93	0.97	0.4	1.77	0.54	26.35	1.16	1.13	0.46	58.26
Coal vol.	1.46	1.62	4.39	36.34	2.33	2.47	1.15	1.14	2.15	15.81	1.72	0.92	1.21	1.1	3.42	19.95	1.81	1.01	63.66
Electricity vol.	1.02	0.8	2.04	1.51	33.65	0.53	0.68	0.46	1.7	1.42	24.33	0.56	0.84	0.43	2.32	1.62	25.54	0.57	66.35
Clean vol.	0.99	1.56	1	2.34	1.25	34.83	0.75	0.5	0.9	1.38	1.04	23.51	0.6	0.54	0.91	1.43	0.87	25.59	65.17
EUA skew	21.35	0.98	1.4	1.69	1.16	1.06	39.47	0.71	0.73	1.28	0.99	0.93	23.38	0.66	0.89	1.29	0.99	1.05	60.53
Brent skew	0.54	20.23	0.53	1.19	0.72	0.42	0.51	35.31	0.55	1.07	0.7	0.49	0.51	34.36	0.57	1.17	0.62	0.52	64.69
NG skew	1.03	0.71	17.67	1.41	1.36	0.45	0.83	0.52	38.11	0.77	1.29	0.42	0.82	0.51	31.36	0.85	1.44	0.45	61.89
Coal skew	1.01	1.25	2.48	17.28	2.25	0.99	0.75	1.12	1.4	32.98	1.97	0.86	0.83	1.04	1.92	29.06	1.92	0.88	67.02
Electricity skew	0.91	0.82	1.25	1.19	26.07	0.61	0.8	0.55	1.5	1.38	32.77	0.66	0.83	0.53	1.73	1.38	26.35	0.68	67.23
Clean skew	0.8	0.75	0.65	0.75	0.8	23.81	0.64	0.46	0.66	0.95	0.76	33.16	0.64	0.5	0.63	0.96	0.6	32.49	66.84
EUA kurtosis	23.79	0.44	0.72	1.23	0.73	0.65	28.2	0.41	0.45	0.93	0.65	0.76	37.79	0.37	0.5	1.02	0.57	0.79	62.21

TABLE 8 (Continued)

	EUA vol.	Brent vol.	NG vol.	Coal vol.	Electricity vol.	Clean vol.	EUA skew	Brent skew	NG ske-w	Coal ske-w	Electricity skew	Clean skew	EUA kur-tosis	Brent kur-tosis	NG kur-tosis	Coal kur-tosis	Electrici-ty kurtosis	Clean kur-tosis	FROM others
Brent kurtosis	0.49	21.43	0.48	1.07	0.65	0.44	0.49	34.07	0.49	0.92	0.67	0.52	0.47	35.16	0.51	1.02	0.56	0.55	64.84
NG kurtosis	1.35	0.71	23.59	1.35	1.06	0.39	0.86	0.45	26.5	0.58	1	0.36	1.34	0.44	37.53	0.69	1.39	0.4	62.47
Coal kurtosis	1.07	1.34	2.43	19.88	2.11	1.1	0.78	1.13	1.42	26.23	1.67	0.87	0.96	1.05	2.02	33.29	1.76	0.9	66.71
Electricity kurtosis	0.56	0.61	1.16	1.18	27.32	0.37	0.41	0.45	1.34	1.19	26.59	0.39	0.45	0.42	1.73	1.26	34.15	0.39	65.85
Clean kurtosis	0.76	0.77	0.66	0.77	0.75	25.01	0.65	0.46	0.6	0.88	0.71	31.78	0.57	0.49	0.56	0.89	0.54	33.14	66.86
TO others	60.09	55.77	62.85	59.33	72.32	62.26	64.83	62.63	58.4	58.37	67.38	65.98	61.68	64.36	77.72	66.98	68.06	69.54	
Inc. own	95.4	92.52	104.59	95.67	105.96	97.09	104.3	97.94	96.51	91.35	100.15	99.14	99.47	99.52	115.25	100.27	102.21	102.67	TSI = 64.36
NET	−4.6	−7.48	4.59	−4.33	5.96	−2.91	4.3	−2.06	−3.49	−8.65	0.15	−0.86	−0.53	−0.48	15.25	0.27	2.21	2.67	

