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Abstract: In recent years, climate investment markets have experienced a significant expansion and a growing integration with the traditional energy markets due to increasing concern regarding climate change. This paper examines the risk spillover between climate investment and traditional energy markets in different time-frequency domains and then explores how do various global uncertainties affect the risk spillovers. The results indicate that total spillover between climate investment and traditional energy markets increases with the investment cycle lengthens. Furthermore, the impacts of various global uncertainties on the spillover exhibit dynamic changes at different time-frequency domains. Market uncertainties such as VIX and VOX have higher impacts in short-term while geopolitical uncertainty has a higher long-term impact. Climate-related uncertainties also demonstrate pronounced impacts in certain periods.

Keywords: traditional energy; climate investment; uncertainties; risk spillover; MODWT

JEL: P33; Q41; Q43

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1. Introduction

The global agreement and action for carbon neutrality mark the transition from the traditional development paradigm to a new green development paradigm in response to pressing environmental concerns. The reduction in greenhouse gas (GHG) emissions requires significant investment and financing, necessitating the use of climate finance (Nasreen et al., 2020). In terms of financing instruments, debt is the predominant climate investments on a global scale, closely followed by equity. Globally, the share of equity financing for clean energy declined from 77% in 2013 to 43% in 2020, while that of debt financing more than doubled from 23% in 2013 to 56% in 2020[2]. This is attributable to the maturation and integration of prominent renewable energy technologies, such as solar photovoltaic and onshore wind, which have demonstrated the ability to attract substantial debt financing.

The interplay between climate investment and traditional energy markets manifests as a complex and dynamic phenomenon. This interaction involves vying for finite resources, wielding influence in policy-making spheres, and serving as key architects in steering the trajectory toward a sustainable future. Stakeholder inclinations, as well as the contours of policy and regulatory frameworks, further contribute to shaping this intricate relationship. Moreover, the landscape of climate policy is progressively incorporating investment support instruments as strategic tools to address market failures intertwined with energy investments. This multifaceted integration underscores the evolving sophistication of initiatives aimed at fostering a harmonious coexistence between climate-conscious investments and the traditional energy sector.

There is substantial evidence supporting the notion that the uncertainties, such as the financial market uncertainty, economic policy uncertainty, energy market uncertainty, and geopolitical uncertainty, considerably influence both climate investment and traditional energy markets (Long et al., 2022; Saeed et al., 2021). High uncertainty probably reflects investors' risk avoidance, which may affect the availability of financing for renewable energy projects, while rising economic

[2] IRENA and CPI (2023), Global landscape of renewable energy finance, 2023, International Renewable Energy Agency, Abu Dhabi.

uncertainty may cause companies to adopt a wait-and-see attitude toward long-term investment and expansion of operations. More importantly, some emerging uncertainties, such as climate-related uncertainty, also affect the risk relationship between climate investment and traditional energy markets.

This paper develops an overall risk transmission network between climate investment and traditional energy markets under different time scales and further examines the impact of different uncertainties on the spillover. The main contribution of this paper is as follows. First, a time-frequency decomposition based on the maximum overlapping discrete wavelet transform (MODWT) is proposed to explore the risk spillover effect under different investment cycles. Second, the spillover among climate investment market and traditional energy market as two overall systems is analysed. Finally, two climate-related uncertainties are introduced, carbon downside uncertainty and investor attention to climate change.

The remainder of this paper is organised as follows. The next section presents literature review. Section 3 introduces the research design, including the methodology and data. Sections 4 demonstrates the results of the empirical analysis, as well as the conclusion and policy implications are proposed in section 5.

2. Literature review

2.1.Nexus between climate investment and traditional energy commodities

Extensive research has been conducted on the interconnection between climate investment and traditional energy markets; however, a definitive consensus is yet to be reached. Climate investment markets differ from traditional bonds or stocks in terms of various factors, such as trade limitations and issue scale (Cortellini & Panetta, 2021). Oil, gas and coal prices in the United States have played an active role in shaping the profitability of clean energy, but these energy prices make a limited contribution to extreme risks (Reboredo & Ugolini, 2018). Global coal futures exhibit the highest transmission capacity and are most susceptible to extreme shocks (Su et al., 2023). Policy frameworks and regulations play an indispensable role in the relationship between clean energy and traditional energy markets, such as feed-in tariffs, tax credits, and subsidies (Chen et al., 2022). However, volatility spillovers among energy markets have been proven to be weak in the long run (Umar et al., 2022).

Given the heterogeneity of economic agents and changing market conditions, the connectivity between climate investment and traditional energy markets may change with frequency. Energy markets are sticky in the short run and fully elastic in the long run, leading to different transmission frequencies than those in other markets (Ortas & Álvarez, 2016). The concerns of polluters and regulators lie primarily in low-frequency market connectivity, whereas financial participants are mainly interested in high-frequency spillovers (Jiang et al., 2020). A multivariate wavelet method was introduced to investigate the correlation between the U.S. carbon emission trading market and several energy prices (Sousa et al., 2014). Urom et al. (2021) relied on wavelets and spillovers based on a time-varying parameter model with stochastic volatility to investigate the lead-lag relationships among global green markets across different time domains. However, limited studies have applied time-frequency methods to investigate the nexus between climate investment and traditional energy markets. Reboredo et al. (2020) examined the connectedness of green bonds with various asset classes across different investment horizons based on wavelet coherence. The study conducted by Nguyen et al. (2021) also investigated the interrelationships between green bonds and other asset markets utilizing the rolling window wavelet correlation approach.

2.2.Impact of uncertainty on the spillover effect

There is wide evidence that various categories of market uncertainty impact the spillover between climate investment and traditional energy markets. Yadav et al. (2023) found that macro uncertainty, including the VIX, influences volatility in energy markets, and this influence is transmitted through volatility persistence. Nikitopoulos et al. (2023) revealed that the connection between green bonds and VIX is time-varying and state-dependent. While green bonds may be influenced by oil volatility to some extent, they have been found to be weakly connected to uncertainty indices, including the OVX (Pham & Nguyen, 2022). Previous study showed that the EPU spillovers from other countries increase local bond market volatility, especially during financial crises (Gong et al., 2023). Additionally, all measures of geopolitical uncertainty transmit positive shocks to green investments, including green equity and green bonds (Sohag et al., 2022). Geopolitical threats and acts also affect the returns on green bonds, with an increase in geopolitical threats and West Texas Intermediate (WTI) crude oil positively impacting the returns (Tang et al., 2023). Therefore, geopolitical risks play a significant role in shaping the spillover between green bonds and energy markets (Doğan et al., 2023). EPU has both positive and negative effects on renewable energy innovation, depending on factors such as institutional quality and political orientation (Feng & Zheng, 2022). Geopolitical risks also affect the volatility and risk spillover of natural resource prices, including crude oil and natural gas, indicating a dynamic relationship between geopolitical risks and energy markets (Li et al., 2023).

Climate-related uncertainties also have become a key factor affecting credit markets, energy markets, and other financial markets (Serletis & Xu, 2023). There appears to be a consensus in the previous literature on the fact that climate-related risks impact equity returns (Venturini, 2022). Many studies have used the Google search volume index (GSVI) based on keywords to assess investor attention to energy markets. Yao et al. (2017) found that investor attention contributed 15% to the long-run fluctuation of WTI oil prices. Prange (2021) analysed how investor attention affects the correlations among energy, stock, and commodity markets under different market conditions. Information about extreme climate change may cause investors to become pessimistic and eventually affect their trading behaviour. Pham and Cepni (2022) documented a substantial increase in the spillover between green bond returns and investor attention at the lower and upper tails of the distributions. Van Benthem et al. (2022) explored how concerns about climate risks influence the way investors allocate their capital and exercise their oversight of firms and how this investor response affects companies in the energy sector. The volatility of carbon price is also an ideal proxy variable for climate policy uncertainty as carbon price and climate change are closely linked (Van den Bremer & Van der Ploeg, 2021). Oyegunle et al. (2023) found that carbon pricing policies impact the credit risk of high-emitting sectors, such as the energy sector, in resource-based economies such as Canada. Additionally, the financial impact of a rapid increase in carbon prices on corporate firms can be substantial, with the energy, materials and utilities sectors being the most affected.

