Asymmetry in Higher Moment Spillovers : Evidence from Sustainable and Traditional Investments

He, Xie

Hamori, Shigeyuki

(Citation)
神戸大学経済学研究科 Discussion Paper,2316:1-44

(Issue Date)
2023-09

(Resource Type)
technical report

(Version)
Version of Record

(URL)
https://hdl.handle.net/20.500.14094/0100483289

Asymmetry in Higher Moment Spillovers: Evidence from Sustainable and Traditional Investments

Xie He
Shigeyuki Hamori

September 2023

Discussion Paper No. 2316

GRADUATE SCHOOL OF ECONOMICS

KOBE UNIVERSITY

ROKKO, KOBE, JAPAN

Asymmetry in Higher Moment Spillovers: Evidence from Sustainable and Traditional Investments

Xie He
Graduate School of Economics, Kobe University
2-1, Rokkodai, Nada-Ku, Kobe 657-8501 JAPAN

Shigeyuki Hamori (corresponding author)
Graduate School of Economics, Kobe University
2-1, Rokkodai, Nada-Ku, Kobe 657-8501 JAPAN
Email: hamori@econ.kobe-u.ac.jp

Abstract

This study presents a framework that breaks down kurtosis into positive and negative shocks, distinguishing between "good" and "bad" kurtosis. We analyze asymmetric kurtosis spillovers among sustainable and traditional investments. Our findings indicate that within the system encompassing sustainable and traditional investments, good kurtosis spillover generally surpasses bad kurtosis spillover in the majority of periods. However, during specific extreme events such as Brexit and COVID-19, bad kurtosis spillover takes on a dominant role.

Key words: Higher moments; Conditional kurtosis; Spillover effect;
JEL classification: G15; F3; C32
Funding: This work was supported by Sawamura Masaka Foundation.

1. Introduction

The presence of asymmetric volatility in financial markets, where good news and bad news have distinct impacts on the evolution of market prices and their volatilities, has long been acknowledged in the literature. Specifically, volatility stemming from market downturns is typically more pronounced than the volatility associated with market upturns of the same magnitude. This raises an essential question: "Does the volatility resulting from good news propagate across financial markets in the same manner as the volatility stemming from bad news?" In other words, does asymmetry manifest in volatility spillover? This question holds significant importance. For investors, it constitutes a central concern when managing optimal portfolio diversification and asset allocation strategies. For policymakers, it plays a pivotal role in crafting policies aimed at mitigating the transmission of detrimental shocks across markets and enhancing financial stability (BenSaïda, 2019). In recent years, an increasing number of studies have started to center their focus on the asymmetry in volatility spillover.

Volatility is commonly regarded as a risk measure: low volatility implies low volatility risk, while high volatility implies high volatility risk. Consequently, volatility spillovers can be interpreted as spillovers of volatility risk (Baruník et al., 2016). Similarly, kurtosis, which is one of the higher moments, can serve as a proxy for extreme risk, as it signifies the probability of extreme outcomes, whether they are extremely positive or negative. Consequently, kurtosis spillovers can be perceived as spillovers of extreme risk. Here, we raise another question: Does asymmetry also manifest in kurtosis spillovers?

To address this inquiry, we reference the methodology of BenSaïda (2019) and employ the GJR with skewness and kurtosis (GJR-SK) model. This model, an extended version of the GJR model designed for higher moments, allows us to decompose kurtosis into components of good and bad kurtosis. The partitioning of volatility into bad and good volatility can be interpreted as a measure of downside and upside volatility risk (Baruník et al., 2016). Similarly, the partitioning of kurtosis into bad and good kurtosis can be regarded as an indicator of extreme downside and upside risk. Guided by this kurtosis decomposition, we investigate asymmetric kurtosis spillovers within sustainable and traditional investments. Our aim is to analyze whether the extreme upside risk introduced by positive news propagates across investments in the same manner as the extreme downside risk stemming from negative news.

To the best of our knowledge, this study is the first to examine the asymmetry in higher moment (kurtosis) spillover. Our study introduces a novel approach to assess the asymmetry in the transmission of extreme risk. Our research framework allows researchers to differentiate between upward and downward extreme risk spillovers and to investigate them independently.

One of the key findings of this study is that, in most periods, the spillover of extreme risk among investments predominantly involves the transmission of extreme upside risk due to good news. However, during specific extreme periods, such as the Brexit vote and the COVID-19 pandemic, the spillover is more focused on extreme downside risk resulting from bad news. This result starkly contrasts with the findings related to the general transmission of volatility risk, where, in most periods, the spillover effect of volatility risk is greater for bad volatility risk arising from bad news. This result can be attributed to two factors: Firstly, the spillover effect of extreme risk in the market is not as responsive to bad news as the spillover effect of general risk. Only relatively severe bad news may trigger an increase in the transmission of downward extreme risk. Secondly, the spillover effect of risk in the market is intertwined with market sentiment. Market expectations for general risk and extreme risk may not necessarily align. While the market generally holds a pessimistic outlook on general risk, it is only in highly unstable market environments that it adopts a pessimistic view of extreme risk.

The structure of the remaining sections of this paper is as follows: Section 2 presents a literature review of relevant studies. Section 3 outlines the methodology used. Section 4 provides data, summary statistics, and empirical research results along with discussions. The concluding section presents the final remarks.

2. Related literature

2.1. Lower moment spillovers and higher moment spillovers

The spillover effect is a vital research topic as it captures the transmission of shocks and movements across markets or sectors. Understanding these interconnections is crucial for comprehending systemic risk, formulating effective monetary and fiscal policies, and making informed investment decisions. It illuminates the interconnected nature of financial systems and the potential cascading effects of a crisis or event in one market onto others. In recent years, the Diebold Yilmaz connectedness (spillover) approach has gained increasing attention from researchers studying the spillover effect. The approach is both computationally straightforward and yields intuitive results. By utilizing a generalized vector autoregression framework, it provides a clear depiction of volatility transmission across markets or sectors. The resulting spillover indices are easily interpretable, making it an appealing tool for researchers and policymakers seeking to understand market interconnectedness and systemic risk. Drawing from the Diebold Yilmaz connectedness approach, a significant body of literature has investigated returns and volatilities spillovers (e.g., Baele, 2005; Chan et al., 2018; X. He et al., 2020; Huo & Ahmed, 2017; Liu & Hamori, 2020; Tiwari et al., 2018).

Indeed, while much of the existing research has focused on lower moment spillovers such as returns and volatility, delving into higher moment spillovers can yield distinct insights. Higher moments, such as skewness and kurtosis, can capture more nuanced characteristics of asset distributions and their extreme movements, providing a deeper grasp of market dynamics and systemic risks. Unlike volatility spillover, higher moment spillovers can encompass extreme tail comovements between markets. Additionally, higher moment spillovers can effectively identify significant events that return and volatility spillover might not adequately capture (Bouri et al., 2021). To capture time-varying skewness or kurtosis, either realized measures utilizing high-frequency data or model-based estimates relying on specific econometric models to predict changes in these higher moments over time are necessary. In recent times, an increasing number of studies have unveiled the presence of higher moment spillovers (such as skewness and kurtosis) in financial markets (e.g., He & Hamori, 2023; X. He & Hamori, 2021; Nekhili & Bouri, 2023; Nyakurukwa & Seetharam, 2023; H. Zhang et al., 2023).

2.2. *Asymmetric spillovers*

In the analysis of market dynamics and crisis transmission, understanding how volatility reacts to shocks (or news) has become a significant concern. However, the asymmetry in volatility spillover has received limited attention, and the identification of transmission mechanisms heavily relies on model design (BenSaïda, 2019). For instance, Reboredo et al. (2016) measured downside and upside risk transmission through the conditional value-at-risk (CoVaR) computed from pair copulas. Yarovaya et al. (2017) employed an asymmetric causality test to investigate pairwise spillovers. By employing a recently-developed quantile-on-quantile (QQ) method, Duan et al. (2023) analyzed the potential asymmetry and non-linearity of the market connection between Bitcoin and green and traditional assets.

Barndorff-Nielsen et al. (2010) decomposed realized volatility into a positive semivariance estimator RS+ and a negative semivariance estimator RS− to capture changes arising from positive and negative shocks, respectively. Building on these realized semivariance measures and the Diebold-Yilmaz approach, some researchers have explored asymmetric volatility spillovers across markets (e.g., Baruník et al., 2016, 2017; Mensi et al., 2021, 2022).

However, realized measures have their limitations. Firstly, they rely on intraday high-frequency data, which can present certain challenges in data acquisition. Secondly, high-frequency data are affected by microstructure noise, and stock returns include a jump component, impacting the accuracy of realized volatility estimators. To address these limitations, BenSaïda (2019) proposed a model-based semivariance estimate based on the

Glosten Jagannathan-Runkle (GJR) model and explored asymmetric spillovers across G7 stock markets using this model-based estimate.

2.3. Spillovers in sustainable and traditional investments

Over the past decade, sustainable investing has emerged as a transformative paradigm in the financial sector, seeking to merge environmental, social, and governance (ESG) considerations with traditional investment strategies. Rooted in the belief that long-term success is intricately linked to a broader societal and environmental context, this approach transcends mere financial returns, emphasizing responsible stewardship of capital. As global challenges like climate change and social inequities become increasingly pressing, there's a growing recognition of the pivotal role that finance plays in shaping sustainable outcomes. Consequently, sustainable investing has not only experienced increased adoption by institutional and retail investors alike but has also begun to reshape the contours of the global investment landscape.

Given its relatively nascent emergence, sustainable investments, while promising, still have limited market depth compared to traditional investments. This results in heightened risk associated with sustainable investments. Consequently, it underscores the imperative to explore effective diversification and risk mitigation strategies for these promising yet inherently riskier sustainable assets.

As the size and number of participants in the carbon market expand, the linkage of prices between carbon assets and other financial products, such as energy assets, appears to be growing stronger (Ren et al., 2022a). The nexus between the volatility of energy markets and the carbon market seems indisputable. However, the connection between the volatility of the crude oil market and the carbon market remains a subject of divergent opinions. Indeed, some studies have confirmed a strong bidirectional spillover effect between the carbon market and the crude oil market (i.e., Ji et al., 2018; Ren et al., 2022b; Y. Wang & Guo, 2018). However, there are still some studies that present contrary evidence. For example, Zhang & Sun (2016) argue that no significant volatility spillover is found between the European carbon trading market and crude oil markets.

As an extension of the widely studied "Carbon-Energy" system, the "Carbon-Energy-Finance" system has gained attention in recent years. This system posits that the carbon market is interconnected not only with traditional energy markets but also with some financial markets. For example, the research of Tan et al. (2020) on the EU ETS indicates that the volatility of the carbon market is closely related to the volatility of the stock market.

Green stocks, renewable energy stocks, and ESG (Environmental, Social, and Governance) stocks are three crucial stock-based sustainable investments. Green stocks primarily focus on environmental factors, such as the S&P 500 Bond Investment Grade Carbon Efficient Index, which mainly involves companies with low carbon emissions relative to their sales. ESG stocks not only emphasize environmental factors but also highlight companies that excel in their environmental, social, and governance practices. The investment scope of renewable energy stocks is even more specific, as it only encompasses firms in the clean energy sector. Research on the nexus between ESG stocks and green stocks with the traditional energy market is relatively limited, with most studies focusing on the relationships between renewable energy stocks and the traditional energy market. The volatility spillover effects between new energy stocks and traditional energy markets have been confirmed by many researchers (i.e., Attarzadeh & Balcilar, 2022; Caporale et al., 2023; Liu & Hamori, 2020; Song et al., 2019; Umar et al., 2022), and many studies have found that the spillover effects between the crude oil market and new energy stocks are the most significant (i.e., Liu & Hamori, 2020; Song et al., 2019; Umar et al., 2022).