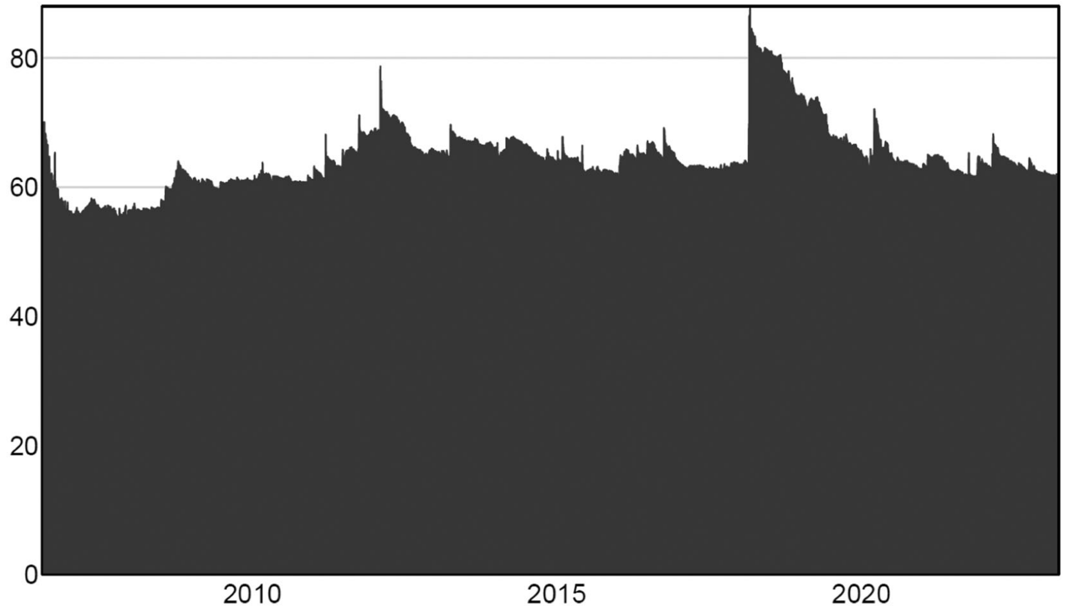

FIGURE 10 The total spillover index of the three conditional moments [volatility, skewness and (excess) kurtosis]. This figure displays the time-varying dynamics of the total conditional spillover index among all three higher order moments using the generalised forecast error variance decomposition of TVP-VAR. The lag order for the TVP-VAR estimations is 1 (based on the SIC criterion) and the forecasting range adopted for generalised forecast error variance decompositions is 10 days. SIC, Schwarz information criterion.

TABLE 9 The spillover contribution of each moment.

This table reports the cross and own spillover contributions of each moment to the total spillover index (as described in Section 3.3) for a forecast horizon of 10 days, with an optimal lag of 1.

The system of spillovers of the three moments	
Cross conditional volatility spillovers	18.60%
Cross conditional skewness spillovers	20.11%
Cross conditional kurtosis spillovers	20.24%
Own conditional volatility spillovers	14.74%
Own conditional skewness spillovers	13.23%
Own conditional kurtosis spillovers	13.09%
Total	100.00%
Percentage of cross spillovers of the three moments out of the Total (i.e., 100%)	58.94%
Percentage of total own spillovers of the three moments out of the Total (i.e., 100%)	41.06%

Cross conditional spillover of (excess) kurtosis is the highest (20.24%), followed by cross conditional spillover of skewness (20.11%) and cross conditional spillover of skewness (18.60%). However, when compared to own conditional spillovers, volatility is the highest (14.74%), followed by own conditional spillover of Skewness (13.23%), and own conditional spillover of (excess) kurtosis (13.09%). These results are comparable to the study of Zhou et al. (2022). Interestingly, when the cross spillovers of the three moments are combined, the contribution exceeds 58%, which is substantial; hence, it should not be ignored when analysing the spillover effect of various moments in the carbon and energy markets. This evidence complements the growing strand of literature highlighting the utility of estimating the spillover effect in higher-order moments in financial markets (see Bonato et al., 2020; Bouri, 2023; Bouri et al., 2021, 2023; He & Hamori, 2021; Zhang, Jin, et al., 2022), by revealing that the spillover effects across moments are important in the carbon-energy system and, for the sake of completeness of the spillover analysis, should not be ignored.[15]