3. Methodology and Data

3.1.Methodology

The modelling process is divided into three steps. First, the return series of each market are decomposed and reconstructed into short, intermediate, and long terms using MODWT algorithm. Second, spillover networks at different time scales are constructed between climate investment and traditional energy markets. Third, the second layer of the spillover network is constructed to examine the impact of various uncertainties on the spillovers between climate investment and traditional energy markets under different investment cycles.

3.1.1. MODWT algorithm

Based on the classical discrete wavelet transform (DWT) algorithm, the MODWT algorithm proposed by Percival and Walden (2000) is a highly redundant, nonorthogonal wavelet transform with discrete wavelet smoothing that is not affected by the choice of the starting point of the time series and is more suitable for the multiscale analyses of financial asset time series.

The DWT method can decompose the time series $X_t, t = 0,1,2, \cdots N-1, N$ into multiple subsequences based on the wavelet filter $\mathrm{h_l}$ and scale filter $\mathrm{g_l}$. The wavelet coefficients and scale coefficients can be expressed as follows:

$$W_{j,t} = \sum_{l=0}^{L-1} h_{j,t} X(t-l) \tag{1}$$

$$V_{j,t} = \sum_{j=0}^{L-1} g_{j,t} X(t-l) \tag{2}$$

where $j = 1, 2, .., J$ represents the scale coefficient and $l = 0, 1, 2, ..L-1$, L represents the length of the wavelet filter.

The MODWT wavelet filter and the scale filter on the jth decomposition scale can be expressed as follows:

$$\tilde{h}_{j,l} = \frac{h_{j,l}}{2^{j/2}} \tag{3}$$

$$\tilde{g}_{j,l} = \frac{g_{j,l}}{2^{j/2}} \tag{4}$$

The wavelet coefficient and scale coefficient are expressed as follows:

$$\tilde{W}_{j,l} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{h}_{j,t} X(t-l) \tag{5}$$

$$\tilde{V}_j, l = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{g}_{j,t} X(t-l) \tag{6}$$

The original time series X_t can be decomposed and reconstructed into multiple multiscale time series and a trend time series:

$$X_t = \sum_{j=1}^{J} \tilde{w}_j^T \tilde{w}_j + \tilde{v}_j^T \tilde{y}_j = \sum_{j=1}^{J} \tilde{d}_j + \tilde{S}_j \tag{7}$$

where $\tilde{d}_j$ denotes the wavelet component of X_t at scale j, and $\tilde{S}_j$ is the trend component of X_t. Considering that the analysis in this paper is based on daily data, we assume that $J = 8$, which enables us to obtain short-term data from the high-frequency component $d_1: 2^1 = 2\ days,\ d_2: 2^2 = 4\ days$. Similarly, intermediate frequency components $d_3: 2^3 = 8\ days,\ d_4: 2^4 = 16\ days,\ d_5: 2^5 = 32\ days$ are obtained for intermediate-term data, while low-frequency components $d_6: 2^6 = 64\ days,$ $d_7: 2^7 = 128\ days,\ d_8: 2^8 = 256\ days$ are obtained for long-term data.

3.1.2. Spillover network construction

The spillover network can be used to track the dynamic spillover relationship of time series based on the generalized VAR model (Diebold and Yilmaz, 2012). Considering a moving average expression of a VAR model with N variables:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{8}$$

where $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$。

In the VAR model framework, the generalized K-step forward prediction error $\Psi_{ij}(K)$ is decomposed as follows:

$$\Psi_{ij}(K) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{K-1} (e_i' A_k \Sigma e_j)^2}{\sum_{k=0}^{K-1} (e_i' A_k \Sigma A_k' e_i)} \tag{9}$$

where Σ is the variance matrix of the error vector ε, Ψ_{ii} is the standard error term of the ith equation of the table, and e_i denotes the selection term; that is, the ith

element equals to 1, and the other cases are zero.

To adjust the sum of elements in each row of the variance decomposition table to 1, the variance decomposition matrix is normalized to

$$\tilde{\Psi}_{ij}(K) = \frac{\Psi_{ij}(K)}{\sum_{j=1}^{N} \Psi_{ij}(K)} \tag{10}$$

Thus, the total connectedness index (TCI), the directional spillover of asset i from asset j ($DS_{i \leftarrow j}$), and the net directional spillover of asset i and asset j (NS) are expressed as follows:

$$TCI_t(K) = \frac{\sum_{i,j-1,i \neq j}^{N} \tilde{\Psi}_{ij,t}(K)}{N} \times 100 \tag{11}$$

$$DS_{i \leftarrow j,t}(K) = \frac{\sum_{i=1,j \neq i}^{N} \tilde{\Psi}_{ij,t}(K)}{N} \times 100 \tag{12}$$

$$NS_{i,t}(K) = DS_{i \to j,t}(K) - DS_{i \to j,t}(K) \tag{13}$$

To better understand the aggregate spillover index, we decompose it into a pairwise connectedness index (PCI), which measures the connectivity of markets i and j (Gabauer, 2021):

$$PCI_{ij,t}(K) = 200 \times \left(\frac{\tilde{\Psi}_{ij,t}(K) + \tilde{\Psi}_{ji,t}(K)}{\tilde{\Psi}_{ii,t}(K) + \tilde{\Psi}_{ij,t}(K) + \tilde{\Psi}_{ji,t}(K) + \tilde{\Psi}_{jj,t}(K))} \right), 0 \leq PCI_t(K) \leq 100 \tag{14}$$

A $VAR(p)$ model is constructed using AIC information quasi-measures to obtain the most lagged order p. In addition, a rolling window technique of fixed length ω is used to obtain the dynamic spillover index. Thus, a sequence includes $N = T - \omega + 1$ windows with window period $W_n = \{W_{i,n}\}$ denoted as follows:

$$W_{i,n} = \{R_{i,n}, R_{i,n+1}, \dots, R_{i,n-1+\omega}\} \tag{15}$$

where i denotes the time series $n = 1,2, \dots, N$. In this paper, the window period is set to 200 days.

3.2.Measurement of climate-related uncertainties

3.2.1. Carbon downside uncertainty

The generalized autoregression conditional heteroskedasticity–value at risk (GARCH–VaR) model is used to obtain the upside and downside VaRs to characterize carbon market risk (Bollerslev, 1986).

$$\text{Mean equation: } r_t = u_t + \varepsilon_t = \alpha_1 r_{t-1} + \varepsilon_t; \varepsilon_t = h_t^{1/2} z_t \tag{16}$$

$$\text{Variance equation: } h_t = \beta_0 + \sum_{i=1}^{q_1} \beta_{1,i} \varepsilon_{t-i}^2 + \sum_{j=1}^{p_1} \beta_{2,j} h_{t-j} \tag{17}$$

To provide a given quantile for the distribution of the return of carbon markets, VaR_t^α is defined as the α-quantile of the distribution of the log return, with α chosen as either 5% or 95% at the behest of the carbon price risks of going down and up:

$$P(r_t > VaR_t^\alpha) = \alpha \tag{18}$$

According to the definition $r_t = u_t + h_t^{1/2} z_t$ and the assumption that z_t follows skew generalized error distribution (SGED), the α-th quantile of rt can be calculated as

$$VaR_t^\alpha = u_t - h_t^{1/2} z_\alpha \tag{19}$$

where z_α denotes the α-th quantile of SGED. According to the above formula, once we have an estimation of the volatility and the expected return, the value of VaR can be obtained directly.

