Energy Economics 134 (2024) 107586

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Measuring crisis from climate risk spillovers in European electricity markets

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ARTICLE INFO

Keywords:
Climate risk
Electricity market
Risk spillover
Frequency domain

ABSTRACT

This paper studies how climate risks spill over to European electricity markets across time and frequency domains using the connectedness network approach. By introducing three climate risk measures—the climate policy uncertainty index, climate physical risk index, and climate concern index—the empirical results reveal the vulnerability of European electricity markets to volatile climate policies and extreme climate crisis events. Overall, the spillover effects in the climate–electricity nexus are primarily concentrated in the medium- and long-term frequency domains, indicating that the impact of climate risk shocks is persistent. Compared with the impact of climate physical risks and climate concern shocks, the spillovers from climate policy uncertainty shocks to the electricity market are higher and more persistent. These findings highlight the need to consider the heterogeneous impacts of climate risks on electricity markets at different frequency bands.

1. Introduction

In the advent of the 21st century, climate warming has intensified the instability of the climate system, resulting in frequent occurrences of extreme weather and climate crisis events worldwide, thus continuously escalating climate risks (Emanuel, 2005; Pokhrel et al., 2021; Ma et al., 2024). This situation not only threatens the survival and development of human beings but also affects the global economy, society, and ecology, making it one of the most prominent risks facing the world today (Stern, 2013; Hsiang et al., 2013; Diaz and Moore, 2017; Yang et al., 2023; Ren et al., 2023c; Li et al., 2023; Pham et al., 2024). The challenges of sustainable development resulting from climate change have increasingly become a global crisis affecting survival and development (Ma et al., 2023). Electricity, as the primary energy source for human activities, is especially vulnerable to the impact of climate change. In the first half of 2023, adverse hydrological conditions, such as droughts and high temperatures, led to an 8.5% reduction in global hydropower generation, surpassing the largest annual drop in the past two decades (Ember, 2023). The exacerbation of climate change has resulted in a heightened occurrence of extreme weather events such as high temperatures and heavy rains. These events can cause severe imbalances in electricity supply and demand and may even endanger global electricity security (van Vliet et al., 2016).

Climate change can increase the risk of electricity production capacity, weakening the stability of the electricity industry. First, as extreme weather events increase, electricity generation facilities, supply chains, and logistics may face various risks, leading to delays in electricity production. Second, a strong association exists between temperature and electricity load. Extremely hot or cold weather can result in a substantial surge in electricity consumption for equipment such as air conditioners and heating systems, posing a huge supply risk to the electricity system. Third, policy measures aimed at mitigating climate change will result in constraints on traditional fossil fuel-based power generation, while the stability of renewable energy generation lags behind that of fossil fuel-based power generation, making the power system more fragile. Fourth, climate policy uncertainty and climate concern shocks can affect power utilities' investment decisions, leading to risks of electricity supply shortages (Fuss et al., 2008).

Climate risk not only causes electricity security incidents leading to electricity shortages but also directly impacts electricity market prices. For example, Spain experienced severe cold and snowstorms in January 2021, causing electricity prices to skyrocket to nearly 95 euros per megawatt-hour, three times greater than the average yearly price observed in 2020 (Institute for Energy Research, 2021). In July 2022,

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https://doi.org/10.1016/j.eneco.2024.107586
Received 31 December 2023; Received in revised form 16 April 2024; Accepted 21 April 2024
Available online 30 April 2024

extreme heatwaves in the UK caused insufficient electricity supply, resulting in temporary outages in the eastern part of London. Electricity prices for utility companies in the UK had a significant jump, reaching an unprecedented peak of 9724.54 pounds per megawatt-hour, a direct increase of 5000% compared with the usual price of 178 pounds (Bloomberg, 2022). Weather factors, especially extreme climate risks, have become important drivers of price fluctuations in the European electricity market (Pechan and Eisenack, 2014; Nahmmacher et al., 2016; Mosquera-López et al., 2018).