Furthermore, we compute the evolution of the spillover contribution of each conditional moment [volatility, skewness and (excess) kurtosis] and plot it in Figure 11. For example, the evolution of the cross spillovers for the three conditional moments exhibits an uptrend around the beginning of the sample period and some peaks coinciding with the pandemic outbreak in early 2020, reflecting the impact of the COVID-19 outbreak on the dynamics of the contribution of each conditional moment to the TSI. This evidence is somewhat related to the literature highlighting how extreme events and crisis periods can shape the return distribution of assets and move it away from the normal distribution (see, Zhang et al., 2023b), ultimately making the higher-order moments interact more and become more significant contributors to the spillover effects in the overall system of assets (Bouri, 2023; Bouri et al., 2023). Therefore, H4 is accepted, confirming the importance of cross higher-order moment spillovers in the carbon-energy system and, for the sake of completeness of the spillover analysis, they should not be ignored.

Our analysis considers a broader and more comprehensive view on systemic risk in the system of EUA, Brent oil, NG, coal, electricity and clean energy markets based on spillovers in high-order moments jointly estimated in the same system of spillovers. This is important given that our sample period (July 19, 2006 to March 30, 2023) includes the Russia-Ukraine conflict, when energy (crude oil and NG) prices increased significantly. Our analysis nicely complements studies on systemic risk spillovers via the TVP-VAR approach which limits the spillover effect to the volatility only (Ji et al., 2018; Uddin et al., 2018; Wang & Guo, 2018; Zhang & Sun, 2016), which is too restrictive because information flow can be transmitted via skewness and kurtosis under extreme events and nonnormal return distributions. Notably, the significant spillover contribution of each conditional moment [volatility, skewness and (excess) kurtosis] to the TSI, plotted in Figure 10 on average (see Table 8) and across time (see Figure 11), underlines the importance of studying the spillover effect of the three moments jointly estimated within the same system. Such evidence is new to the related literature (e.g., Bonato et al., 2020; Bouri, 2023; Bouri et al., 2021, 2023; Dai et al., 2021; Zhang, Jin, et al., 2022) and can be understood 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 in high-order moments.

[15]We have conducted the analysis using the spillover approach of Diebold and Yilmaz (2012, 2014) and the results of spillovers as well as the spillover contribution of each moment remain qualitatively the same. If anything, the average level of spillovers in the system of each moment increases slightly. These results are not reported here, but they are available upon request from the authors.