The historical log returns of carbon assets with the dynamic 5% and 95% VaRs represent the carbon market risk downward index (CD) and the carbon market risk upward index (CU) respectively, as shown in **Figure 1**. The CD index is used to reflect the uncertainty from the carbon market, in that the downward and upward carbon risk indices are in direct opposition to each other.

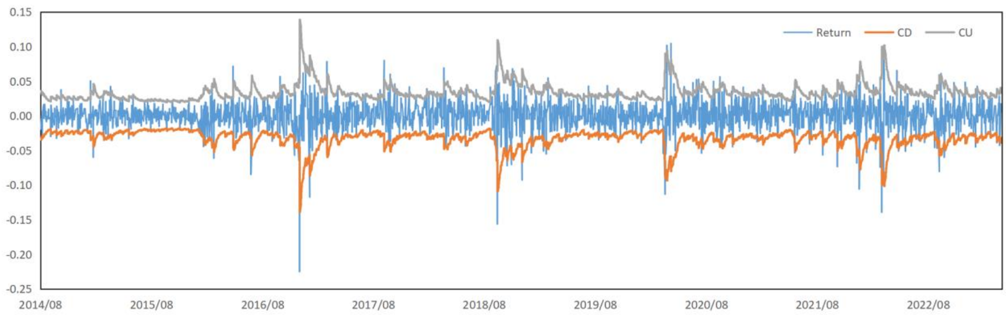


Figure 1 Carbon market risk upside and downside indices

3.2.2. Attention to climate change

Investors' online search behaviour is widely used as a measure of investor attention. Search indices provided by search engines are popular and valid proxies.

Using the GSVI, we set the keywords of climate concern as “climate change” and “global warming” to measure investors’ attention to climate change (ACC). In this paper, daily ACC data are constructed following Zhang et.al (2021), as shown in **Figure 2**.

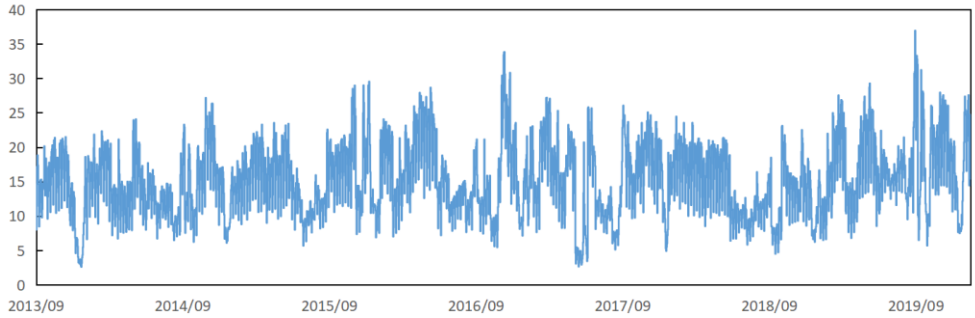


Figure 2 Attention to climate change index

3.3.Data

As shown in **Table 1**, at the market level, the S&P green bond index (GB) and the S&P global clean energy index (CLE) are considered as the proxy of climate investment markets (CIM). Traditional energy markets (TE) include the three main types of primary energy: crude oil (OIL), natural gas (NGS), and coal (COAL) markets. Daily data are collected from *investing.com* from March 1, 2013 to March 14, 2023. Through three DY spillover networks under different time domains, we can obtain the average PCIs between climate investment and traditional energy markets, including green bond and clean energy in the short term (CTS), intermediate term (CTI), and long term (CTL).

Table 1 Description of variables

Variables	Indices	Abbreviation
Green bond	S&P Green Bond Index	GB
Clean energy stock	S&P Global Clean Energy Index	CLE
Crude oil	Bloomberg WTI Crude Oil subindex	OIL
Natural gas	Bloomberg Natural Gas Subindex	NGS
Coal	Newcastle Coal Future	COAL
Uncertainties	CBOE Volatility Index	VIX
	CBOE Crude Oil ETF Volatility Index	OVX
	US Economic Policy Uncertainty Index	EPU
	Geopolitical Risk Index	GPR
	Carbon Market Risk Downward Index	CD
	Attention to Climate Change	ACC

To accurately reflect the current global uncertainty, the following six uncertainty indices are selected: the CBOE volatility index (VIX), CBOE crude oil ETF volatility index (OVX), US economic policy uncertainty index (EPU), geopolitical risk index (GPR), carbon downside uncertainty (CD) and attention to climate change (ACC). The OVX measures unpredictability in the crude oil market, while the VIX shows volatility in the world stock market. It is common practice to quantify the daily uncertainty of global economic policy using the EPU (Baker et al., 2016). Geopolitical uncertainty is represented by the GPR (Baur & Smales, 2020; Liu et al., 2019). Except for the VIX and OVX, which are sourced from the CHOICE database, all other indices are collected on the website of policy uncertainty.

Table 2 provides a descriptive statistic of the variables. The return of clean energy has the largest mean, followed by coal, while the natural gas market return is the smallest. The standard deviations show that the natural gas and oil markets have the most dramatic volatility. The skewness, kurtosis and JB statistic show that all return series are spiky and thick-tailed. Among the uncertainties, EPU fluctuates the most, followed by GPR, while the stability of CD is relatively high. All the series pass the ADF tests.

Table 2 Descriptive Statistics

	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB Statistics	ADF
GB	-0.0001	0.0000	0.0227	-0.0242	0.0036	-0.3456	8.2040	2899.528***	-31.5413***
CLE	0.0003	0.0008	0.1103	-0.1250	0.0149	-0.4170	11.1765	7106.890***	-17.4038***
OIL	-0.0004	0.0010	0.2205	-0.3408	0.0269	-1.3919	27.2864	62870.35***	-53.4450***
NGS	-0.0009	-0.0006	0.1664	-0.1920	0.0305	-0.2401	6.7200	1480.202***	-53.6531***
COAL	0.0002	0.0000	0.3406	-0.4325	0.0216	-3.1413	120.4017	1454257***	-47.1693***
VIX	-0.0007	0.1200	17.640	-24.860	1.9821	-2.5701	34.374	88522.3***	-54.3719***
OVX	-0.0040	-0.1300	130.22	-90.610	5.6559	4.9060	244.42	5129940***	-9.20782***
EPU	-9.0133	-5.8800	358.28	-381.67	61.820	-0.4784	7.6902	2020.22***	-34.2059***
GPR	102.844	95.560	341.50	57.812	34.105	3.1804	18.631	25107.8***	-5.70105***
CD	-0.0330	-0.0297	-0.0178	-0.139	0.0128	-2.7502	14.060	13452.62***	-7.62690***
ACC	-0.0011	0.0800	21.750	-21.840	3.3911	-0.0716	5.51981	561.6170***	-12.8056***

Note: *, **, *** indicate significant at the 10%, 5%, and 1% significance levels, respectively.