Green bonds are considered essential investment vehicles within sustainable investing. They represent new forms of asset classes that not only engage in market-centric business practices but also derive their legitimacy and innovation by strongly focusing on environmentally and sustainable capital transactions (Rao et al., 2022).

Most of the research primarily focuses on the spillover effects between green bonds and the energy market (i.e., Nguyen et al., 2021; Pham, 2016; Reboredo, 2018; Reboredo et al., 2020). However, some studies have also identified a pronounced spillover effect between green bonds and precious metals such as gold and silver (i.e., Naeem et al., 2021).

3. Methodology

3.1. GJR-GARCH-SK model

We propose to infer the volatility and kurtosis measure of each investment from the Glosten Jagannathan-Runkle (GJR) with skewness and kurtosis (GJR-SK) model. The formulation of the GJR-SK model is given as follows.

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \tag{1a}$$

$$\eta_t = h_t^{-1/2} \varepsilon_t \tag{1b}$$

$$\eta_t | I_{t-1} \sim \Delta(0,1,s_t,k_t) \tag{1c}$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 \varepsilon_{t-1}^2 I_{\{\eta_{t-1}<0\}} \tag{1d}$$

$$s_t = \gamma_0 + \gamma_1 \eta_{t-1}^3 + \gamma_2 s_{t-1} + \gamma_3 \eta_{t-1}^3 I_{\{\eta_{t-1}<0\}} \tag{1e}$$

$$k_t = \delta_0 + \delta_1 \eta_{t-1}^4 + \delta_2 k_{t-1} + \delta_3 \eta_{t-1}^4 I_{\{\eta_{t-1}<0\}} \tag{1f}$$

Here α_0, α_1 are parameters of the AR model and β_{i-1}, γ_{i-1}, and δ_{i-1}, $i = 1,2,3$ are parameters of the GJR-SK model. I_A is an indicator function that returns 1 if A is true and 0 otherwise. Δ is a probability density function with mean 0, variance 1, and time-varying skewness s_t, and kurtosis k_t. The probability density function $\Delta(0,1,s_t,k_t)$ can be given by Gram-Charlier expansion using Chebyshev-Hermite polynomials.

Next, following BenSaïda (2019) 's line of thought, we define the good volatility $h_{i,t}^+$ and bad volatility $h_{i,t}^-$ to correspond to positive and negative shocks, respectively.

$$\begin{cases} h_{i,t}^+ = h_{i,t} I_{\{\eta_{t-1} \geq 0\}} \\ h_{i,t}^- = h_{i,t} I_{\{\eta_{t-1} < 0\}} \end{cases} \tag{2}$$

Similarly, we also define the good kurtosis $k_{i,t}^+$ and bad kurtosis $k_{i,t}^-$ as follows.

$$\begin{cases} k_{i,t}^+ = k_{i,t} I_{\{\eta_{t-1} \geq 0\}} \\ k_{i,t}^- = k_{i,t} I_{\{\eta_{t-1} < 0\}} \end{cases} \tag{3}$$

We note that the total volatility (kurtosis) of an asset i at any time t is simply the sum of the good and bad volatility (kurtosis) components. Hence, $h_{i,t} = h_{i,t}^+ + h_{i,t}^-$ and $k_{i,t} = k_{i,t}^+ + k_{i,t}^-$.

3.2. TVR-VAR based Asymmetric spillover approach

Antonakakis et al. (2020) introduced a simple measure of dynamic spillovers across markets by using a time-varying parameter vector autoregressive model (TVP-VAR). Consider an N-variable TVP-VAR(1) model as follows:

$$\boldsymbol{y}_t^+ = \boldsymbol{\Phi}_t^+ \boldsymbol{y}_{t-1}^+ + \boldsymbol{\varepsilon}_t^+, \qquad \boldsymbol{\varepsilon}_t^+ | \boldsymbol{\Omega}_{t-1}^+ \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_t^+), \tag{4a}$$

$$\mathrm{vec}(\boldsymbol{\Phi}_t^+) = \mathrm{vec}(\boldsymbol{\Phi}_{t-1}^+) + \boldsymbol{\eta}_t^+, \qquad \boldsymbol{\eta}_t^+ | \boldsymbol{\Omega}_{t-1}^+ \sim \boldsymbol{N}(\boldsymbol{0}, \Xi_t^+), \tag{4b}$$

$$\boldsymbol{y}_t^- = \boldsymbol{\Phi}_t^- \boldsymbol{y}_{t-1}^- + \boldsymbol{\varepsilon}_t^-, \qquad \boldsymbol{\varepsilon}_t^- | \boldsymbol{\Omega}_{t-1}^- \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_t^-), \tag{4c}$$

$$\mathrm{vec}(\boldsymbol{\Phi}_t^-) = \mathrm{vec}(\boldsymbol{\Phi}_{t-1}^-) + \boldsymbol{\eta}_t^-, \qquad \boldsymbol{\eta}_t^- | \boldsymbol{\Omega}_{t-1}^- \sim \boldsymbol{N}(\boldsymbol{0}, \Xi_t^-), \tag{4d}$$

where $\boldsymbol{y}_t^+$ can be an $N \times 1$ dimensional of good volatilities $\boldsymbol{h}_{i,t}^+ = (h_{1,t}^+, \cdots, h_{n,t}^+)'$ or good kurtosis $\boldsymbol{k}_{i,t}^+ = (k_{1,t}^+, \cdots, k_{n,t}^+)'$, while $\boldsymbol{y}_t^-$ can be an $N \times 1$ dimensional bad volatility $h_{i,t}^+$ or bad kurtosis $k_{i,t}^+$. $\boldsymbol{\Omega}_{t-1}^+$ and $\boldsymbol{\Omega}_{t-1}^-$ represent all available information up to $t-1$. $\boldsymbol{\Phi}_t^+$ and $\boldsymbol{\Phi}_t^-$ are $N \times N$ matrices and their vectorization $\mathrm{vec}(\boldsymbol{\Phi}_t^+)$ or $\mathrm{vec}(\boldsymbol{\Phi}_t^-)$ is an $N^2 \times 1$ vector. The shocks $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$ are $N \times 1$ and $N^2 \times 1$ dimensional vectors, respectively. Moreover, variance-covariance matrices $\boldsymbol{\Sigma}_t^+, \boldsymbol{\Sigma}_t^-$ and Ξ_t^+, Ξ_t^- are $N \times N$ and $N^2 \times N^2$ dimensional matrices, respectively.

Using the Wold representation theorem, the TVP-VAR can be transformed into a TVP-VMA. To ease the notational burden, we replace $\boldsymbol{y_t}$ with either the good volatility (kurtosis) $\boldsymbol{y}_t^+$ or bad volatility (kurtosis) $\boldsymbol{y}_t^-$ as follows.

$$\boldsymbol{y_t} = \sum_{j=1}^{\infty} \boldsymbol{\Lambda}_{jt} \boldsymbol{\varepsilon}_{t-j} + \boldsymbol{\varepsilon}_t. \tag{5}$$

We can then calculate the generalized forecast error variance decomposition (GFEVD), which was introduced by Koop et al. (1996), and Pesaran & Shin (1998), using TVP-VMA coefficients to compute the dynamic connectedness measures (Diebold & Yilmaz, 2009, 2012, 2014).

The H-step-ahead GFEVD under the generalized VAR framework can be expressed as follows:

$$\theta_{jk,t}^{H} = \frac{\Sigma_{kk,t}^{-1} \sum_{h=0}^{H-1} \left(e_j' \mathbf{\Lambda}_{h,t} \mathbf{\Sigma}_t e_k\right)^2}{\sum_{h=0}^{H-1} \left(e_j' \mathbf{\Lambda}_{h,t} \mathbf{\Sigma}_t \mathbf{\Lambda}_{h,t}' e_j\right)}, \tag{6}$$

After the normalization, the pairwise connectedness index from the k −th variable to the j −th variable at horizon H at time t can be calculated by

$$\tilde{\theta}_{jk,t}^{H} = \frac{\theta_{jk,t}^{H}}{\sum_{k=1}^{N} \theta_{jk,t}^{H}}, \tag{7}$$

Meanwhile, the total connectedness index can be represented as

$$S_t^H = \frac{1}{N} \sum_{j,k=1, j \neq k}^{N} \tilde{\theta}_{jk,t}^{H} \,. \tag{8}$$

Moreover, the directional connectedness (From), which measures the total spillover to the k −th variable from all remaining variables in the system, can be calculated as

$$S_{k \leftarrow \cdot, t}^{H} = \frac{1}{N} \sum_{j=1, j \neq k}^{N} \tilde{\theta}_{kj,t}^{H} \,. \tag{9}$$

Similarly, the directional connectedness (To), which measures the total directional spillover from the k −th variable to all the remaining variables in the system, can be calculated as

$$S_{\cdot \leftarrow k, t}^{H} = \frac{1}{N} \sum_{j=1, j \neq k}^{N} \tilde{\theta}_{jk,t}^{H} \,. \tag{10}$$

3.3. Spillover asymmetry

To detect the potential asymmetry in the risk transmission across markets, we denote the good total volatility (kurtosis) spillover index as S_t^{H+}, and the bad total volatility (kurtosis) spillover index as S_t^{H-}. The total spillover asymmetry A_t^H, can be defined as the difference between the good and the bad spillover indices:

$$A_t^H = S_t^{H+} - S_t^{H-} \tag{11}$$

Similarly, the directional spillover measures for k −th variable are ($S_{k\leftarrow\cdot,t}^{H+}, S_{k\leftarrow\cdot,t}^{H-}$, $S_{\cdot\leftarrow k,t}^{H+}, S_{\cdot\leftarrow k,t}^{H-}$) from equation (9) and (10). Then the directional spillover asymmetry can be calculated as

$$A_{k\leftarrow\cdot,t}^{H+} = S_{k\leftarrow\cdot,t}^{H+} - S_{k\leftarrow\cdot,t}^{H-} \tag{12a}$$

$$A_{\cdot\leftarrow k,t}^{H+} = S_{\cdot\leftarrow k,t}^{H+} - S_{\cdot\leftarrow k,t}^{H-} \tag{12b}$$

If the spillover asymmetry indices are null, the contributions from the good and bad volatilities are identical; hence, the risk transmission is symmetric. Alternatively, asymmetric connectedness in terms of magnitude and direction is the result of different good and bad spillover indices. A positive asymmetry index means that the good volatility spills over markets more intensely than the bad volatility. Similarly, a negative asymmetry index means that the bad volatility spills over markets more intensely than the good volatility.

3.4. Bootstrapping the spillover asymmetry

The bootstrapping technique in this paper is summarized as follows:

(i) Re-sample, with replacement, the returns as a block, i.e., the re-sampling is performed with respect to time *t*. For a given day, we draw the returns of all markets to keep the connectedness structure between variables;

(ii) Re-estimate the good and bad volatilities (kurtosis);

(iii) Compute the time-varying bootstrap asymmetry spillover indices to check for time-dependency;

(iv) Repeat the previous steps (*i*) to (*iii*) B times.