The European Union (EU) has been actively pursuing the establishment of a united European electricity market since the signing of the European Single Act. This effort has resulted in strong interconnectedness in European electricity market prices (Sikorska-Pastuszka and Papież, 2023). Numerous studies have attempted to investigate the price linkage among European regional electricity markets (Le Pen and Sévi, 2010; Ciarreta and Zarraga, 2015; Hellwig et al., 2020; Ren et al., 2024). Le Pen and Sévi (2010) employed the VAR-BEKK model to examine the relationship between the forward electricity markets of Germany, Poland, and the UK and revealed the presence of return spillover effects within these three forward markets. Ciarreta and Zarraga (2015) used the GARCH model to evaluate the degree of integration within electricity markets in six European countries. They found that, except for the weak integration between Spain–France and Germany–France, price and volatility spillovers were significant in other regions, with the degree of price convergence gradually increasing. Hellwig et al. (2020) examined the process of integrating electricity markets in Central and Western Europe and discovered that increasing the interconnector capacity at the border between Germany and Austria/Switzerland has the potential to reduce electricity prices in Switzerland. A similar, if less pronounced, effect is observed at the borders between France and Switzerland, as well as Italy and Switzerland.

In many European countries, electricity is highly marketized, making price volatility a primary risk in the electricity market. For instance, Europe frequently experiences negative electricity prices or sudden price spikes due to weather factors. Consequently, some researchers have begun to study the extreme price risks in European electricity markets and examine risk spillovers between regional electricity markets (Xiao et al., 2019; Ly et al., 2022; Uribe et al., 2020). Xiao et al. (2019) used the Diebold and Yilmaz (DY) spillover index to analyze the interconnectedness of European electricity markets. Their findings indicated a significant level of interconnectedness among European electricity markets over the examined timeframe spanning from 2013 to 2017. Ly et al. (2022) used the copula-GARCH and dynamic state space models to examine the five active electricity markets in Europe. Their findings revealed the presence of tail dependencies and significant comovements among these markets. Notably, these interdependencies were particularly pronounced during periods of high electricity demand, suggesting the potential for collective prosperity or collapse within European electricity markets. Uribe et al. (2020) examined the integration and transmission of shocks in the Nord Pool market. Their findings indicated that a greater level of integration among regional markets facilitates increased risk sharing. In addition, they revealed that external shocks propagate asymmetrically at the extreme ends of the price distribution.

Building upon the exploration of risk spillover relationships in electricity markets, researchers have gradually started to study the driving factors of risk spillover in the electricity market (Do et al., 2020; Ma et al., 2022; Abdullah et al., 2023; Rao et al., 2023; Ren et al., 2023b; Chuliá et al., 2024). By combining the DY spillover index and the Baruník and Křehlík (BK) time–frequency domain decomposition method, Do et al. (2020) found that the risk correlation between the Irish and the UK electricity markets varies over time and demonstrated that energy policies, institutional structures, and political ideologies are key driving factors for this phenomenon. Ma et al. (2022) combined Lasso regression with the DY spillover index and BK frequency approach to study the impact of economic policy uncertainty on risk spillover effects among the integrated electricity markets in Europe. They found that increased economic policy uncertainty significantly increases risk spillover levels, particularly in the medium and long run. Abdullah et al. (2023) used CAViaR to estimate downside tail risks and QVAR to study tail risk transmission between electricity markets. They found that geopolitical risks are important driving factors for the spread of extreme risks in the electricity market. Chuliá et al. (2024) combined the QVAR method with the DY spillover index to study the effects of natural gas prices on electricity markets in Europe. Their findings indicate that electricity prices exhibit a heightened sensitivity to fluctuations in natural gas prices under extreme circumstances, highlighting the need to separate electricity markets from natural gas prices to mitigate the risks associated with excessive reliance on natural gas prices during turbulent periods.