4. Empirical results

4.1.Decomposition and reconstruction of return series

Figure 3 shows the wavelet decomposition and reconstruction results of the time series data. The fluctuation range of the traditional energy market is greater than that of the clean energy and green bond markets, and that of the crude oil market is the largest. With the increase in the time scale, the volatility degree of each market weakens, showing a stable trend in the long-term signal. In the short term, the returns of all markets experience sharp fluctuations in the periods of 2016, 2017 and 2020. The price volatility in 2016 and 2017 is attributable to increased uncertainty in the world economy, such as Brexit and the US Federal Reserve’s interest rate hike.

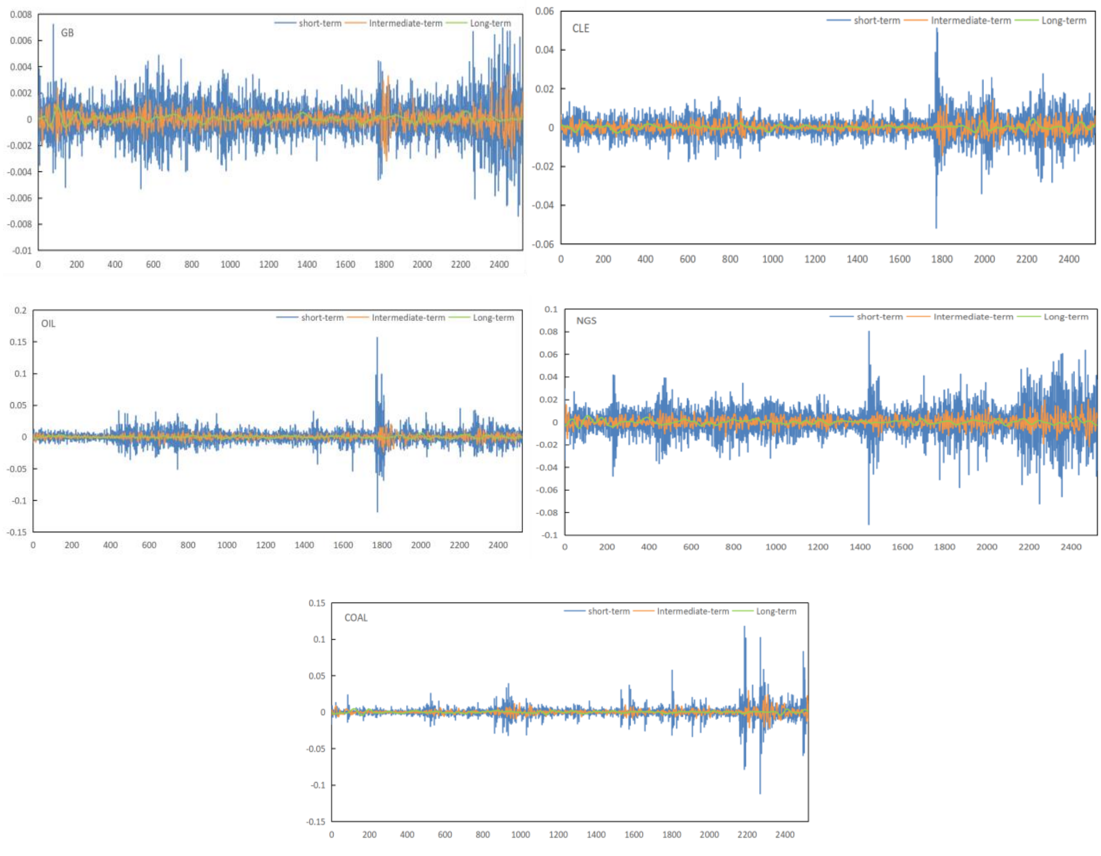


Figure 3 Maximal overlap discrete wavelet transform results

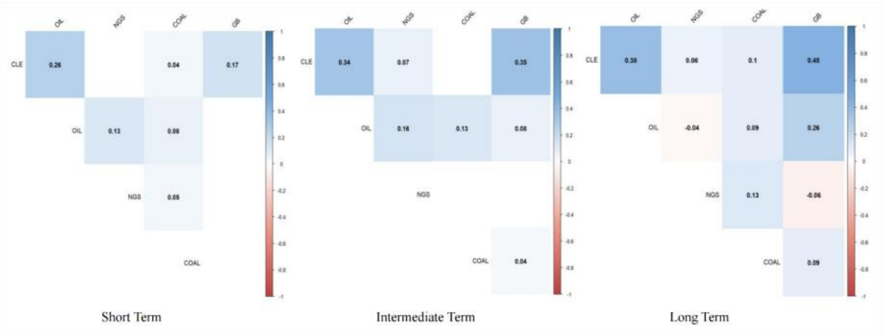


Figure 4 Correlation between climate investment and traditional energy markets

Figure 4 demonstrates the change in the correlation between climate investment and traditional energy markets at different time scales. The blank indicates that the correlation coefficient is not significant at a significance level of 10%. The correlation between green bonds and clean energy stock is significantly positive and increases with the time scale. The correlation between green bonds and oil markets is significantly positive in the intermediate and long terms. In the long term, there is a significant correlation among all markets, indicating that the MODWT method effectively captures the long-term information of the time series.

4.2.Multi-timescale spillovers between climate investment and traditional energy markets

4.2.1. Static spillover effects

Based on the AIC, the lag order of the VAR model is set to 6, and the variance decomposition period $H = 10$ is chosen at the short-, intermediate-, and long-term return levels. As shown in **Table 3**, the systematic total connectedness index (TCI) increases with the increase of time scale. The TCI values of short, intermediate and long terms are 20.60%, 24.55%, and 27.60%, respectively. Short-term investments are primarily influenced by stochastic factors such as market noise and unexpected events, resulting in a weak transmission effect. Conversely, long-term investments are predominantly driven by their fundamentals and logic, leading to a strong and stable risk transmission effect.

Table 3 Static spillover indices

Short term	GB	CLE	OIL	NGS	COAL	FROM

GB	80.10	6.79	4.97	3.67	4.47	19.9
CLE	7.25	76.08	8.73	3.84	4.10	23.92
OIL	4.15	9.17	77.88	4.31	4.49	22.12
NGS	5.11	3.71	6.36	80.56	4.26	19.44
COAL	4.61	3.45	4.77	4.78	82.40	17.6
TO	21.11	23.11	24.84	16.59	17.32	102.98
Inc.Own	101.21	99.20	102.72	97.15	99.72	**TCI**
NET	1.21	-0.80	2.72	-2.85	-0.28	20.60
Intermediate term						
GB	72.39	10.85	4.5	5.05	7.22	27.61
CLE	7.40	73.52	8.85	4.96	5.26	26.48
OIL	4.35	10.11	75.65	6.48	3.4	24.35
NGS	4.54	5.63	6.26	77.26	6.31	22.74
COAL	4.45	6.64	5.33	5.15	78.44	21.56
TO	20.74	33.24	24.94	21.64	22.19	122.75
Inc.Own	93.13	106.76	100.59	98.9	100.63	**TCI**
NET	-6.87	6.76	0.59	-1.1	0.63	24.55
Long term						
GB	66.1	13.9	7.71	6.7	5.59	33.9
CLE	7.38	72.64	11.47	3.88	4.63	27.36
OIL	4.46	10.31	74.49	6.17	4.58	25.51
NGS	7.26	7.6	3.98	74.97	6.19	25.03
COAL	5.95	5.67	4.93	9.63	73.81	26.19
TO	25.05	37.48	28.1	26.38	20.99	137.99
Inc.Own	91.15	110.12	102.58	101.35	94.8	**TCI**
NET	-8.85	10.12	2.58	1.35	-5.2	27.60

Note: $From$ represents the spillover effect of the market from other markets represented by the column vector, To represents the spillover effect of the market to other markets represented by the row vector. $Inc.Own$ denotes the total spillover risk of that market including its own market, and NET represents the average net risk spillover of that market.