4. Empirical study

4.1. Data and summary statistics

In this paper, we have selected six principal indices under the sustainable investment theme of S&P Global to represent sustainable investments. These are: S&P Global 1200 ESG Index (ESG), S&P Global 1200 Carbon Efficient Index (CEI), S&P 500 Bond Investment Grade Carbon Efficient Index (BIGCEI), S&P Green Bond Index (GBI), S&P Global Clean Energy Index (GCEI), and S&P Global Carbon Index (Carbon). Collectively, these indices encompass a range of sustainable investment categories, including green bonds, clean energy equities, ESG investments, and carbon-focused investments.

More specifically, the S&P Global 1200 ESG Index (ESG) ranks and weights its Global 1200 member companies based on their Environmental, Social, and Governance (ESG) performance. Companies with higher ESG scores have greater weight in this index. The S&P Global 1200 Carbon Efficient Index (CEI) aligns carbon efficiency with the market capitalization of its Global 1200 companies. It gives preference to companies that have lower carbon emissions relative to their market value. The S&P 500 Bond Investment Grade Carbon Efficient Index (BIGCEI) focuses on investment-grade companies within the S&P 500, combining their market capitalization with carbon efficiency. Similar to CEI, it favors companies with a lower ratio of carbon emissions to market value. The S&P Green Bond Index (GB) tracks global green bonds, which are bonds specifically issued to finance environmentally friendly projects. The S&P Global Clean Energy Index (GCEI) tracks the stock performance of global clean energy companies, promoting investment in the clean energy sector. Lastly, the S&P Global Carbon Index (Carbon) concentrates on the global carbon market, tracking the pricing and performance of carbon trading.

Moreover, in our study, we also selected four representative traditional investments, encompassing stocks, gold, crude oil, and bonds. Specifically, these are: S&P GLOBAL 1200 Index (Stock), S&P GSCI Gold Index (Gold), S&P GSCI Crude Oil Index (Oil), and S&P 500 Bond Index (Bond).

All the indices are plotted in Figure 1. The data spans from September 1, 2015, to July 1, 2023. The data used in this study is sourced from S&P Global.

First, we compute the logarithmic returns of each asset's price series. Subsequently, we estimate conditional volatility and conditional kurtosis based on the GJR-SK model. Table 1 presents the descriptive statistics of the return series. From Table 1, we observe that the mean and variance of the returns across the series are fairly consistent, nearly converging to zero. As for skewness and excess kurtosis, it's evident that all series exhibit negative skewness and positive excess kurtosis. The p-values of the Jarque-Bera (JB) test are consistently below 0.01, rejecting the null hypothesis that all return series are normally distributed. The unit root test conducted by Elliott et al. (1996) shows that all return series exhibit no unit root. The results of the Fisher & Gallagher (2012) weighted portmanteau test reveal the presence of ARCH/GARCH type effects in all return series.

The estimated volatility and kurtosis are depicted in Figure 2 and Figure 3, respectively. It is evident that there exists a certain similarity in the movements of volatility and kurtosis across indices, which strongly suggests the presence of a spillover effect across markets. Furthermore, a discernible distinction between the variations in volatility and kurtosis can be observed. This indicates that the patterns of general volatility and extreme volatility changes are not identical, displaying significant disparities. Lastly, there are distinct periods of high (either volatility or extreme) risk, such as the Brexit vote in mid-2016, the outbreak of the COVID-19 pandemic, and the Russia-Ukraine conflict.

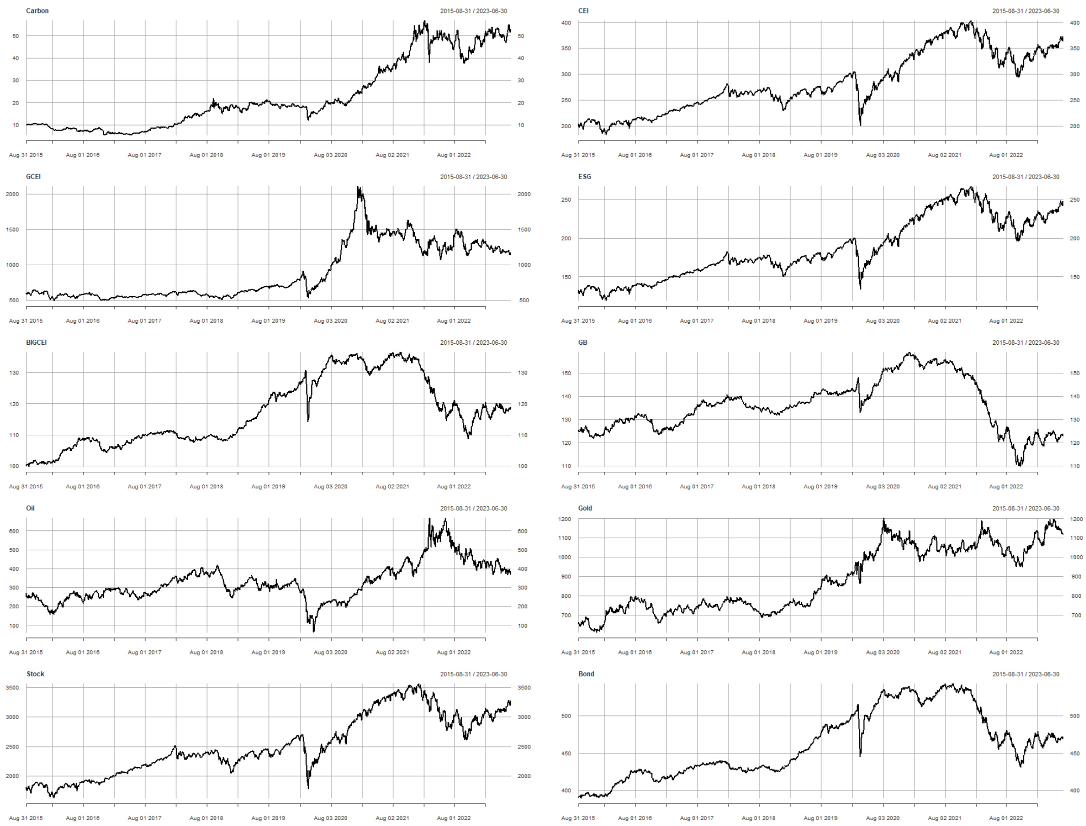


Fig.1: All price series

Note: ESG, CEI, BIGCEI, GB, and GCEI represent the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond refer to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

Table 1: Summary statistics

	Mean	Var	Skew	Kurto	JB	ERS	Q(20)	Q2(20)
ESG	0.00	0.00	–1.08	16.17	0.00	0.00	0.00	0.00
CEI	0.00	0.00	–1.10	16.99	0.00	0.00	0.00	0.00
BIGCEI	0.00	0.00	–0.55	9.04	0.00	0.00	0.00	0.00
GB	0.00	0.00	–0.24	4.75	0.00	0.00	0.00	0.00
GCEI	0.00	0.00	–0.41	7.89	0.00	0.00	0.00	0.00
Carbon	0.00	0.00	–1.06	9.71	0.00	0.00	0.01	0.00
Stock	0.00	0.00	–1.05	15.44	0.00	0.00	0.00	0.00
Gold	0.00	0.00	–0.05	4.25	0.00	0.00	0.01	0.00
Oil	0.00	0.00	–2.85	62.39	0.00	0.00	0.00	0.00
Bond	0.00	0.00	–0.59	11.26	0.00	0.00	0.00	0.00

Note: The table presents descriptive statistics including the mean, variance (Var), skewness (Skew), excess kurtosis (Kurto), and the p-value of the Jarque-Bera test (JB; 1987), the unit root test by Elliott et al. (1996), and the Fisher & Gallagher (2012) weighted portmanteau test with 20 lags. ESG, CEI, BIGCEI, GB, and GCEI represent the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond refer to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