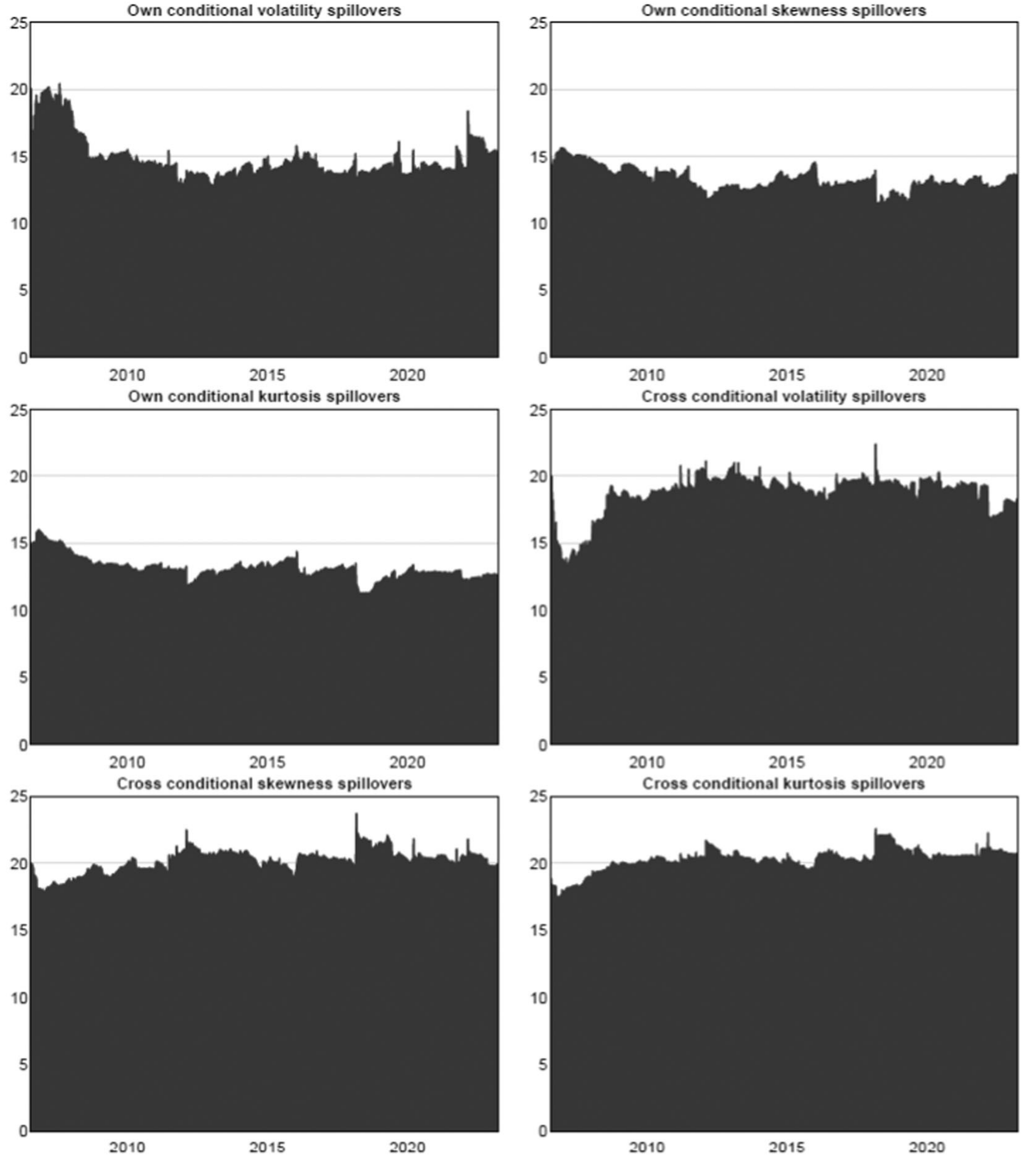

FIGURE 11 The spillover contribution of each conditional moment [volatility, skewness and (excess) kurtosis]. These figures show the percentage of cross and own spillover contributions to the total spillover index (as described in Section 3.3) for a forecast horizon of 10 days, with an optimal lag of 1.

6 | PORTFOLIO IMPLICATIONS

We assess the performance of a portfolio containing the six indices under study. The portfolio is constructed using four techniques, namely minimum CV, minimum CS, minimum conditional kurtosis (CK) spillovers and minimum spillovers of combined three higher-order moments portfolio (ALL). Notably, the portfolio weights are based on the pairwise spillover index (PSI) through the

TVP-VAR spillover analysis. These techniques reflect respectively the spillover effects estimated for the CV, CS conditional (excess) kurtosis and the three moments jointly estimated.

Following Broadstock et al. (2022), who relied on the spillover effects resulting from the TVP-VAR pairwise spillover measures instead of correlations, we calculate the weights of CV, SC, CK and ALL as follows:

$$W_{C_t} = \frac{PSI_t^{-1} \quad I}{I PSI_t^{-1} I}, \tag{9}$$

where *PSI* is the pairwise spillover index (see Equation 10) matrix and I is the identity matrix. Considering TSI, the PSI measures the inter-spillovers between variable i and variable j as follows:

$$PSI_{ijt}^{g}(H) = 2\left(\frac{\tilde{\psi}_{ij,t}^{g}(H) + \tilde{\psi}_{ji,t}^{g}(H)}{\tilde{\psi}_{ii,t}^{g}(H) + \tilde{\psi}_{ij,t}^{g}(H) + \tilde{\psi}_{ji,t}^{g}(H) + \tilde{\psi}_{jj,t}^{g}(H)}\right), 0 \le PSI_{ijt}^{g}(H) \le 1, \tag{10}$$

where PSI is the pairwise spillover index; and the reader can refer to the details of equations presented and described in Subsection 3.2 on the spillover approach.