For the climate investment markets, the green bond market exports risk to other markets in the short term, while receiving risk in the intermediate and long terms. The risk spillover effect between the green bond and natural gas gradually increases with the time scale. The clean energy stock market receives risk from other markets in the short term while exporting risk in the intermediate and long terms. The spillover between clean energy and crude oil is the largest. In the whole system, the net risk spillover effect of the crude oil market is the largest in the short term (2.72%), which is related to the high short-term volatility of the crude oil market itself. As the time scale increases, the risk spillover of the crude oil gradually decreases. Overall, the natural gas market mainly receives net risk spillover from the system as a whole and only exports risk in the long term.

The topology of the short-, intermediate-, and long-term spillover networks is shown in **Figure 5**. In the short term, the green bond market is a net transmitter of the whole system, exporting risks to the natural gas, clean energy stock, and coal markets. As the time scale increases, the green bond market gradually becomes a net receiver, mainly receiving risks from the crude oil and clean energy stock markets. The clean energy stock market is a net receiver in the short run, mainly receiving risks from the coal market. This situation arises due to the inherent risks associated with the coal industry, such as environmental degradation and regulatory pressures, which necessitate a higher risk premium for investors. As the time scale increases, the clean energy stock market gradually becomes a net exporter, spilling risk mainly to the green bond market. These risks are mainly funnelled toward the green bond market, reflecting the growing importance of climate investments and the increasing demand for green bonds.

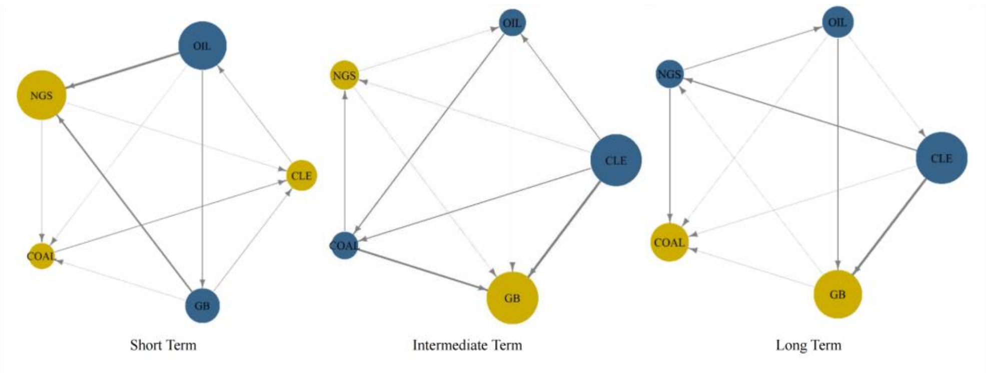


Figure 5 Short-, intermediate-, and long-term network

Note: Each market is represented by a node, with the blue node indicating the net transmitter of risk and the yellow node indicating the net receiver. The larger the node, the greater the net risk of either the output or the receiver. The direction of the arrow indicates the direction of the spillover, and the line thickness indicates the strength of the spillover. The directional arrows connecting the two nodes show the direction and strength of the net spillover relationship between the two markets.

The crude oil market remains an important risk spillover point for the whole system. It is well acknowledged that crude oil prices play a strategic role in energy system. Although it is still debated in academia whether oil prices are the main driver of the financial performance of clean energy companies, the fossil fuel energy system is dependent on lucrative profits and multinational energy companies, and the clean energy transition can be a good alternative and redistribute such profits to producing consumers (Ozdurak, 2021). The natural gas market is gradually changing from a net receiver to a net exporter of risk, receiving oil and green bond market risks in the short term, receiving risk from the coal market in the intermediate term and receiving clean energy stock market risk and exporting risk to the crude oil and coal markets in the long term. The natural gas market receives systemic risk in the short and long terms, and has demonstrated good potential risk hedging and protection in the intermediate term. Natural gas is a low-carbon energy source that needs to compete with coal and clean energy sources. And the alternative role of solar and wind as important clean energy sources has influenced the development of the natural gas market. For natural gas, a striking result is the limited statistical relevance of economic policies and other markets, as this market is characterized by long-term contracts (Khalifa et al., 2015). As a result, the natural gas market is "marginalized" in the system.

4.2.2. Dynamic spillover effects

As shown in **Figure 6**, the total connectedness indices between climate investment and traditional energy markets fluctuate within a range of 10% – 50% throughout the sample period. The year 2016 witnessed the signing and formal entry into force of the Paris Agreement, which led to an increase in worldwide attention to climate investment, with total spillover effects reaching a small peak. During the COVID-19 pandemic, there was a significant surge in the total connectedness indices, reaching their peak in the short, intermediate, and long terms within the specified time frame. The volatility spillover exhibited sensitivity toward extreme events. Notably, long-term volatility spillover effects consistently surpassed those observed in the short term, aligning with our findings from the static analysis.

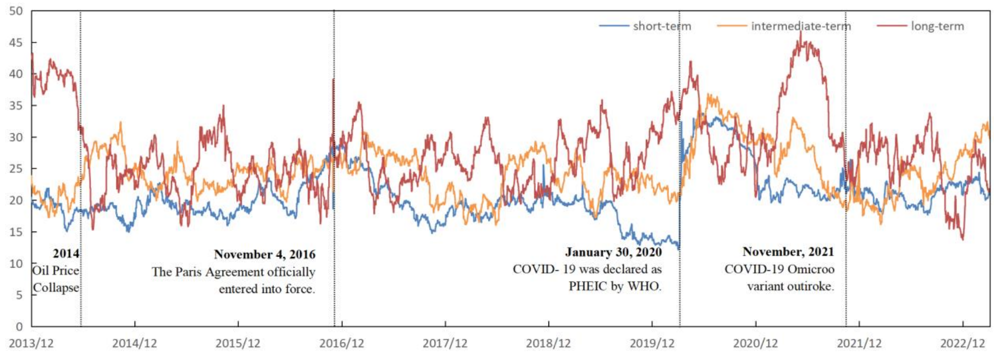


Figure 6 Short-, intermediate- and long-term total connectedness indices

While taking the green bond market (GB) and clean energy stock market (CLE) as a whole, the dynamic spillover indices is also used to explore the temporal characteristics of directional spillovers of the climate investment (CIM) under different investment cycles, as shown in **Figure 7**. The dynamic risk spillover effect of climate investment has time-varying characteristics with different roles in different economic periods and time scales. In the past two years, with the increasing focus on sustainable investment, the short and intermediate term risk spillovers of climate investment on traditional energy markets have continued to strengthen.