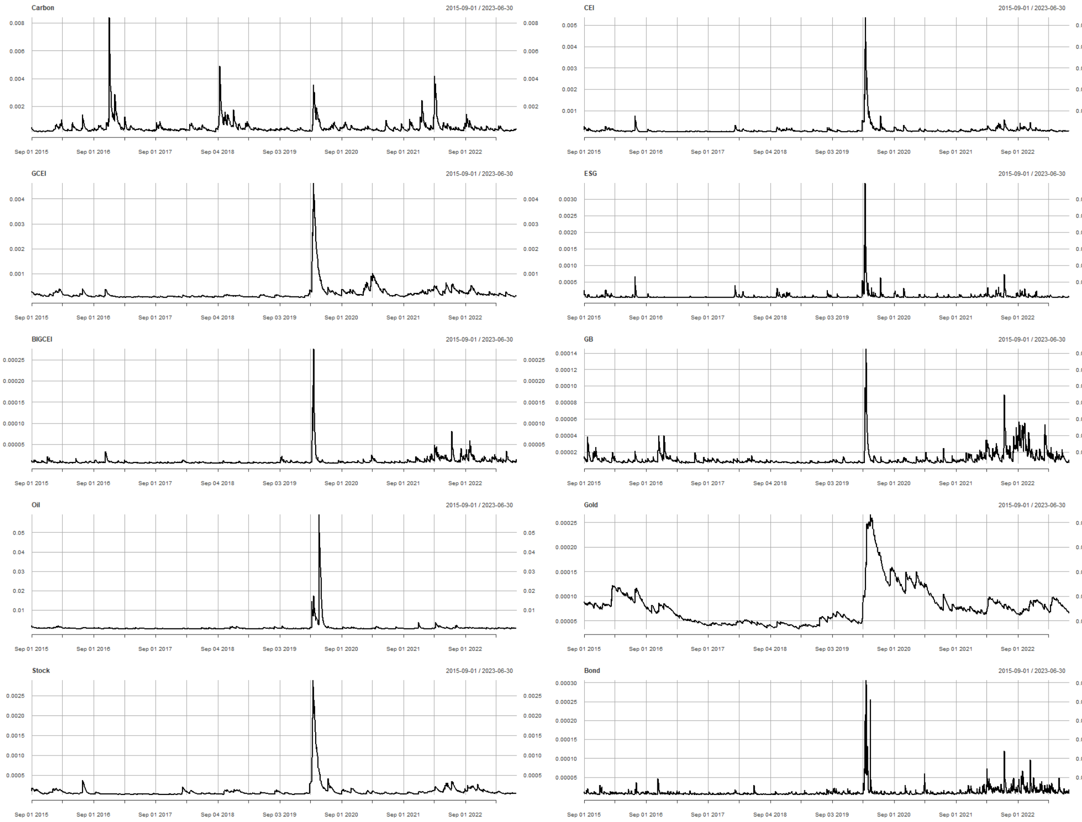


Fig.2: All conditional volatility series

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

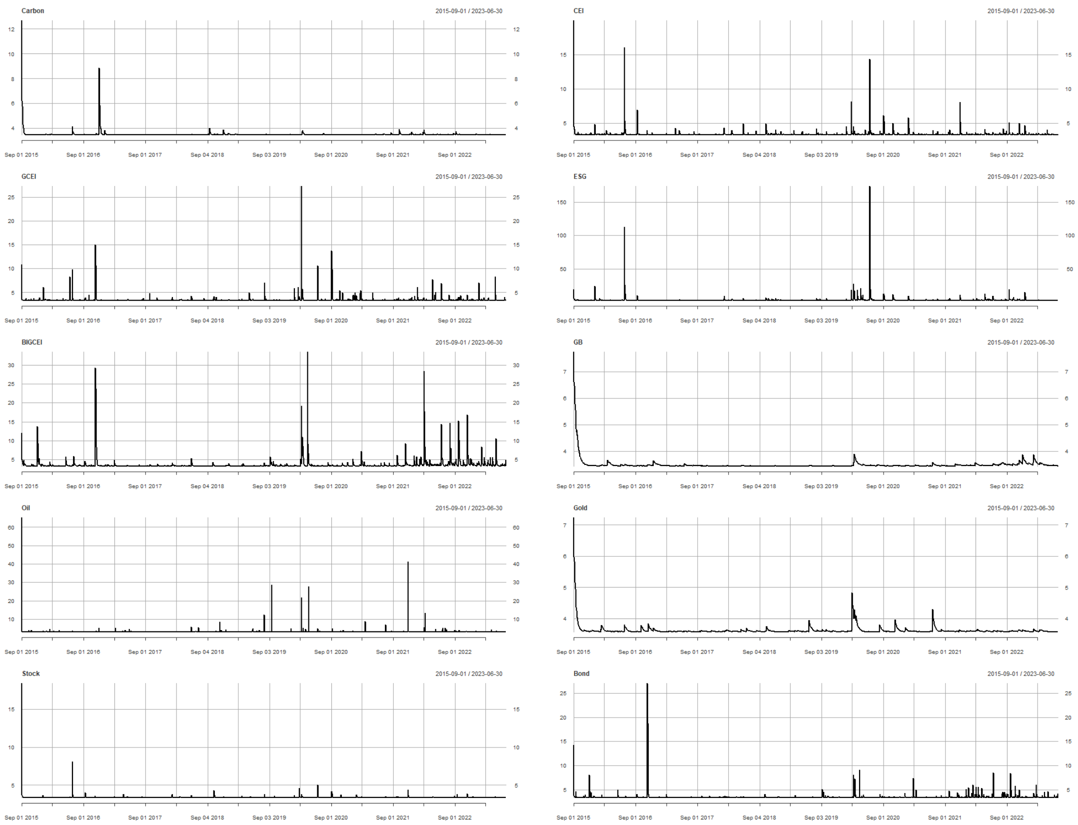


Fig.3: All conditional kurtosis series

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

4.2. Traditional volatility and kurtosis spillovers

As a benchmark, we first report the detailed averaged dynamic (symmetric) volatility and kurtosis spillovers without separating the good from the bad component in Figure 4 and 5, respectively. In fact, we can see that the total volatility spillover across the entire system stands at 65.424 percentage points, while the total kurtosis spillover stands at 48.337 percentage points. This highlights that volatility risk tends to propagate more extensively across various investments compared with extreme risk. In terms of volatility spillover, Oil, CEI, and Stock are the top three investments transmitting spillovers outward, contributing 9.073%, 8.857%, and 8.376% of volatility spillover to other investments, respectively. For kurtosis spillover, Stock, CEI, and ESG are the top three investments transmitting spillovers outward, contributing 8.001%, 7.894%, and 6.345% of kurtosis spillover to other investments, respectively. Interestingly, while Oil transmits higher volatility risk to other investments, it conveys minimal kurtosis risk, accounting for just 1.493% of kurtosis spillover.

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	61.320	6.330	5.440	5.740	2.550	3.240	5.360	2.080	5.430	2.520	3.869
CEI	2.760	22.930	9.870	17.810	4.810	4.780	9.720	2.680	19.650	4.990	7.707
GCEI	3.440	10.750	20.930	7.340	7.230	8.070	16.560	6.900	11.970	6.810	7.907
ESG	1.850	22.550	6.930	29.500	4.890	5.150	7.060	2.270	15.430	4.370	7.050
BIGCEI	3.060	6.260	9.690	5.510	25.740	11.390	8.760	6.150	6.460	16.970	7.425
GB	2.150	6.330	11.170	5.740	12.420	31.370	7.280	7.880	6.660	9.000	6.863
Oil	1.800	5.040	5.390	5.100	1.350	1.680	71.350	1.440	4.350	2.500	2.865
Gold	1.950	5.650	12.150	4.320	7.640	8.690	13.580	32.420	7.250	6.360	6.759
Stock	3.350	19.080	11.700	12.420	5.080	5.030	13.100	3.460	21.620	5.150	7.837
Bond	3.030	6.580	8.850	5.160	18.020	8.850	9.310	5.060	6.560	28.600	7.142
To	2.339	8.857	8.119	6.914	6.399	5.688	9.073	3.792	8.376	5.867	65.424

Spillover
25
20
15
10
5
0

Fig.4: Averaged dynamic volatility spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	74.830	1.840	1.000	1.820	0.750	11.840	0.430	4.230	2.630	0.620	2.516
CEI	1.680	32.040	6.980	22.300	0.930	0.900	3.890	1.520	29.360	0.390	6.795
GCEI	0.810	8.890	50.030	8.380	8.960	0.630	2.230	0.670	10.010	9.390	4.997
ESG	1.340	25.580	7.790	37.060	0.850	0.790	1.760	1.230	22.850	0.760	6.295
BIGCEI	0.340	1.220	9.310	1.120	47.650	2.350	1.240	0.490	1.310	34.980	5.236
GB	7.250	2.100	2.300	2.860	3.290	62.490	0.530	13.660	2.880	2.640	3.751
Oil	0.800	6.480	5.090	3.430	2.900	0.720	71.680	0.680	6.130	2.080	2.831
Gold	4.730	3.160	4.080	2.610	3.070	15.460	0.570	59.160	4.370	2.800	4.085
Stock	2.140	29.370	7.530	20.260	0.900	1.510	3.670	2.060	32.130	0.430	6.787
Bond	0.590	0.300	9.480	0.670	36.490	1.480	0.610	0.350	0.470	49.560	5.044
To	1.968	7.894	5.356	6.345	5.814	3.568	1.493	2.489	8.001	5.409	48.337

Fig.5: Averaged dynamic kurtosis spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

4.3. Averaged dynamic asymmetric spillovers

Next, we present the averaged dynamic good volatility spillover index and the averaged dynamic bad volatility spillover index in Figures 6 and 7, respectively. In addition, Figures 8 and 9 depict the averaged dynamic good kurtosis spillover index and the averaged dynamic bad kurtosis spillover index, respectively.

We find that the contribution of spillovers from volatility shocks among variables to the total forecast error variance is 49.546% for good shocks, while it is 56.163% for bad shocks. This suggests that both good and bad shocks significantly contribute to the system's volatility, with negative shocks having a slightly greater impact. On the other hand, the contribution of spillovers from kurtosis shocks among variables to the total forecast error variance stands at 43.092% for good shocks, compared with an almost equal 42.138% for bad shocks.

For carbon, we found a relatively strong volatility spillover and kurtosis spillover between it and both the stock and crude oil markets. This finding supports the "Carbon-Energy-Finance" system, which posits that the Carbon market is interconnected not only with traditional energy markets but also with some financial markets. For instance, the research of Tan et al. (2020) on the EU ETS also indicates that the volatility of the carbon market closely relates to the volatility of the stock market. Moreover, we observed that the level of bad volatility spillover between them is greater than that of good volatility spillover. Although we also identified a relatively strong kurtosis spillover effect between carbon and stocks or crude oil, the kurtosis spillover effect between them appears to be symmetric, meaning that the levels of good kurtosis spillover and bad kurtosis spillover are nearly equal.

Additionally, for the three stock-based sustainable investments, CEI, GCEI, and ESG, apart from substantial volatility spillovers with the stock market, they also exhibit significant volatility spillovers with the crude oil market. Specifically, we found that the bad volatility spillover between them and the crude oil market is stronger than the good volatility spillover. Among these three stock-based sustainable investments, the volatility spillover effect between GCEI and crude oil is the strongest, regardless of whether it is good or bad volatility and irrespective of the direction of the spillover. The volatility spillover effects between new energy stocks and traditional energy markets, especially the crude oil market, have been confirmed by many researchers (e.g., Attarzadeh & Balcilar, 2022; Caporale et al., 2023; Liu & Hamori, 2020; Song et al., 2019; Umar et al., 2022).

In our research, we observe strong spillover effects in kurtosis between the three stock-based sustainable investments (CEI, GCEI, ESG) and crude oil. Similarly, for kurtosis spillover, the level of bad kurtosis spillover is higher than that of good kurtosis spillover. The only distinction is that CEI transmits the highest kurtosis spillover to crude oil, rather than GCEI.

Finally, for bond-based sustainable investments like BIGCEI and GB, we identify a robust volatility spillover effect between them and gold, regardless of whether it is good or bad volatility. Additionally, the bad volatility spillover between them and gold is stronger than the good volatility spillover. The volatility spillover effect between green bonds and gold is also more pronounced, irrespective of whether it is good or bad volatility.

The findings for kurtosis spillover are generally consistent with these results. The only distinction in kurtosis spillover is that the levels of bad and good kurtosis spillover between bond-based sustainable investments (BIGCEI, GB) and gold are almost identical, indicating symmetrical kurtosis spillover between them.

The strong spillover relationship between green bonds and precious metals can be attributed to the increasing significance of the green bonds market and the stable value of precious metals. Precious metals, particularly gold, are considered stable assets, making them suitable for hedging against market risks. Concurrently, the growing emphasis on sustainable projects is driving the prominence of green bond markets, which are considered effective financial tools for promoting a low-carbon economy. Investors may switch between green bonds and stable precious metals to optimize returns and manage risks, leading to the strong observed spillover effects between these markets (Naeem et al., 2021).

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	79.980	2.570	3.780	1.400	0.680	2.620	3.480	1.180	3.500	0.820	2.003
CEI	1.380	30.510	13.010	17.030	0.970	1.140	7.610	0.830	26.410	1.110	6.949
GCEI	2.640	14.820	37.770	7.250	2.310	2.120	12.450	1.970	16.220	2.440	6.222
ESG	1.200	23.020	8.190	41.190	0.800	1.250	3.820	0.670	19.050	0.810	5.881
BIGCEI	0.780	1.770	3.510	1.130	46.200	8.570	3.220	2.480	1.930	30.400	5.379
GB	2.410	2.310	3.680	1.920	9.670	58.620	3.230	7.830	2.360	7.960	4.137
Oil	2.230	5.650	8.680	2.700	1.030	0.940	68.990	1.820	6.480	1.470	3.100
Gold	1.890	2.000	4.030	1.280	3.010	7.630	6.490	66.320	2.540	4.820	3.369
Stock	1.910	25.970	14.050	13.960	1.040	1.160	9.130	1.080	30.360	1.330	6.963
Bond	1.120	2.170	4.170	1.140	28.860	6.680	5.030	3.610	2.650	44.580	5.543
To	1.556	8.028	6.310	4.781	4.837	3.211	5.446	2.147	8.114	5.116	49.546

Spillover
30
20
10
0

Fig.6: Averaged dynamic good volatility spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	73.860	4.680	3.830	2.680	0.520	2.460	4.680	0.990	5.270	1.020	2.613
CEI	2.580	27.230	10.740	19.400	1.430	2.580	9.700	1.140	23.580	1.640	7.279
GCEI	3.120	13.680	36.650	7.720	2.330	3.190	12.430	2.860	15.320	2.700	6.335
ESG	2.080	23.410	7.300	32.130	2.040	3.320	8.320	0.820	18.210	2.360	6.786
BIGCEI	1.720	3.150	3.580	3.350	38.880	9.620	5.400	3.450	2.900	27.950	6.112
GB	2.640	4.450	4.700	4.330	9.920	44.920	5.640	8.300	4.040	11.060	5.508
Oil	2.480	7.590	8.590	4.770	1.160	0.920	62.230	2.180	8.650	1.440	3.778
Gold	1.880	3.080	5.210	1.900	4.270	9.120	9.190	57.070	4.130	4.150	4.293
Stock	3.140	23.980	12.180	15.260	1.290	2.260	10.750	1.630	28.090	1.420	7.191
Bond	2.090	3.220	3.900	3.400	26.990	10.470	6.420	3.260	2.930	37.340	6.268
To	2.173	8.724	6.003	6.281	4.995	4.394	7.253	2.463	8.503	5.374	56.163