To evaluate the constructed portfolios, we use various measures and metrics, namely annualised average returns (AR), annualised standard deviation of portfolio returns (volatility), Sharpe ratio (SR), 5% VaR and maximum drawdowns (MD) (see Shahzad et al., 2023).

Table 10 shows the performance indicators of different portfolio strategies. Interestingly, the ALL portfolio has the second lowest 5% VaR after the CK and, importantly, the least MD, which make it a relatively attractive portfolio without ignoring the positive performance of the CK portfolio, but only because its AR are positive rather than because its volatility is relatively the lowest. Figure 12 shows the cumulative market value and drawdowns of the long-only unfunded portfolios. The upper panel of this figure shows that the cumulative sum of portfolio returns of the CS, CK and ALL largely exceeds that of the CV over the entire sample period. We notice in all cases a significance decrease in the portfolio returns during the 2008 GFC and notably around the COVID-19 outbreak in early 2020, although it rebounded afterwards, reaching new high levels. Among the CS, CK and ALL portfolios, the ALL portfolio exhibits the

TABLE 10 Performance metrics for the long-only commodities portfolios.

This table reports performance indicators of different portfolio strategies. The three portfolios are based on minimum conditional volatility (CV), minimum conditional skewness (CS) and minimum conditional kurtosis (CK) spillovers. The fourth portfolio (ALL) is based on minimum spillovers of combined three higher order moments. The portfolio weights are based on PSI through TVP-VAR analysis. AR stands for annualised average returns. Volatility is the annualised standard deviation of portfolio returns. SR stands for Sharpe ratio, VaR is the 5% value-at-risk, and MD stands for maximum drawdowns.

	AR	Volatility	Skew	Kurt	SR	Sortino	Calmar	VaR	MD
CV	−6.611	36.968	−3.957	117.072	−0.179	−0.233	−0.079	−3.819	−44.644
CS	−0.135	31.387	−0.067	17.816	−0.004	−0.006	−0.001	−3.243	−27.872
CK	0.766	32.671	0.172	18.381	0.023	0.033	0.000	−3.375	−24.259
ALL	−0.178	32.514	1.306	58.481	−0.005	−0.008	0.000	−3.359	−7.879

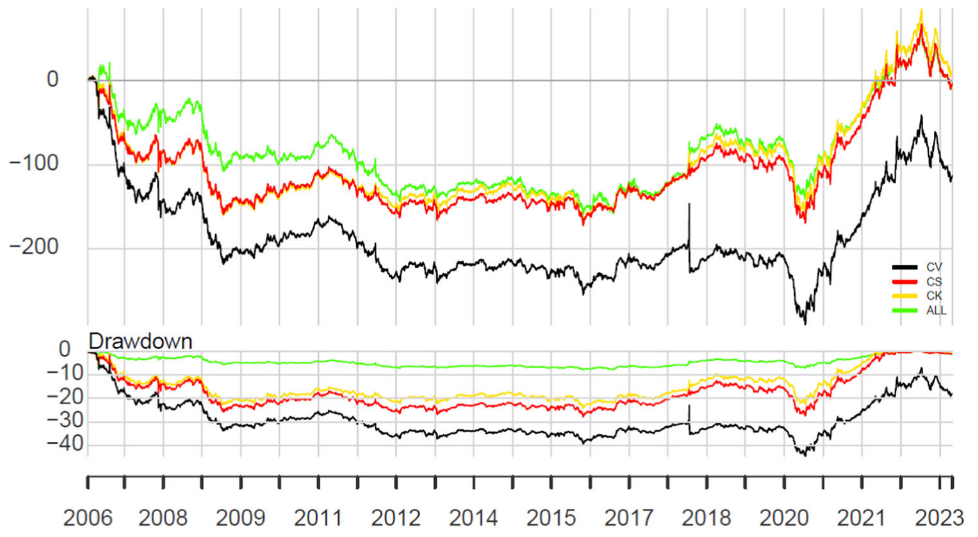

FIGURE 12 Market value and drawdowns of the long-only unfunded portfolios. The upper figure shows cumulative returns (y-axis) of different portfolios over the time (x-axis). The lower figure shows portfolio drawdowns (y-axis) of different portfolios over the time (x-axis). The three portfolios are based on minimum conditional volatility (CV), conditional skewness (CS) and conditional kurtosis (CK) connectedness. The fourth portfolio (ALL) is based on minimum connectedness of combined three higher order moments. The portfolio weights are based on PCI through TVP-VAR analysis. [Color figure can be viewed at wileyonlinelibrary.com]