In summary, existing literature mainly focuses on exploring the risk correlation between electricity markets, including the static relationships, dynamic changes, and asymmetry of risk spillovers. Although some researchers have studied the driving factors of risk spillovers between regional electricity markets, there is a dearth of research quantifying the influence of climate factors on risk spillover between these markets from a climate risk perspective. Considering that extreme weather is the greatest uncertainty factor for future energy and electricity shortages, this paper attempts to answer two questions: (1) How does the risk spillover effect evolve among European regional electricity markets under extreme market conditions? (2) Do physical climate risks and transition risks impact the risk spillover among these markets? If so, does this impact exhibit heterogeneity and dynamism? The results of this study have the potential to assist policymakers in effectively addressing the consequences of climate-related factors on the price volatility of the European electricity market. In addition, the findings can provide a decision-making reference for other countries and regions to consider climate risk factors when promoting electricity marketization reform. Additionally, this research can offer analytical tools for market investors to incorporate climate factors into their electricity price forecasts.

This paper mainly has two contributions. First, unlike previous studies that mostly use volatility to analyze electricity market risks (Tashpulatov, 2013; Ciarreta and Zarraga, 2016; Erdogdu, 2016; Ciarreta et al., 2017; Ioannidis et al., 2021), this paper estimates the downside Value at Risk (VaR) of electricity prices to assess the extreme downside risks. This paper quantifies the extreme risk spillover relationships among European regional electricity markets using the spillover index method developed by Diebold and Yilmaz (2009, 2012). Considering the heterogeneity of climate risk propagation at time and frequency levels, this paper employs the time–frequency domain decomposition method developed by Baruník and Křehlík (2018) to examine the extreme risk spillover across European regional electricity markets in both time and frequency domains. Secondly, this paper incorporates climate risk shocks into the framework of risk spillovers among electricity markets. By introducing climate physical risks, climate policy uncertainty, and climate concern shocks, this paper reveals the heterogeneous impacts of different types of climate risks on electricity markets in various frequency spans, which expands the driving mechanism of risk spillover in the electricity markets.

The remainder of the paper is structured as follows. Section 2 deals with the measurement of extreme risks in the electricity market and the modeling of risk spillovers. Section 3 describes the measurement of climate risks and the prices of European electricity markets. Section 4 presents the empirical results and discussion. Section 5 concludes the paper.

2. Methodology

We use the ARMA-GARCH models to fit each electricity price return respectively and obtain the lower tail extreme risk (i.e. VaRs) of the electricity markets. Next, due to the complex and dynamic interrelationships between climate risks and multiple electricity markets, we use the Diebold and Yilmaz (2012)'s connectedness network approach for analysis. In addition, the Baruník and Křehlík (2018)'s method is further employed to analyze the information spillover in the short-, medium- and long-term periods.

2.1. VaR estimation based on ARMA-GARCH models

The conditional variance of the univariate sequence can be dynamically modeled by introducing the GARCH model to the traditional time series ARMA model. The ARMA(r,s)-GARCH(p,q) model is expressed as follows:

$$\begin{cases} r_t = \lambda_0 + \sum_{i=1}^{r} \lambda_i r_{t-i} + \sum_{j=1}^{s} \theta_j \varepsilon_{t-j} + \varepsilon_t \\ \varepsilon_t = u_t \times \sigma_t \\ u_t \sim i.i.d(01) \\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j u_{t-j} \end{cases}, \tag{1}$$

In the above formula, r_t represents the rate of return sequence of the electricity markets, ε_t represents the random disturbance term, λ_0 and α_0 are the constant terms to be estimated , σ_t^2 represents the time-varying conditional variance, and r, s, p, and q represent the lag order, which is a non-negative positive number.

To increase the goodness-of-fit of the ARMA-GARCH model to the sample data, we use the asymmetric GARCH model [Glosten-Jagannanthan-Runkle (GJR)-GARCH, Glosten et al., 1993] as one of the alternative models, as well as six optional distributions for u_t, which are "generalized error distribution," "skewed generalized error distribution," "normal distribution," "skew normal distribution," "Student's T distribution," and "skewed Student's T distribution." The combinations of the different models and distributions are estimated, and the model that best fits the data is selected using the Bayesian information criterion (BIC). For the electricity market i, its VaR is expressed as follows:

$$VaR_{i,t}^{\alpha} = \mu_{i,t} + \sigma_{i,t} \cdot d_i^{-1}(\alpha) \tag{2}$$

In the above formula, $\sigma_{i,t}$ represents the conditional variance at time t estimated by the GARCH model, $d_i^{-1}(\cdot)$ represents the inverse function of the random disturbance term distribution function, and α represents the significance level of VaR. In this article, 0.05 is utilized.