Fig.7: Averaged dynamic bad volatility spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	81.210	2.900	2.000	2.600	0.980	2.360	3.230	1.020	2.770	0.930	1.879
CEI	1.320	36.960	8.310	17.620	1.080	1.310	2.180	0.800	29.470	0.950	6.304
GCEI	1.540	12.670	57.410	8.310	1.140	1.720	3.010	1.200	11.710	1.270	4.257
ESG	1.480	21.090	6.980	44.340	0.990	1.190	2.190	0.870	20.070	0.810	5.567
BIGCEI	0.430	1.560	0.800	1.320	48.190	4.080	1.110	2.100	1.260	39.150	5.181
GB	1.980	2.640	2.190	1.830	5.410	65.730	0.720	10.140	2.640	6.740	3.429
Oil	2.800	4.290	3.810	3.380	1.790	0.810	76.200	1.290	4.220	1.410	2.380
Gold	1.010	1.500	1.200	1.290	3.220	11.150	1.180	74.060	1.510	3.900	2.596
Stock	1.350	30.170	7.910	17.020	0.860	1.150	2.170	0.850	37.800	0.730	6.221
Bond	0.490	1.680	1.050	1.250	38.380	5.000	1.000	2.530	1.400	47.240	5.278
To	1.240	7.850	3.425	5.462	5.385	2.877	1.679	2.080	7.505	5.589	43.092

Fig.8: Averaged dynamic good kurtosis spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

	Carbon	CEI	GCEI	ESG	BIGCEI	GB	Oil	Gold	Stock	Bond	FROM
Carbon	81.780	2.550	1.850	2.030	1.240	2.340	3.280	1.000	2.590	1.330	1.821
CEI	1.190	39.020	8.650	14.010	0.960	1.240	2.670	0.860	30.460	0.950	6.099
GCEI	1.520	12.540	56.770	7.110	2.070	1.540	3.910	1.050	11.300	2.170	4.321
ESG	1.520	18.590	6.850	54.510	0.670	0.750	2.750	0.690	13.030	0.650	4.550
BIGCEI	0.680	1.550	1.950	1.080	46.300	4.530	1.160	1.960	1.310	39.460	5.368
GB	1.970	2.610	2.070	1.220	6.390	64.980	0.530	10.320	2.580	7.330	3.502
Oil	2.540	5.050	4.900	3.990	1.670	0.590	74.250	0.970	4.660	1.370	2.574
Gold	1.110	1.680	1.230	1.080	3.290	11.510	0.990	73.820	1.530	3.750	2.617
Stock	1.340	32.240	8.330	10.430	0.850	1.130	2.650	0.920	41.320	0.800	5.869
Bond	0.680	1.680	1.890	0.950	39.120	5.230	0.900	2.290	1.430	45.830	5.417
To	1.255	7.849	3.772	4.190	5.626	2.886	1.884	2.006	6.889	5.781	42.138

Fig.9: Averaged dynamic bad kurtosis spillover index

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

4.4. Dynamic asymmetric spillovers

Conclusions drawn solely based on Averaged dynamic asymmetric spillovers without further analysis of directional transmission or the evolution of spillover indices over time could potentially be misleading (BenSaïda, 2019). Therefore, this section shifts our focus to dynamic asymmetric spillovers. Figure 10 and Figure 11 depict the dynamic total volatility spillover index and dynamic total kurtosis spillover index, respectively. Each of these figures contains two lines: black represents positive (good) spillover, and red represents negative (bad) spillover. If both lines coincide, it indicates symmetric spillovers.

Figure 10 reveals that bad volatility spillover exceeds good volatility spillover in most periods, indicating that the total volatility spillover in the entire system is asymmetric in most cases. Particularly, the outbreak of COVID-19 significantly influenced bad volatility spillover. In other periods, the difference between good and bad volatility spillover was less pronounced, but the onset of COVID-19 in late 2019 intensified bad volatility spillover, keeping it high for an extended period. Meanwhile, while good volatility spillover also increased during this period, it started to decline soon after, leading to a notable difference between the two during this timeframe.

On the other hand, compared to Figure 10 where bad volatility spillover exceeded good volatility spillover in most periods, Figure 11 illustrates that periods with bad kurtosis spillover surpassing good kurtosis spillover are much less frequent. In fact, instances of bad kurtosis spillover surpassing good kurtosis spillover primarily occurred during the Brexit referendum in mid-2016 and the period of COVID-19.

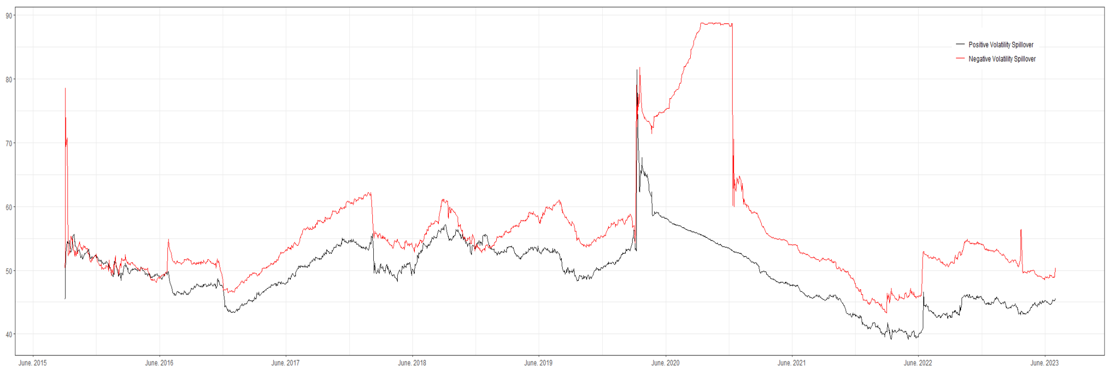


Fig.10: Dynamic total volatility spillover

Note: The black line represents the positive (good) total volatility spillover, while the red line indicates the negative (bad) total volatility spillover.

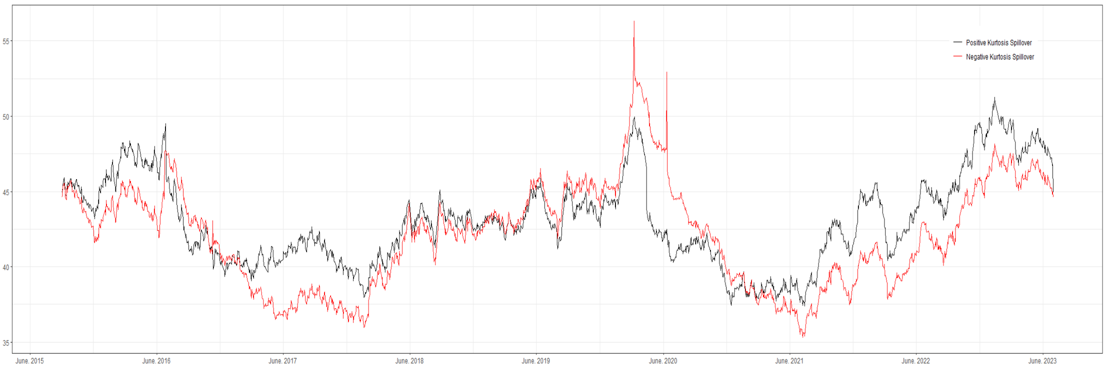


Fig.11: Dynamic total kurtosis spillover

Note: The black line represents the positive (good) total kurtosis spillover, while the red line indicates the negative (bad) total kurtosis spillover.

These results are also confirmed by Figures 12 and 13. Respectively, Figures 12 and 13 illustrate the total volatility spillover asymmetry and total kurtosis spillover asymmetry calculated using Equation 11. In these figures, the periods when bad volatility (kurtosis) spillover exceeds good volatility (kurtosis) spillover (indicating negative asymmetry) are shown by the green shaded areas, while the periods when good volatility (kurtosis) spillover exceeds bad volatility (kurtosis) spillover (indicating positive asymmetry) are represented by the blue shaded areas. The red lines denote the upper and lower bounds of the time-varying 95% confidence interval.

Figure 12 demonstrates that the volatility spillover asymmetry is predominantly negative, with a substantial increase in negative spillover asymmetry during the COVID-19 period. Meanwhile, Figure 13 indicates that negative kurtosis spillover asymmetry is most prominent during the Brexit period in 2016 and the onset of the COVID-19 pandemic.

In financial markets, the phenomenon of negative volatility asymmetry is more prevalent than positive asymmetry, as demonstrated by various studies (e.g., Baruník et al., 2016, 2017; Mensi et al., 2021; X. Wang & Wu, 2018). Our research on volatility spillover asymmetry reaffirms this observation. However, our investigation into kurtosis spillover asymmetry has yielded contrasting results. The occurrence of negative kurtosis asymmetry appears to be more common, whereas positive kurtosis asymmetry is observed only in specific periods.

BenSaïda (2019) and X. Wang & Wu (2018) argue that spillover asymmetry reflects two key aspects. Firstly, it indicates the sensitivity of market participants to both good and bad news. Secondly, it captures market sentiment, whether it leans toward optimism or pessimism, and participants' expectations. Viewing this from the first perspective, it's plausible to assert that market participants are generally more responsive to negative news, which often triggers herd behavior more readily. Consequently, unfavorable news tends to lead to more significant volatility, and this effect is more prone to transmission through spillover channels. This underscores that general volatility risk and volatility spillover are more influenced by negative news. However, extreme volatility, or extreme risk, is less affected by negative news compared to general volatility risk. Only exceptionally severe negative news might drive an increase in extreme volatility and corresponding extreme volatility spillover.

Considering the second perspective, the prevalence of negative spillover asymmetry in most periods indicates that pessimistic sentiment has largely dominated. This has resulted in an overrepresentation of bad volatility spillover. However, this pessimistic sentiment primarily pertains to volatility risk rather than extreme risk. Investors' expectations for volatility risk, reflecting general volatility, and extreme risk, representing extreme volatility, may diverge. In most periods, investors lean toward pessimism concerning volatility risk but exhibit relatively greater optimism toward extreme risk. Yet, during exceptionally extreme periods like the Brexit vote and COVID-19, investor sentiment becomes extremely pessimistic. Consequently, investors harbor pessimistic views not only about volatility risk but also about extreme risk.