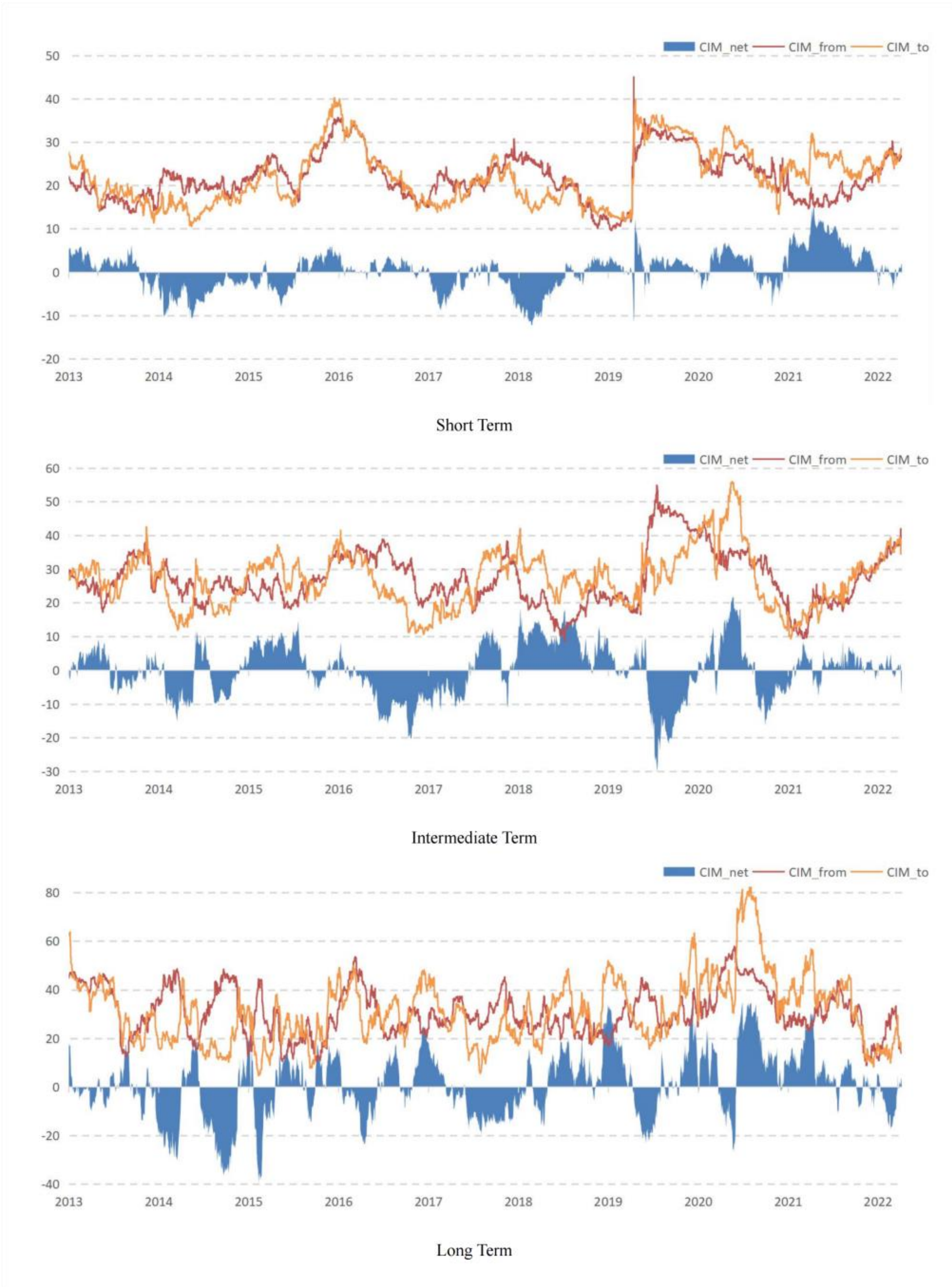
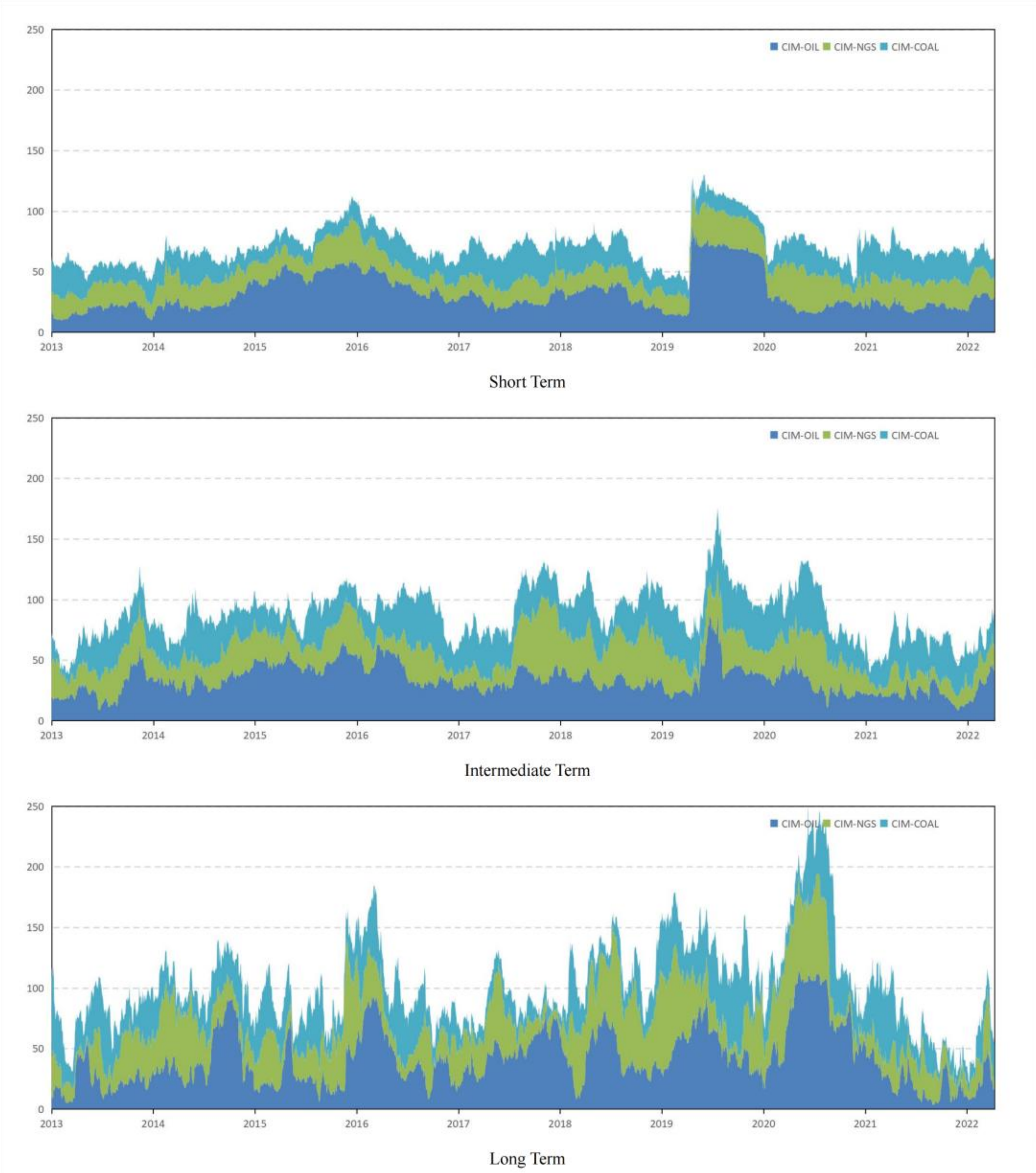


Figure 7 Dynamic risk spillover effects of the climate investment markets

Note: CIM_from represents the risk spillover of the climate investment markets (green bond and clean energy) receiving from other markets and CIM_to represents the risk spillover of the climate investment markets to other markets of the system. After offsetting the spillovers, CIM_net denotes a net directional spillover from the climate investment markets.

Figure 8 demonstrates the dynamic pairwise connectedness index (PCI) among the climate investment and the crude oil market ($CIM - OIL$), natural gas market ($CIM - NGS$), and coal market ($CIM - COAL$). In 2016, with the issuance of the first green asset-backed bond and the subsequent rise in green bond investments, there was a notable surge in the PCI of the climate investment at long term. Amidst the ongoing impact of COVID-19 pandemic on global economic growth around 2020, investors focusing on climate investment as a means to hedge their investments. Consequently, there has been an increase in the PCI of the climate investment markets at short and intermediate term. The risks associated with the COVID-19 pandemic do not distract investors from environmental issues (Garel & Petit-Romec, 2021). Instead, investors expect the epidemic to spur green investments and adjust carbon and clean energy investment strategies to this new market landscape (Ding et al., 2022).