2.2. Time domain connectedness network

Let us consider a VAR model with n variables and p periods lagged as follows:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon \qquad \varepsilon \sim (0, \Sigma),$$

where ε is the $i.i.d.$ random disturbance vector. If the above VAR(p) model is stationary, it can be converted into a vector moving average (VMA) model as follows:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i},$$

where A_i is the coefficient matrix to be estimated with dimension N × N and satisfies $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$. In particular, A_0 is defined as the identity matrix. The A_i matrix can be iteratively calculated from the Φ_i matrix.

Based on generalized variance decomposition, for variable x_i in the forecast error variance of its H-step ahead, the part from variable x_j can be calculated by the following formula:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \tag{3}$$

In the formula, Σ represents the variance and covariance matrix of the random disturbance vectorε, σ_{ii} represents the standard deviation of the i-th variable, and e_i represents the selection vector; that is, except for the i-th element, which is 1, the remaining elements are all 0 and have a length of N column vector.

Due to the calculation assumptions of generalized variance decomposition, the decomposition results of the above variables do not add up to 1. Therefore, the following standardization should be carried out:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}, \tag{4}$$

By carrying out the above standardization, $\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = 1$, $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = N$.

Based on the results, we can define the total spillover index, directional spillover index, and net spillover index.

The total spillover index (Total) denotes the total spillover level of the system:

$$Total(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \bullet 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N} \bullet 100. \tag{5}$$

The directed spillover index is used to measure the directional information spillover between markets and can be defined as TO and FROM, respectively, according to the direction. TO measures the spillover from one market to all other markets, while FROM measures the spillover that one market receives from all other markets. The relevant calculation methods are as follows:

$$TO_{i\cdot}^{g}(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \bullet 100, \tag{6}$$

$$FROM_{\cdot i}^{g}(H) = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \widetilde{\theta}_{ji}^{g}(H)} \bullet 100. \tag{7}$$

Correspondingly, the net spillover index is the TO index of a market minus the FROM index, which is used to indicate the net spillover of this market to the rest of the system. If this value is positive, the market has a net contribution; otherwise, the market plays the role of an information receiver.

$$NET_{\cdot i}^{g}(H) = TO_{i\cdot}^{g}(H) - FROM_{\cdot i}^{g}(H). \tag{8}$$

2.3. Frequency domain connectedness network

Baruník and Křehlík (2018) proposed a frequency domain connectedness network model based on the DY connectedness network model. The basic idea is based on spectrum variance decomposition, which can further decompose the results of the connectedness network model into different periods, such as short, medium, and long term.

Specifically, the generalized causation spectrum at a specific frequency ω is defined as the following formula:

$$(\Theta(\omega))_{j,k} = \frac{\sigma_{kk}^{-1} \left| (\Psi(e^{-i\omega})\Sigma)_{j,k} \right|^2}{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{j,j}}, \tag{9}$$

Table 1
Vocabulary lists for climate policy uncertainty index.

Countries	Climate	Policy	Uncertainty
United Kingdom	green energy/carbon dioxide/climate/climate risk/ renewable energy/greenhouse gas emission/greenhouse/CO_2/emissions/global warming/climate change/environmental	regulation/legislation/prime minister's office/Parliament/ Environment Agency/Department for Environment, Food and Rural Affairs/10 Downing Street/law/policy/regulatory/policies	uncertainty/uncertain/ uncertainties
France	dioxyde de carbone/ risque de climat/ serre/ climat/CO_2/émissions/ réchauffement global/changement climatique/énergie verte/ émissions de gas à effet de serre/énergie renouvelable/ environnemental	régulation/législation/le Palais de l'Elysée/Congrès/Ministère de la Transition écologique/droit/politique/régulatoire/politiques	incertitude/uncertain/ incertitudes
Germany	Kohlendioxid/Klima/Klimarisiko/ Klimawandel/ Treibhausgasemissionen/Treibhaus/CO_2/globale Erwärmung/ grüne Energie/erneuerbare Energie/Umwelt Emissionen/	Regulierung/Gesetzgebung/Bundeskanzleramt/Kongress/UBA/ Gesetz/Politik	Unsicherheit/ Ungewissheit/ Ungewissheiten

where $(\Theta(\omega))_{j,k}$ represents the part of the spectral decomposition of the j-th variable that can be explained by variable k at frequency ω. The above formula can be regularized as follows:

$$(\widetilde{\Theta}(\omega))_{j,k} = \frac{(\Theta(\omega))_{j,k}}{\sum_{k=1}^{n}(\Theta(\omega))_{j,k}}. \tag{10}$$