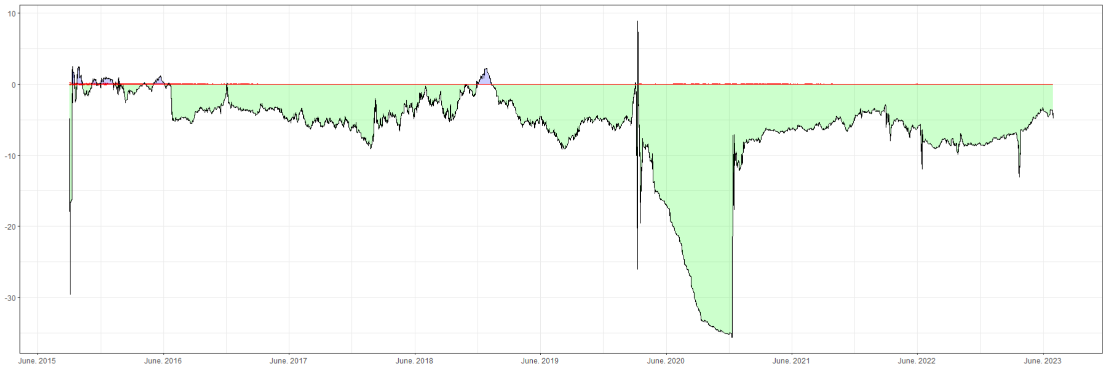


Fig.12: Total volatility spillover asymmetry index

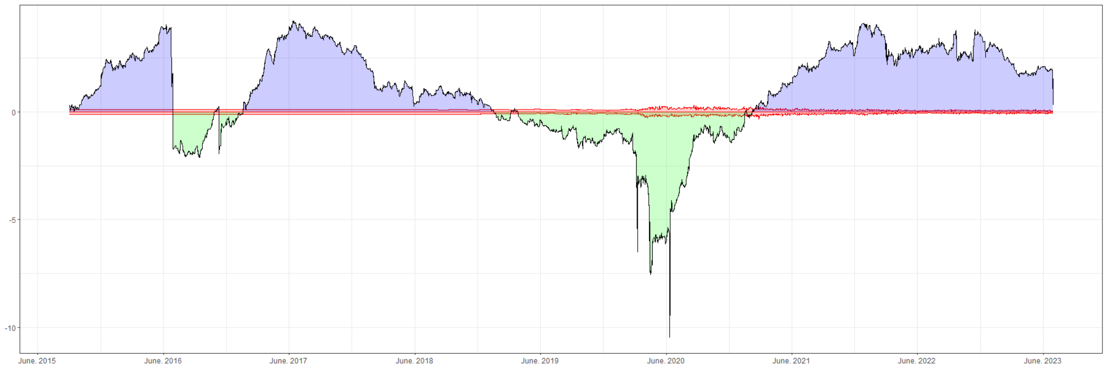
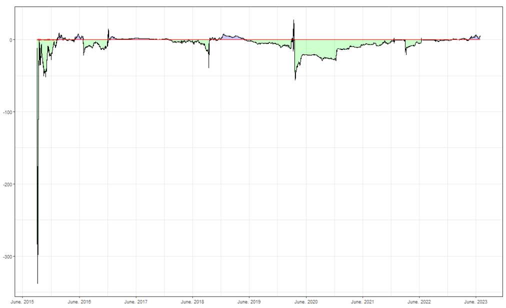


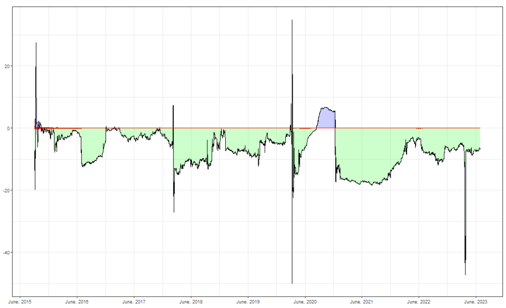
Fig.13: Total kurtosis spillover asymmetry index

Figures 14 and 15 illustrate the volatility spillover asymmetry index and the kurtosis spillover asymmetry index to other investments, as given in equation 12a. Meanwhile, Figures 16 and 17 present the volatility spillover asymmetry index and the kurtosis spillover asymmetry index from other investments, following equation 12b. These figures yield intriguing insights not readily accessible through traditional symmetric spillover analysis or averaged dynamic asymmetric spillover analysis.

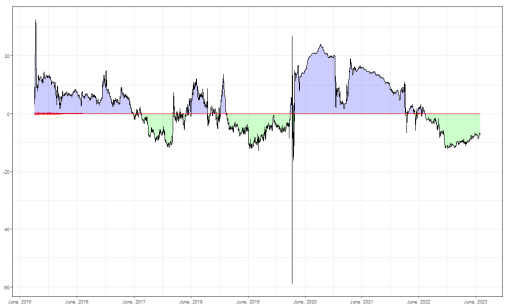
For instance, two notable findings emerge. Firstly, spillover asymmetry prevails across various investments, albeit with varying degrees of intensity. Secondly, in the context of volatility spillover, most investments during the vast majority of periods tend to transmit or receive unfavorable volatility spillovers from other investments. However, in the case of kurtosis spillover, there exists greater diversity among investments. For example, ESG predominantly transmits and receives more favorable kurtosis spillover in most periods, whereas GCEI and BIGCEI exhibit the opposite trend.



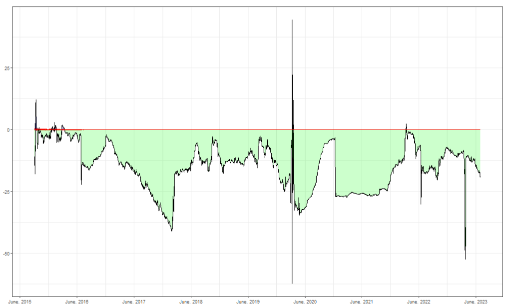
(a) Carbon.



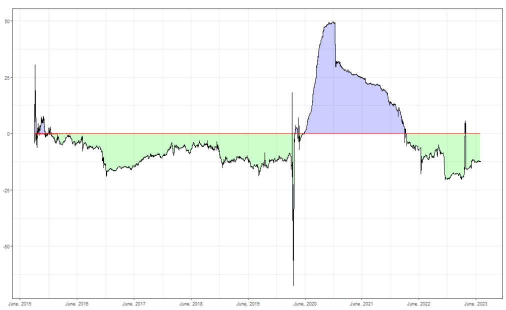
(b) CEI

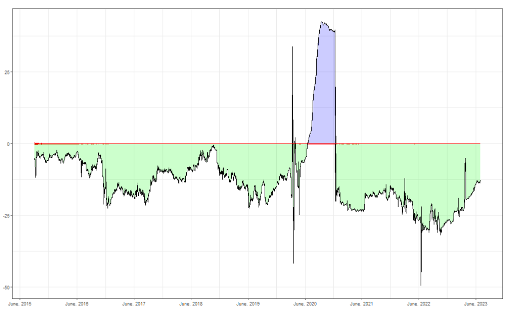


(c) GCEI

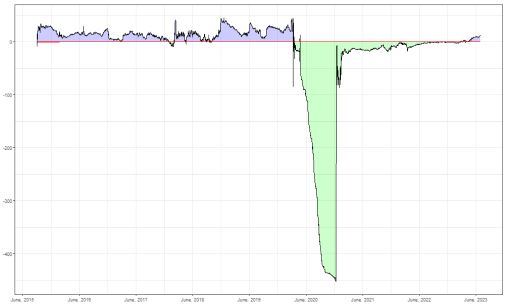


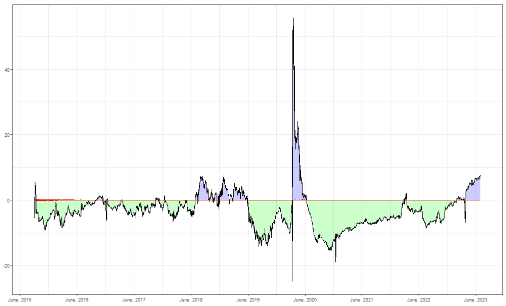
(d) ESG



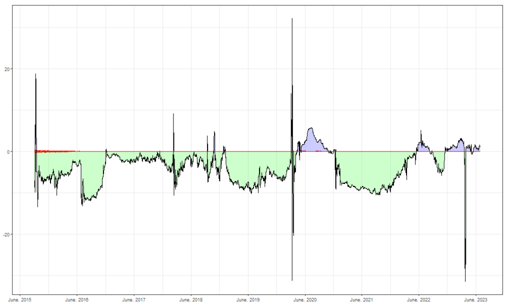


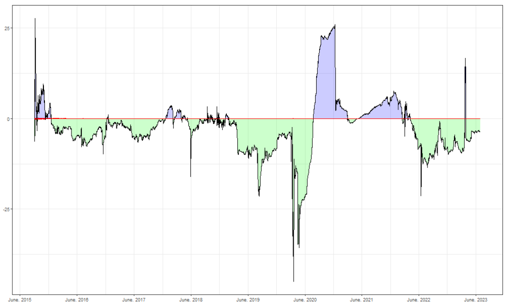
(e) BIGCEI (f) GB





(g) Oil (h) Gold

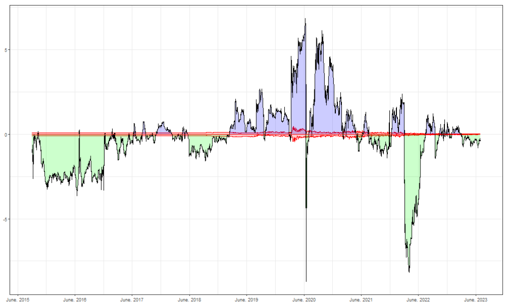


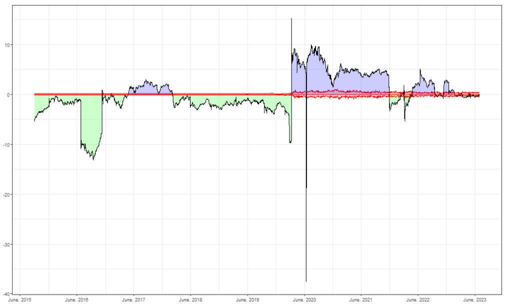


(i) Stock (j) Bond

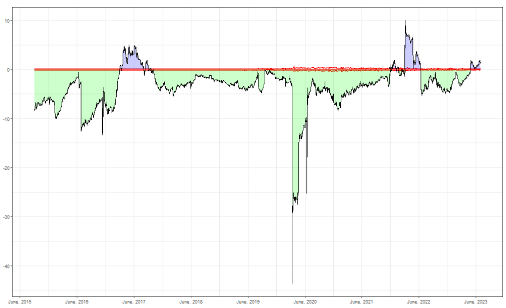
Fig.14: Volatility spillover asymmetry index to other investments.

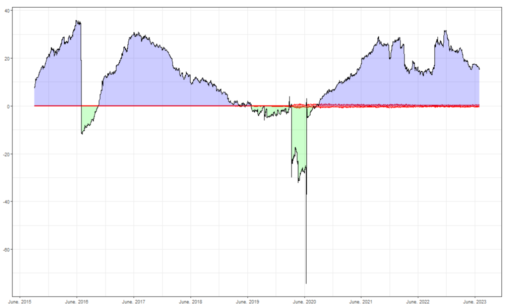
Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.