Short Term

Intermediate Term

Long Term

Figure 8 Pairwise connectedness indices (PCI) of the climate investment market

4.3.Impact of uncertainties

From the dynamic analysis, we obtain the PCI between climate investment and traditional energy markets in the short term (CTS), intermediate term (CTI), and long term (CTL) under different time domains. Then, DY spillover method is used again to examine the impact of various global uncertainties. Based on the AIC, we select a 7^{th}-order VAR model in the short term and 8^{th}-order VAR models in the intermediate and long terms. The variance decomposition period is $H = 10$. The spillover matrices are shown in **Table 4**. The TCIs are 24.21%, 25.64%, and 23.00% in the short, intermediate, and long terms, respectively, which indicates that in the intermediate term, market uncertainty indicators have a greater impact on risk spillovers from climate investment to traditional energy markets.

Table 4 Static spillover indices of uncertainty indicators

Short term	**CTS**	**CD**	**ACC**	**VIX**	**OVX**	**EPU**	**GPR**	**FROM**
CTS	75.77	5.48	3.51	5.04	4.69	2.64	2.86	24.23
CD	5.87	72.19	2.49	4.44	5.33	4.6	5.08	27.81
ACC	3.54	2.92	81.64	2.93	3.37	2.66	2.95	18.36
VIX	4.45	3.04	2.53	71.54	12.55	3.36	2.54	28.46
OVX	3.57	3.49	3.32	12.2	70.51	3.73	3.18	29.49
EPU	4.56	3.68	3.38	4.96	4.8	74.79	3.83	25.21
GPR	2.32	2.64	1.82	2.8	2.45	3.92	84.06	15.94
TO	24.31	21.26	17.05	32.37	33.19	20.89	20.44	169.5
Inc.Own	100.08	93.45	98.69	103.9	103.7	95.68	104.5	**TCI**
NET	0.08	-6.55	-1.31	3.9	3.7	-4.32	4.5	24.21
Intermediate term								
CTI	76.86	4.49	4.06	3.35	4.19	3.87	3.17	23.14
CD	4.09	71.52	2.86	5.43	6.37	5.52	4.2	28.48
ACC	4.32	2.93	79.47	2.95	3.8	3.09	3.43	20.53
VIX	3.60	3.57	2.70	71.14	12.24	3.81	2.96	28.86
OVX	4.77	4.41	3.64	11.76	68.01	3.93	3.48	31.99
EPU	4.63	5.17	4.2	5.51	4.91	71.5	4.09	28.50
GPR	3.51	2.42	2.54	3.15	2.51	3.87	82	18
TO	24.92	22.99	19.99	32.16	34.01	24.1	21.33	179.51
Inc.Own	101.78	94.51	99.47	103.3	102.02	95.6	103.33	**TCI**
NET	1.78	-5.49	-0.53	3.3	2.02	-4.4	3.33	25.64
Long term								

CTL	81.64	3.36	2.69	2.84	3.32	2.21	3.94	18.36
CD	3.81	72.71	2.25	5.5	5.38	4.9	5.45	27.29
ACC	2.74	2.89	82.28	2.9	3.42	3.03	2.74	17.72
VIX	2.88	3.42	2.49	72.51	12.77	3.34	2.61	27.49
OVX	3.25	3.58	3.25	12.17	70.92	3.65	3.19	29.08
EPU	3.21	4.21	3.38	4.87	4.62	76.07	3.64	23.93
GPR	3.45	2.61	2.2	2.48	2.54	3.84	82.88	17.12
TO	19.33	20.07	16.25	30.76	32.05	20.97	21.56	160.99
Inc.Own	100.97	92.78	98.53	103.27	102.97	97.04	104.44	**TCI**
NET	0.97	-7.22	-1.47	3.27	2.97	-2.96	4.44	23.00

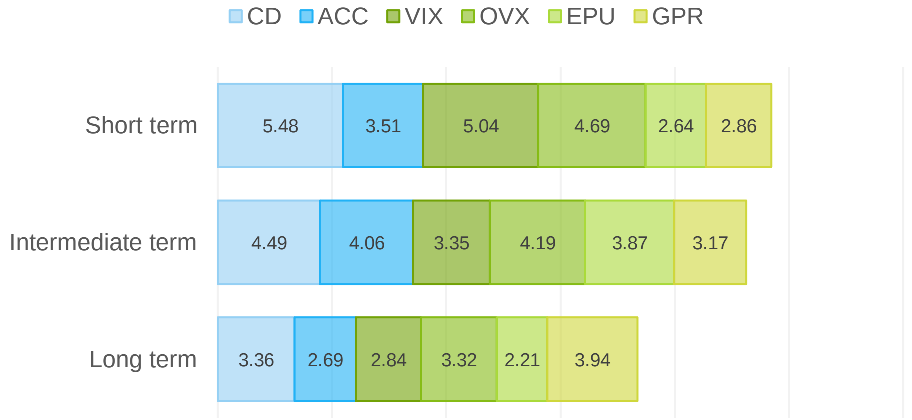


Figure 9 The impact of various global uncertainties on the PCI

Figure 9 illustrates the impact of various global uncertainties on the PCI between climate investment and traditional energy markets across short, intermediate and long-term horizons, showing each of these uncertainties affects the risk spillovers to varying degrees across the time-frequency domains. In the short term, CD exerts the most substantial influence on the spillovers, with an impact of 5.48%. The highest short-term impact indicates that fluctuations in the carbon market immediately trigger risk contagion between the climate investment and traditional energy markets, making the relationship highly sensitive to short-term shocks in carbon pricing. Following CD, the VIX (5.04%) and OVX (4.69%) also have significant short-term impacts on the connectedness between climate investment and traditional energy markets. It highlights the quick response of markets to these uncertainties.

As for the intermediate term, ACC and EPU become more influential, with impacts of 4.06% and 4.19%, respectively. In contrast to the immediate transmission effects observed with CD, VIX, and OVX, the impact of ACC and EPU necessitates a longer period to materialize, as these uncertainties are indicative of broader, more systemic concerns. Investor sensitivity to climate news reaches its peak in the intermediate term, possibly due to the time required for climate-related information to fully impact investment decisions. Similarly, EPU derived from news coverage of economic policy uncertainty, indicates that investor sentiment in the intermediate term is particularly responsive to uncertainties related to economic policy changes. The heightened influence during this period suggests that investors adjust their portfolios based on evolving expectations about future market conditions, especially with regard to climate and economic policy adjustments.

In the long term, GPR emerges as the most significant factor, with an impact of 3.94%. The enduring nature of geopolitical risk enables it to exert a sustained influence on market dynamics, overshadowing other uncertainties over time. For example, the recent energy crisis and geopolitical uncertainty have generated ripple effects on international affairs (Jin et al., 2023). These effects are also more pronounced at a low frequency, indicating that conflicts can impose a profound effect on energy markets. The predominance of GPR in the long term suggests that political risks become deeply ingrained in market expectations, affecting the connectedness between the climate investment and traditional energy markets over the extended periods. This stands in contrast to the diminishing impact of market volatility indices such as CD, VIX, and OVX, whose effects diminish as the time horizon lengthens.