In the above formula, $(\widetilde{\Theta}(\omega))_{j,k}$ represents the directional risk spillover from variable k to variable j at a given frequency ω. For a given frequency interval $d = (a,b)$, a, $b \in (-\pi,\pi)$, $a < b$, the generalized variance decomposition in this frequency interval d can be defined as follows:

$$\left(\widetilde{\Theta}_d\right)_{j,k} = \int_a^b (\widetilde{\Theta}(\omega))_{j,k} d\omega. \tag{11}$$

where $\left(\widetilde{\Theta}_d\right)_{j,k}$ represents the directional risk spillover from variable k to variable j under a given frequency interval d. Therefore, for different frequency bands, the corresponding short-, medium-, and long-term risk spillover indicators can be obtained. Following Diebold and Yilmaz (2012), the total spillover index under a given frequency interval d can be expressed by the following formula:

$$S^d = \frac{\sum_{j=1, j\neq k}^{n}\left(\widetilde{\Theta}_d\right)_{j,k}}{\sum_{j,k}\left(\widetilde{\Theta}_d\right)_{j,k}} = 1 - \frac{\sum_{j=1}^{n}\left(\widetilde{\Theta}_d\right)_{j,j}}{\sum_{j,k}\left(\widetilde{\Theta}_d\right)_{j,k}}. \tag{12}$$

To be consistent with the results of Diebold and Yilmaz (2012), a weight function is further added to Eq. (12). The modified total spillover index under a given frequency interval d is expressed as follows:

$$\widetilde{S}^d = S^d \bullet \Gamma(d), \tag{13}$$

In the above formula, the weight function $\Gamma(d) = \sum_{j,k=1}^{n}\left(\widetilde{\Theta}_d\right)_{j,k} / \sum_{j,k=1}^{n}(\widetilde{\Theta})_{j,k} = 1/k\sum_{j,k=1}^{n}\left(\widetilde{\Theta}_d\right)_{j,k}$, which represents the proportion of the spillovers in the frequency interval d to the spillovers of the total system. In this way, the sum of the modified total spillover index under all frequency bands is equal to the total spillovers of the traditional DY connectedness approach; that is, $S = \sum_d \widetilde{S}^d$.

3. Data sample

3.1. Climate risk indices

Referring to Guo et al. (2023), this paper employs three indices to characterize climate risks from the perspective of risk perception. We use the European climate policy uncertainty (CPU) index and the climate physical risk (CPR) index to reflect the climate transition risk and climate physical risk, respectively. We also employ the climate concern (CCI) index to measure the general attention of market investors to climate risks. Using these three climate risk indices, this paper can clearly depict the heterogeneous effects of climate risks from different sources on the European electricity markets.

The CPU is constructed using the text mining method to extract climate policy news from European media. Following Guo et al. (2023), three major European native language newspapers from the UK, France, and Germany are selected to obtain news text data, namely, the Financial Times, Le Monde, and Die Welt, respectively. The index construction method is as follows. First, create specific vocabulary lists for "climate," "policy," and "uncertainty," respectively. Second, check whether each news item contains the words in the vocabulary list. Third, obtain the frequency data of these articles containing the keywords and divide the data by its standard deviation. Finally, the final index is obtained by calculating and standardizing the average of the weekly data of the three