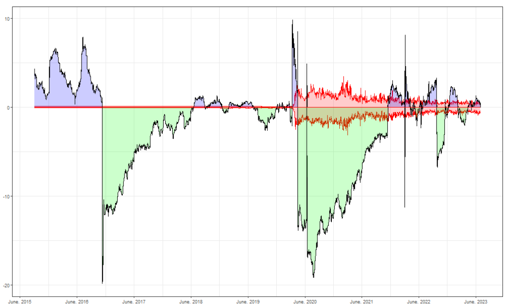


(a) Carbon. (b) CEI

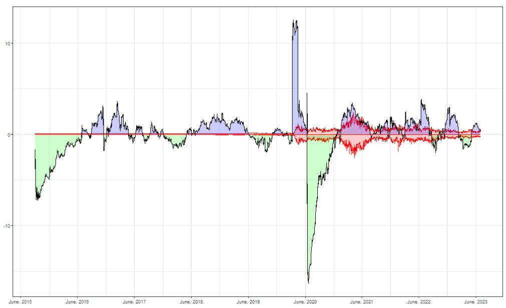




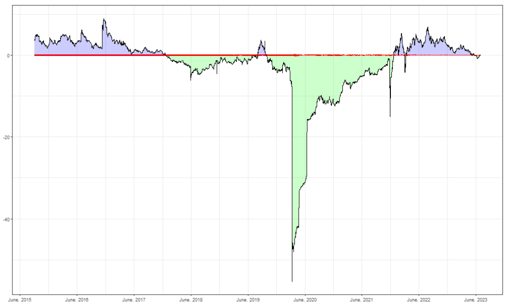
(c) GCEI (d) ESG



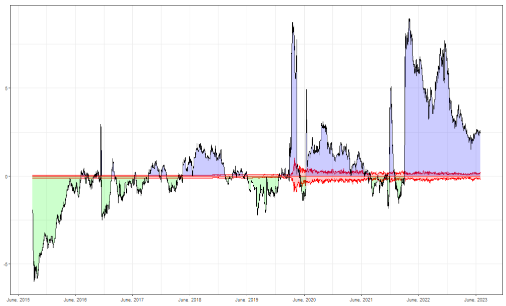
(e) BIGCEI



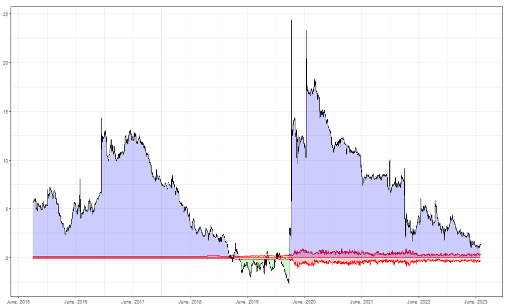
(f) GB



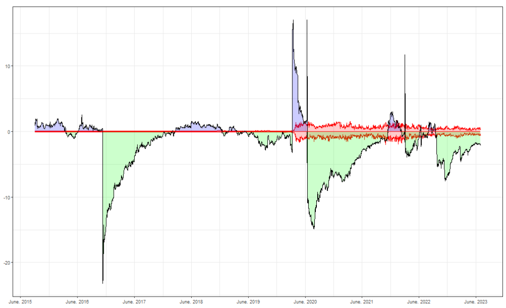
(g) Oil



(h) Gold



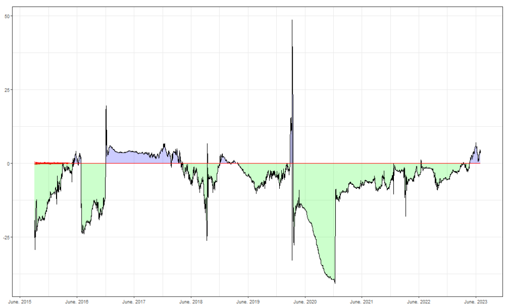
(i) Stock



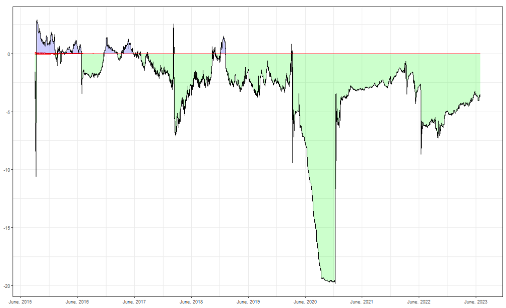
(j) Bond

Fig.15: Kurtosis spillover asymmetry index to other investments.

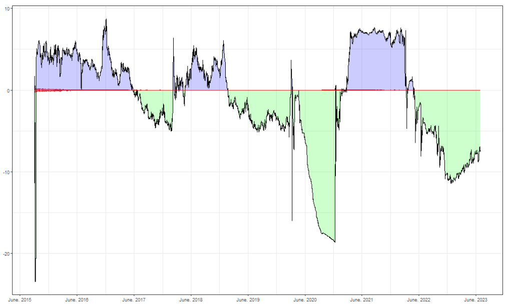
Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.



(a) Carbon.

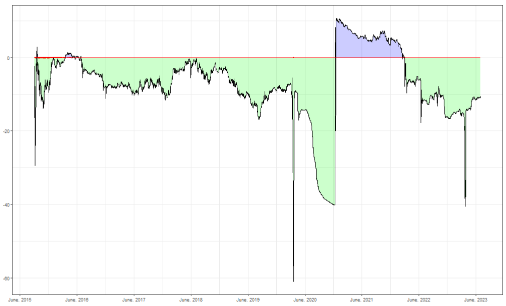


(b) CEI

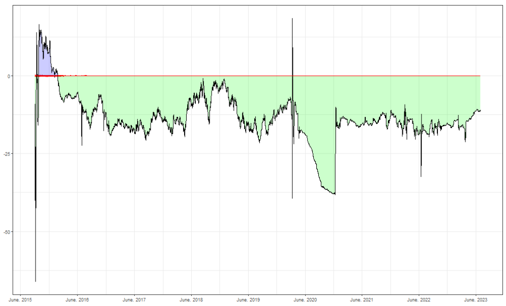


(c) GCEI

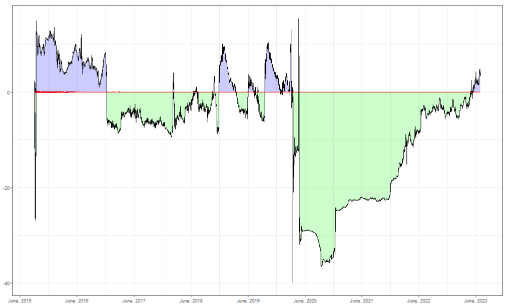
(d) ESG



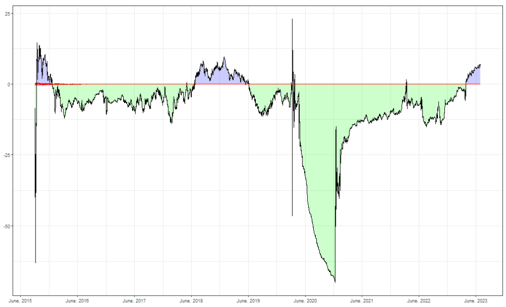
(e) BIGCEI



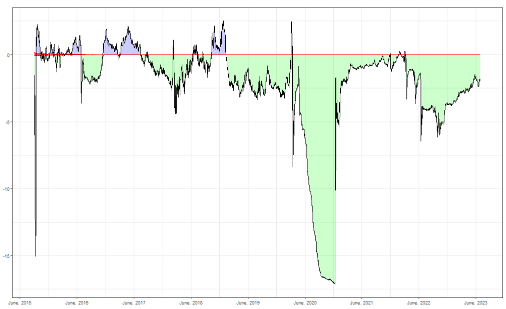
(f) GB



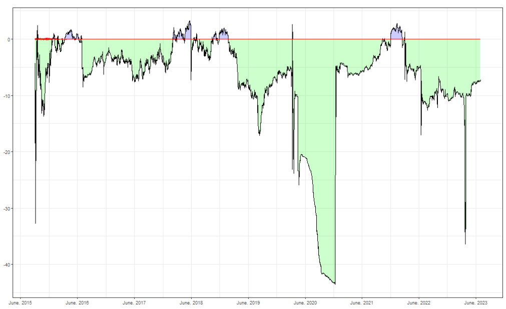
(g) Oil



(h) Gold



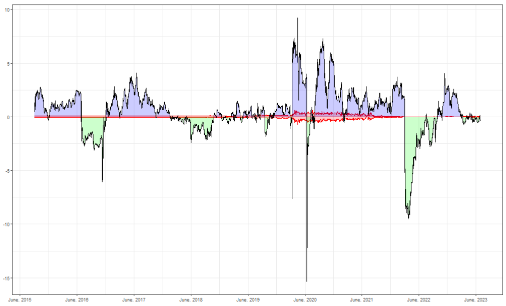
(i) Stock

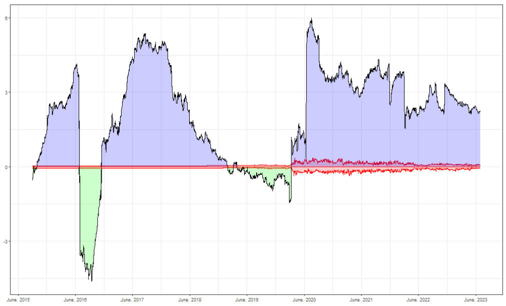


(j) Bond

Fig.16: Volatility spillover asymmetry index from other investments.

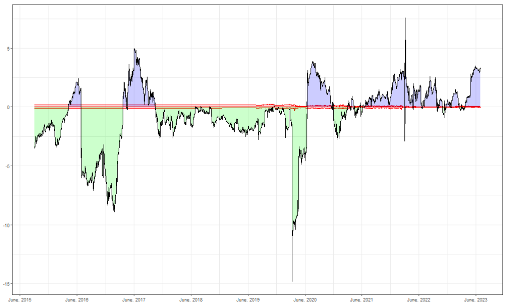
Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

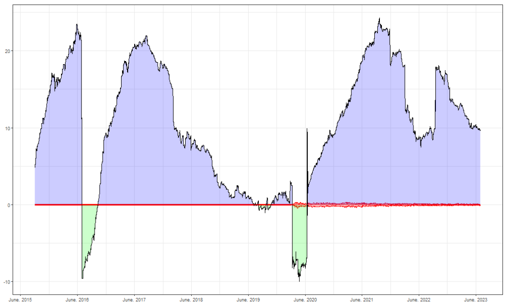




(a) Carbon.

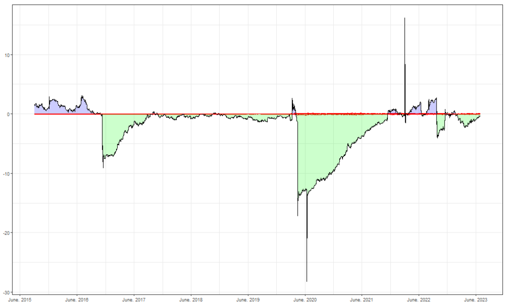
(b) CEI

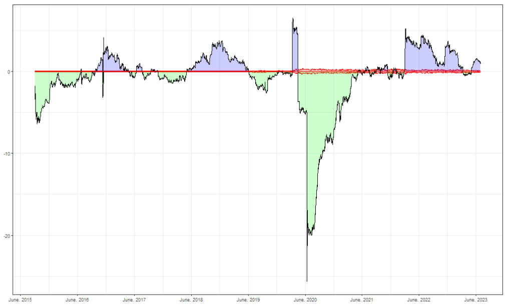




(c) GCEI

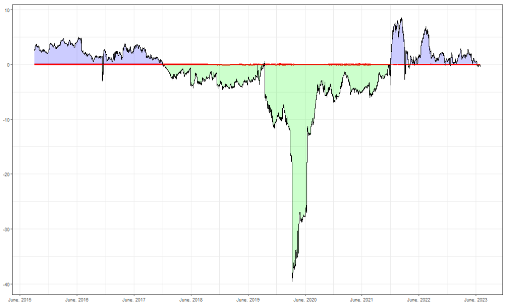
(d) ESG

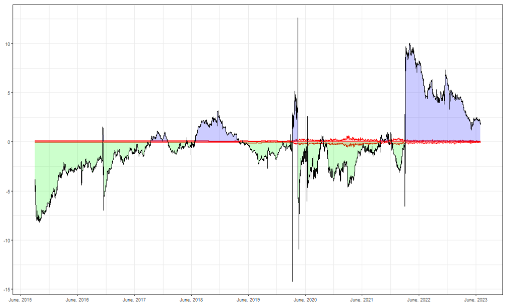




(e) BIGCEI

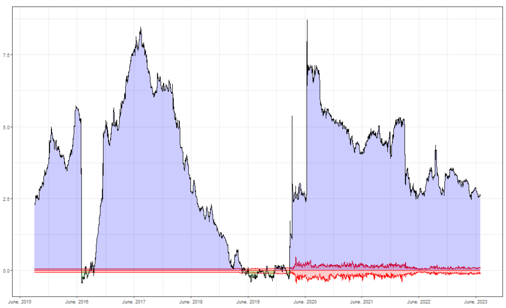
(f) GB

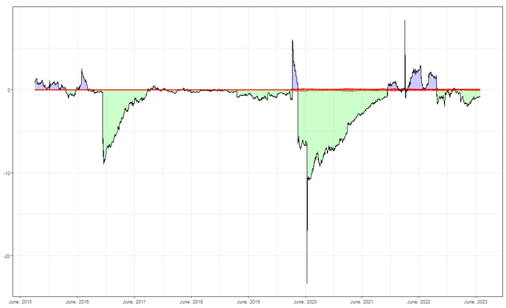




(g) Oil

(h) Gold





(i) Stock (j) Bond

Fig.17: Kurtosis spillover asymmetry index from other investments.