highest cumulative returns, for most of the period, except from early 2022 till the end of the period when the CK slightly outperforms. As for the portfolio drawdowns at the lower panel of Figure 12, they show comparable trends. However, the ALL portfolio shows the most attractive drawdowns' value throughout the sample period, reaching the zero mark after the pandemic near the end of the sample period.

Taken together, the results from Table 10 and Figure 12 highlight the utility and relevance of considering the spillover effects estimated jointly in the system containing the higher-order conditional moments of the market returns of EUA, Brent, NG, Coal, Nordic electricity and Clean energy. Generally, the above results highlight the portfolio implications of considering higher-order moments, which is somewhat supported by previous evidence on the utility of considering skewness for the forecasting of VaR (Wang et al., 2022), tail risk of energy returns and the spillover effect of high-order moments and co-moments for portfolio allocation and risk management (Dai et al., 2021; Nekhili & Bouri, 2023).

7 | CONCLUSION

Unlike previous studies on the carbon-energy nexus, which tend to consider the spillover effect in the volatility, we enrich the related literature by considering the spillover effect in higher-order moments. As such, we cope with the nonnormality of the return distribution of carbon and various energy markets arising from the occurrence of extreme events and shocks. Using a spillover approach in a time-varying setting, we consider daily data from July 19, 2006 to March 30, 2023 on EUA, Brent oil, NG, Coal, Electricity and Clean energy markets. The empirical results show the following. First, the spillover effect in the carbon-energy system for three moments differs across moments and tends to intensify during crisis periods. Furthermore, the carbon and NG markets are notably interconnected via their higher moments. Second, intensity of the TSI measured jointly for CV, CS and conditional (excess) kurtosis is larger than the TSI measured individually for each moment, reflecting the significant cross-moment spillovers and their contribution to the total spillover in the system of the three moments. Third, overall, the performance of the portfolio improves after considering some higher moments.

The findings of this study raise policy implications and practical recommendations in light of the importance of carbon allowances as a risk tool against global warming within the green transition and the EU's 2030 climate ambition as well as the role of energy markets in the functioning of the global economy and portfolio diversification. Notably, the reported evidence on the spillover effects in not only volatility but skewness and kurtosis between carbon and energy assets points to the relevance of considering return asymmetry and fat tails in the spillover analysis. This might also concern the design of policies and early warning systems necessary for monitoring and maintaining financial stability, especially under potential economic, financial or health crises which seem to spread the intensity of risk spillover to higher-order moments. This should also concern the European industry given that significant spillover effects arising from energy markets to the carbon markets might harm Europe's industry, which requires policymakers to balance disruptions in energy supplies and buffer the impact of crisis periods on the green transition. In fact, our analysis provides a comprehensive view on systemic risk in the EUA, Brent oil, NG, coal, electricity and clean energy markets based on the three higher-order moments, under the extreme events and large deviation of the return series from the normal distribution. This is useful for investors and policymakers who should be aware that an important amount of information on systemic risk can be missed from the system of spillovers between carbon and energy markets if spillovers in higher-order moments in the same system are not captured, which might result in making limited portfolio and risk management decisions, ultimately undermining portfolio decarbonisation and thus the decision to reduce investments in carbon-intensive assets and increase investments in carbon-efficient assets. Furthermore, evidence that the performance of the portfolio improves after considering some higher moments spillovers should reflect the utility of considering high-order moments as well as jointly estimating the spillovers in three moments in the same system, which is new to the academic literature on spillovers in higher moments. Notably, it can be useful and relevant for portfolio managers seeking to improve the performance of their portfolios under the energy transition. Accordingly, it should matter for asset allocation, the calculation of risk measures, and possibly the pricing of financial derivatives.