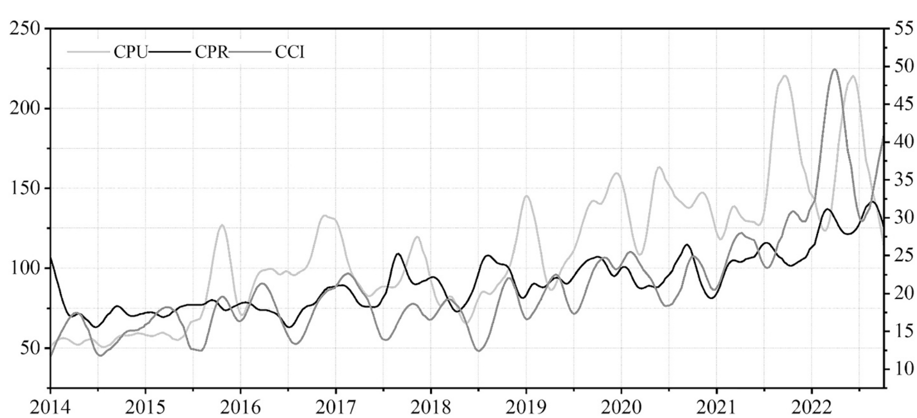

Fig. 1. Trend chart of the three climate risk indices.
Note: To better display the trend, spline smoothing is used on the original data.

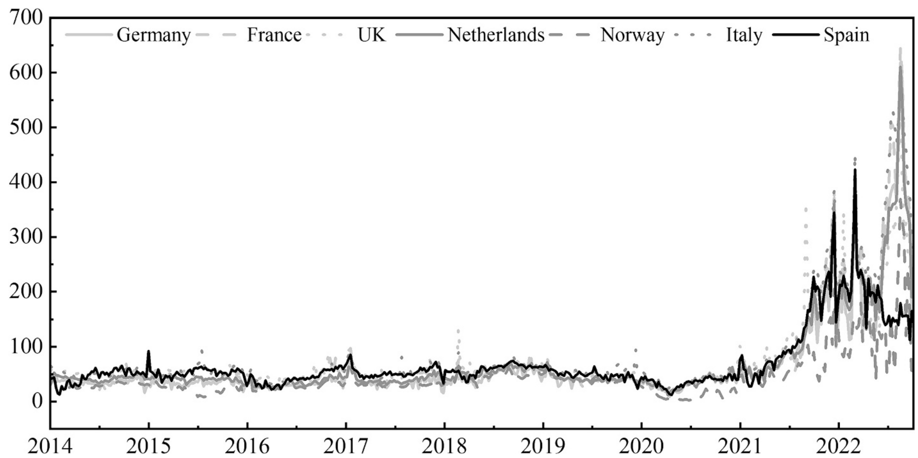

Fig. 2. Overview of weekly price series of seven electricity markets.

Table 2
Descriptive statistics of sample.

	Mean	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Jarque-Bera
CPU	110.264	470.888	14.200	72.631	1.454	5.909	301.135***
CPR	21.471	42.214	9.155	5.301	0.633	3.565	34.185***
CCI	20.982	95.000	4.520	8.747	2.179	15.071	2930.339***
Germany	65.200	618.510	8.516	80.179	3.623	17.961	4916.234***
France	73.088	646.690	10.352	90.207	3.328	15.098	3392.329***
UK	77.876	547.565	16.171	69.965	3.041	13.335	2558.647***
Netherlands	69.223	610.560	11.438	78.104	3.422	16.420	4037.766***
Norway	42.916	368.953	1.619	41.175	4.007	24.273	9194.102***
Italy	85.825	585.068	22.618	92.512	3.116	12.898	2434.277***
Spain	67.809	422.964	12.280	53.229	2.728	11.722	1883.005***

Note: *** denote significance at the 1% level.

countries. The vocabulary list was selected with reference to the CPU index in Gavriilidis (2021), and English was translated into the corresponding French and German languages. Table 1 shows the keyword lists for the different languages.

Different from the construction of CPU, we created CPR and CCI using Google Search. By selecting climate-related keywords, we can obtain corresponding Google search volumes for CPR and CCI. For physical risk, we refer to the main climate risk types included in the international disaster database EM-DAT, selecting Flood, Hurricane, Drought, Wildfire, Extreme Weather, and Extreme Climate as keywords. For the CCI, the two hottest keywords, "global warming" and "climate change risk," are chosen. The high-frequency but short-period Google search volume is then spliced with the low-frequency but long-period Google search volume as the weight. Finally, we use the average search volume of each keyword to obtain the CPR and CCI indices.