Note: ESG, CEI, BIGCEI, GB, and GCEI refer to the S&P Global 1200 ESG Index, S&P Global 1200 Carbon Efficient Index, S&P 500 Bond Investment Grade Carbon Efficient Index, S&P Green Bond Index, and S&P Global Clean Energy Index, respectively. Stock, Gold, Oil, and Bond correspond to the S&P GLOBAL 1200 Index, S&P GSCI Gold Index, S&P GSCI Crude Oil Index, and S&P 500 Bond Index, respectively.

5. Conclusions and discussions

Citing the research of Barndorff-Nielsen et al. (2010) and BenSaïda (2019), we expanded the analysis of asymmetric spillover effects to higher moments (kurtosis) using the GJR-SK model. We explored asymmetric volatility spillover and asymmetric kurtosis spillover among sustainable and traditional investments.

For carbon, we observed robust volatility and kurtosis spillovers with both stocks and crude oil. The negative volatility spillover exceeded the positive volatility spillover, whereas the kurtosis spillover exhibited symmetry.

Among the three stock-based sustainable investments—CEI, GCEI, and ESG—we identified substantial volatility and kurtosis spillovers with crude oil. These spillovers showed asymmetry, with the negative volatility (kurtosis) spillover surpassing the positive volatility (kurtosis) spillover.

Regarding the two bond-based sustainable investments, BIGCEI and GB, we noted significant volatility and kurtosis spillovers with gold. The adverse volatility spillover was more pronounced than the favorable volatility spillover, while the kurtosis spillover demonstrated symmetry.

By investigating the dynamic changes in spillover effects, we have discovered that good kurtosis spillover generally surpasses bad kurtosis spillover in most periods.

However, during specific extreme events such as Brexit and COVID-19, bad kurtosis spillover becomes predominant. This finding contrasts significantly with the observation in volatility spillover, where bad volatility spillover exceeds good volatility spillover in most periods. The potential reason for this disparity in results lies in the sensitivity of kurtosis spillover, which represents extreme volatility spillover, to negative news. Moreover, market expectations regarding general volatility and extreme volatility may diverge. While the market commonly adopts a pessimistic stance towards general risk, it only tends to do so for extreme risk in highly turbulent market conditions.

Hence, through vigilant monitoring of kurtosis spillover, policymakers can acquire insights into market sentiment and devise timely interventions to stabilize financial markets during periods of heightened pessimism. Investors can also capitalize on tracking kurtosis spillover, employing it as an indicator of market sentiment and making well-informed decisions regarding portfolio diversification and risk management, especially during instances of pronounced market volatility.

6. References

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management 2020, Vol. 13, Page 84*, *13*(4), 84. https://doi.org/10.3390/JRFM13040084

Attarzadeh, A., & Balcilar, M. (2022). On the dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets: a time-varying analysis. *Environmental Science and Pollution Research*, *29*(43), 65185–65196. https://doi.org/10.1007/s11356-022-20115-2

Baele, L. (2005). Volatility Spillover Effects in European Equity Markets. *Journal of Financial and Quantitative Analysis*, *40*(2), 373–401.

Barndorff-Nielsen, O. E., Kinnebrock, S., & Shephard, N. (2010). Measuring Downside Risk – Realized Semivariance*. In *Volatility and Time Series Econometrics* (pp. 117–136). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199549498.003.0007

Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, *27*, 55–78. https://doi.org/10.1016/j.finmar.2015.09.003

Baruník, J., Kočenda, E., & Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, *77*, 39–56. https://doi.org/10.1016/j.jimonfin.2017.06.003

BenSaïda, A. (2019). Good and bad volatility spillovers: An asymmetric connectedness. *Journal of Financial Markets*, *43*, 78–95. https://doi.org/10.1016/j.finmar.2018.12.005

Caporale, G. M., Spagnolo, N., & Almajali, A. (2023). Connectedness between fossil and renewable energy stock indices: The impact of the COP policies. *Economic Modelling*, *123*, 106273. https://doi.org/10.1016/J.ECONMOD.2023.106273

Chan, W. H., Shelton, B., & Wu, Y. W. (2018). Volatility Spillovers Arising from the Financialization of Commodities. *Journal of Risk and Financial Management 2018, Vol. 11, Page 72*, *11*(4), 72. https://doi.org/10.3390/JRFM11040072

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Forecast-based measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *40*(2), 373–401.

Duan, K., Zhao, Y., Wang, Z., & Chang, Y. (2023). Asymmetric spillover from Bitcoin to green and traditional assets: A comparison with gold. *International Review of Economics & Finance*, *88*, 1397–1417. https://doi.org/10.1016/j.iref.2023.06.036

He, X., & Hamori, S. (2021). Is volatility spillover enough for investor decisions? A new viewpoint from higher moments. *Journal of International Money and Finance*, *116*, 102412. https://doi.org/10.1016/j.jimonfin.2021.102412

HE, X., & HAMORI, S. (2023). DIFFERENT MOMENTS CREATE DIFFERENT SPILLOVERS: A STUDY OF COMMODITY MARKETS. *The Singapore Economic Review*, 1–22. https://doi.org/10.1142/S021759082350025X

He, X., Takiguchi, T., Nakajima, T., & Hamori, S. (2020). Spillover effects between energies, gold, and stock: the United States versus China. *Energy & Environment*, 0958305X2090708. https://doi.org/10.1177/0958305X20907081

Huo, R., & Ahmed, A. D. (2017). Return and volatility spillovers effects: Evaluating the impact of Shanghai-Hong Kong Stock Connect. *Economic Modelling*, *61*(C), 260–272.

Ji, Q., Zhang, D., & Geng, J. (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, *198*, 972–978.

https://doi.org/10.1016/j.jclepro.2018.07.126

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119–147.

Liu, T., & Hamori, S. (2020). Spillovers to Renewable Energy Stocks in the US and Europe: Are They Different? *Energies*, *13*(12), 3162. https://doi.org/10.3390/en13123162

Mensi, W., Al Rababa'a, A. R., Vo, X. V., & Kang, S. H. (2021). Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. *Energy Economics*, *98*, 105262. https://doi.org/10.1016/j.eneco.2021.105262

Mensi, W., Shafiullah, M., Vo, X. V., & Kang, S. H. (2022). Asymmetric spillovers and connectedness between crude oil and currency markets using high-frequency data. *Resources Policy*, *77*, 102678. https://doi.org/10.1016/j.resourpol.2022.102678

Naeem, M. A., Adekoya, O. B., & Oliyide, J. A. (2021). Asymmetric spillovers between green bonds and commodities. *Journal of Cleaner Production*, *314*, 128100. https://doi.org/10.1016/j.jclepro.2021.128100

Nekhili, R., & Bouri, E. (2023). Higher-order moments and co-moments' contribution to spillover analysis and portfolio risk management. *Energy Economics*, *119*, 106596. https://doi.org/10.1016/j.eneco.2023.106596

Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, *40*, 101739. https://doi.org/10.1016/j.frl.2020.101739

Nyakurukwa, K., & Seetharam, Y. (2023). Higher moment connectedness of cryptocurrencies: a time-frequency approach. *Journal of Economics and Finance*. https://doi.org/10.1007/s12197-023-

09627-w

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17–29.

Pham, L. (2016). Is it risky to go green? A volatility analysis of the green bond market. *Journal of Sustainable Finance & Investment*, *6*(4), 263–291. https://doi.org/10.1080/20430795.2016.1237244

Rao, A., Gupta, M., Sharma, G. D., Mahendru, M., & Agrawal, A. (2022). Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. *International Journal of Managerial Finance*, *18*(4), 725–755. https://doi.org/10.1108/IJMF-04-2022-0165

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, *74*, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A. (2016). Downside and upside risk spillovers between exchange rates and stock prices. *Journal of Banking & Finance*, *62*, 76–96. https://doi.org/10.1016/j.jbankfin.2015.10.011

Reboredo, J. C., Ugolini, A., & Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, *86*, 104629. https://doi.org/10.1016/j.eneco.2019.104629

Ren, X., Dou, Y., Dong, K., & Li, Y. (2022a). Information spillover and market connectedness: multi-scale quantile-on-quantile analysis of the crude oil and carbon markets. *Applied Economics*, *54*(38), 4465–4485. https://doi.org/10.1080/00036846.2022.2030855

Ren, X., Dou, Y., Dong, K., & Li, Y. (2022b). Information spillover and market connectedness: multi-scale quantile-on-quantile analysis of the crude oil and carbon markets. *Applied Economics*, *54*(38), 4465–4485. https://doi.org/10.1080/00036846.2022.2030855

Song, Y., Ji, Q., Du, Y.-J., & Geng, J.-B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Economics*, *84*, 104564. https://doi.org/10.1016/j.eneco.2019.104564

Tan, X., Sirichand, K., Vivian, A., & Wang, X. (2020). How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics. *Energy Economics*, *90*, 104870. https://doi.org/10.1016/j.eneco.2020.104870

Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance*, *70*(C), 194–202.

Umar, M., Farid, S., & Naeem, M. A. (2022). Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy*, *240*, 122702. https://doi.org/10.1016/j.energy.2021.122702

Wang, X., & Wu, C. (2018). Asymmetric volatility spillovers between crude oil and international financial markets. *Energy Economics*, *74*, 592–604. https://doi.org/10.1016/j.eneco.2018.06.022

Wang, Y., & Guo, Z. (2018). The dynamic spillover between carbon and energy markets: New evidence. *Energy*, *149*(C), 24–33.

Yarovaya, L., Brzeszczyński, J., & Lau, C. K. M. (2017). Asymmetry in spillover effects: Evidence for international stock index futures markets. *International Review of Financial Analysis*, *53*, 94–111. https://doi.org/10.1016/j.irfa.2017.07.007

Zhang, H., Jin, C., Bouri, E., Gao, W., & Xu, Y. (2023). Realized higher-order moments spillovers between commodity and stock markets: Evidence from China. *Journal of Commodity Markets*, *30*, 100275. https://doi.org/10.1016/j.jcomm.2022.100275

Zhang, Y.-J., & Sun, Y.-F. (2016). The dynamic volatility spillover between European carbon trading market and fossil energy market. *Journal of Cleaner Production*, *112*, 2654–2663. https://doi.org/10.1016/j.jclepro.2015.09.118