For the dynamic analysis, the risk spillover from CD, VIX, OVX, EPU to the PCI between climate investment and traditional energy markets in the short, intermediate and long terms is shown in **Figure 10.** Generally, all uncertainties exert a more pronounced impact on the connectedness in the short compared to the intermediate and long term. In the short term, the spillovers from VIX and OVX had exhibited a substantial increase and attained their extreme levels during the COVID-19 pandemic. EPU and GPR had a stable impact on the connectedness between the climate investment and traditional energy markets after Russia-Ukraine conflict. The impact of ACC had shown a significant increase since the signing of the Glasgow Climate Pact at the

COP26 in November 2021. The contracting parties of the pact committed to gradually reducing the use of coal and decreasing subsidies for fossil fuels.

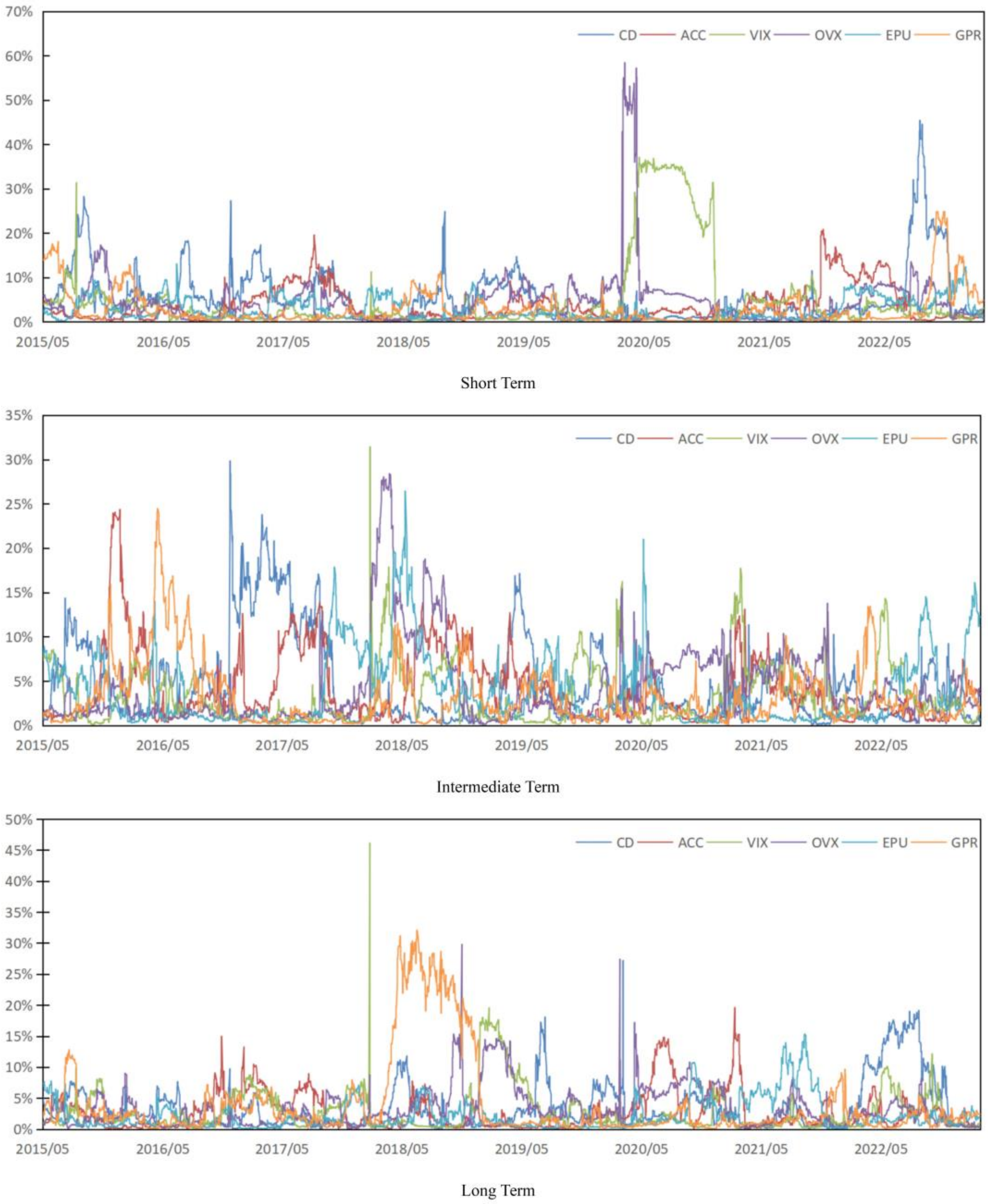


Figure 10 The dynamic impact of various global uncertainties on the PCI

In the intermediate term, each uncertainty had a relatively equal influence on the connectedness between climate investment and traditional energy markets throughout the period, with the impact of ACC and EPU lager than the short and long terms. Further, the impact of ACC was more associated with the external climate events and global agreements, such as the Paris Agreement. The global emphasis on reducing carbon emissions and transitioning towards renewable energy sources had resulted in increased investment in clean energy technologies and infrastructure. This shift in investment patterns had also influenced the behaviour of energy markets, with a growing focus on sustainable practices and environmentally friendly solutions, which bolstered the connectedness between climate investment and traditional energy markets.

Over the long term, the connectedness between climate investment and traditional energy markets has been influenced by the sustained increase in GPR. For example, from the latter half of 2018 to 2019, the surge in unilateralism presented a significant and lasting challenge to the global governance system, resulting in a notable rise in GPR. This period witnessed a corresponding up-tick in the impact of GPR on the connectedness between climate investment and traditional energy markets. Further, a brief and sharp movement in VIX in early February 2018 led to the impact of VIX on the connectedness between climate investment and traditional energy markets increased sharply in the long term. In contrast to short and intermediate terms, long-term spillovers are shaped by more persistent and structural changes in uncertainties that have a lasting impact.

5. Conclusion

This study provides new insights into the dynamic linkage between climate investment and traditional energy markets. The impact of various types of uncertainties on risk contagion at different time scales are explored. Two dimensions of climate-related uncertainties, CD and ACC are constructed, considering escalating concerns over climate challenges. A novel time-frequency domain approach is proposed to explore the spillover among climate investment and traditional energy markets under different investment cycles. The results show that the green bond market acts as a net transmitter of systemic risks in the short term while clean energy stock market exports risks in the intermediate and long terms. Further, the impact of various global uncertainties on spillover between climate investment and traditional energy markets varies significantly across different time-frequency domains. VIX and OVX show substantial short-term effects, indicating short-term fluctuations in equity and energy markets are highly effective in triggering immediate risk contagion across climate investment and traditional energy markets. However, their influence diminishes over time as markets adjust and stabilize. In the intermediate term, uncertainties such as ACC and EPU become more dominant. The heightened influence of ACC highlights the critical role of climate-related news and global climate agreements in shaping investment decisions. Over the long term, GPR takes precedence as the most significant factor influencing the spillover between climate investment and traditional energy markets, indicating that long-term spillovers are more susceptible to persistent geopolitical risks than to transient market volatilities or policy changes.

Our results provide guidance for policy development on differentiated regulatory regimes and risk-prevention measures at different time scales, highlight that the intensity of risk spillovers between climate investment and traditional energy markets are highly contingent on the type of uncertainties and the time horizon considered. Policymakers should focus on addressing the impacts of market conditions on traditional energy and climate investment markets under different investment cycles. While market uncertainties exert a more immediate and transient impact, the challenge of climate change and geopolitical risks have a more enduring and profound influence over a longer term. With growing environmental and climate concerns, the decisions and policy design of climate investment markets should not be independent of relevant information from climate change. Sudden short-term changes in climate-related uncertainty may affect the confidence of market participants.

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