Further research is recommended based on the spillover effect estimated jointly for the three moments, while considering the impact of global risk factors. This might be a signal for investments to continue their switch towards net-zero emissions.

DATA AVAILABILITY STATEMENT

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

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APPENDIX

(see Figures A1 and A2)

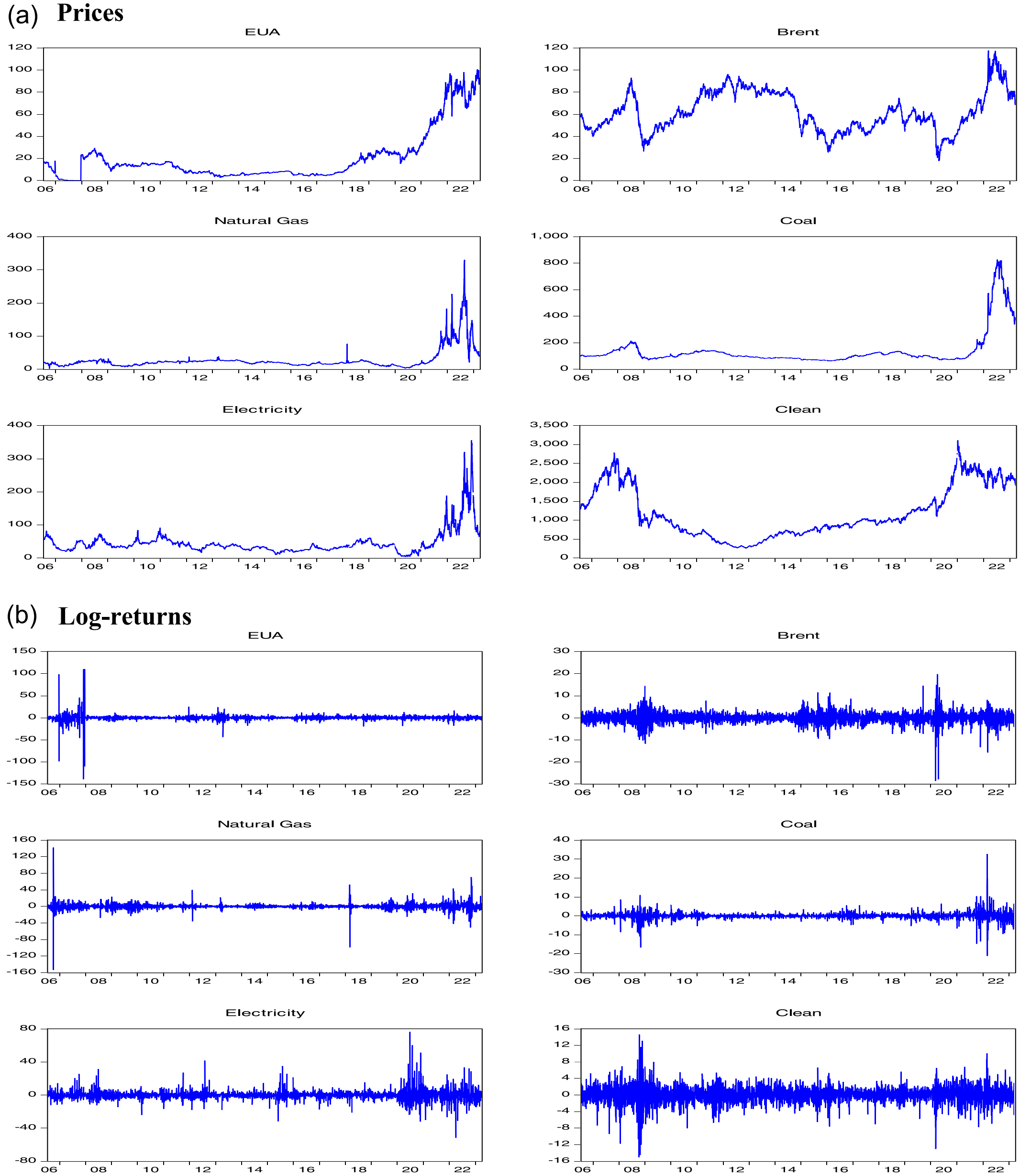

FIGURE A1 Plot of the prices (a) and log-returns (b) of the six indices under study. (a) Prices. (b) Log-returns. [Color figure can be viewed at wileyonlinelibrary.com]

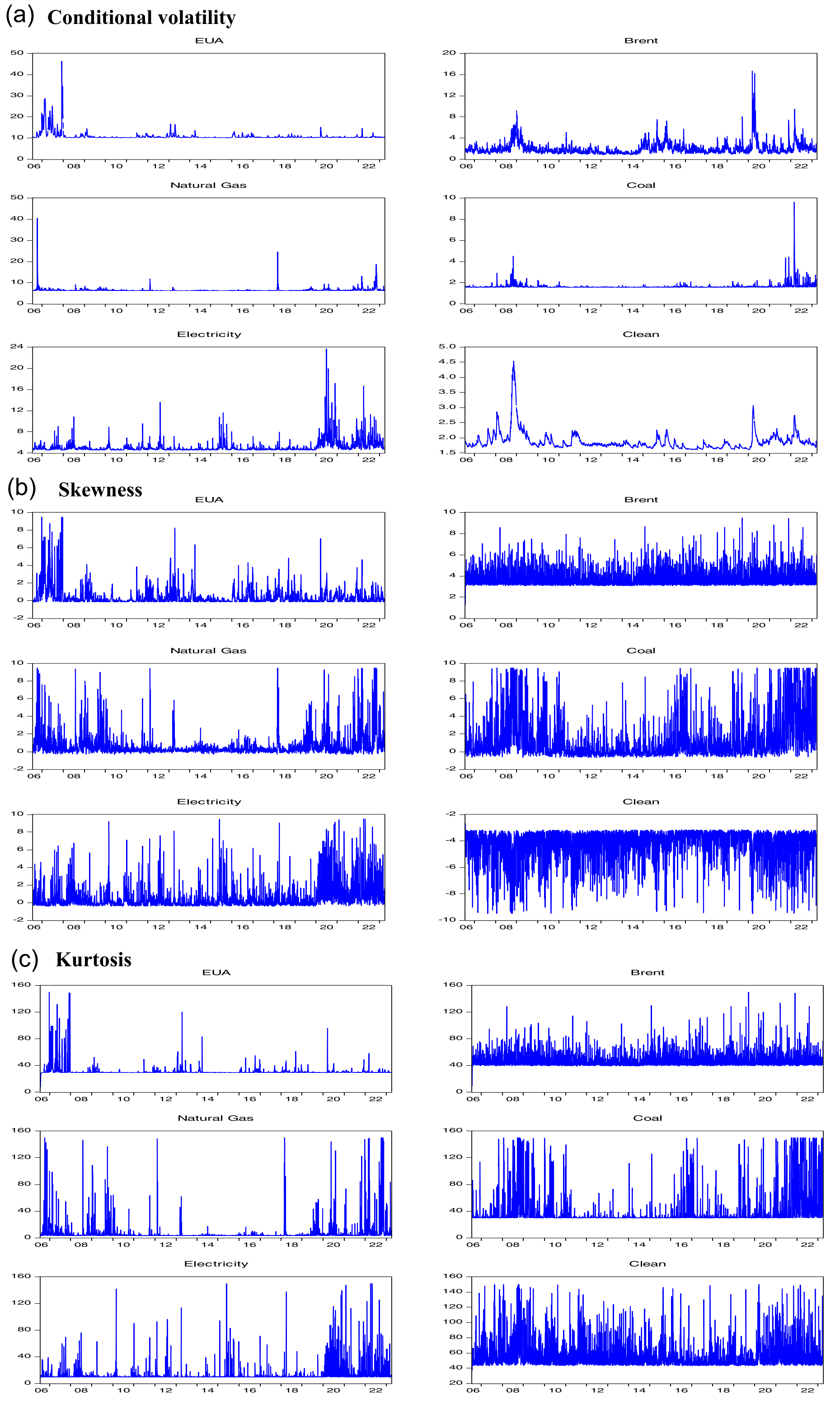

FIGURE A2 Plot of the conditional volatility, skewness and kurtosis. (a) Conditional volatility. (b) Skewness. (c) Kurtosis. [Color figure can be viewed at wileyonlinelibrary.com]