The data are collected on a weekly frequency, from January 2014 to October 2022, encompassing a total of 427 weeks. All climate risk indices are initially differenced to estimate the VAR model.

3.2. Data description

The trend chart of the three climate risk indices is shown in Fig. 1. The overall trend of climate risk exhibits an increase over time. The three types of risk indices present high correlation, while the climate policy uncertainty presents higher volatility than the other two risks.

Fig. 2. presents the price (weekly average) data of the seven electricity markets. The price structure can be clearly divided into two stages. In the first stage, the prices in all electricity markets were relatively low before 2021, being below 100 euros/MWh most of the time, with relatively small fluctuations. In the second stage, electricity prices start to rise rapidly after 2021, presenting significant fluctuations. The descriptive statistics for all weekly original data of the sample are shown in Table 2. In the modeling phase, the climate risk index adopts a difference, while the electricity price data adopt a logarithmic difference. The ARMA-GARCH optimal fitting models of the electricity market returns are reported in Table 3.

Table 3
Optional fitting ARMA-GARCH models.

	ARMA lag	GARCH model	Distribution	Loglikelihood	BIC
Germany	(0,2)	gjr-GARCH	sged	747.8	−0.452
France	(1,2)	gjr-GARCH	ged	779.8	−0.472
UK	(0, 2)	gjr-GARCH	sstd	1780.3	−1.108
Netherlands	(1,1)	gjr-GARCH	ged	2444,7	−1.532
Norway	(0,1)	gjr-GARCH	sstd	2031.5	−1.270
Italy	(1, 1)	gjr-GARCH	sged	3082.4	−1.935
Spain	(2,2)	gjr-GARCH	sstd	2014.4	−1.251

Notes: "ged," "sged," "norm," "snorm," "std," and "sstd" represent "generalized error distribution," "skewed generalized error distribution," "normal distribution," "skew normal distribution," "Student's T distribution," and "skewed Student's T distribution", respectively.

4. Empirical results and discussion

4.1. Static analysis in time–frequency spans

By applying the time–frequency domain spillover method proposed

Table 4
Risk spillover table in the time domain (%).

	CPU	CPR	CCI	Germany	France	UK	Netherlands	Norway	Italy	Spain	FROM
CPU	90.73	0.86	1.90	1.72	0.03	0.18	3.57	0.77	0.12	0.12	9.27
CPR	0.35	89.63	6.05	0.90	0.40	0.49	0.60	0.60	0.93	0.05	10.37
CCI	0.17	5.86	90.61	0.79	0.11	0.09	0.17	1.91	0.05	0.23	9.39
Germany	0.50	0.83	0.33	72.24	7.17	0.32	11.05	1.61	3.29	2.66	27.76
France	0.34	0.65	0.07	8.39	78.69	0.44	6.21	0.13	1.31	3.76	21.31
UK	0.15	0.20	0.38	0.69	0.58	76.29	8.19	10.11	3.16	0.25	23.71
Netherlands	1.12	0.39	0.37	9.33	4.59	10.60	52.70	15.38	4.51	1.02	47.30
Norway	0.88	0.24	1.45	3.19	0.42	5.09	8.26	79.04	0.89	0.53	20.96
Italy	0.11	2.33	0.50	1.69	1.94	3.24	4.79	0.72	82.53	2.16	17.47
Spain	0.18	0.18	0.34	4.42	6.47	0.16	1.29	0.91	1.50	84.56	15.44
TO	3.80	11.55	11.38	31.12	21.69	20.62	44.15	32.14	15.75	10.79	TOTAL
NET	−5.47	1.18	1.98	3.36	0.38	−3.09	−3.15	11.18	−1.72	−4.65	20.30

Note: The number in row *a*, column *b* represents the spillovers from variable *b* to variable *a*. FROM measures the spillover effects from all other variables to one certain variable, while TO measures the spillover effects of a certain variable to all other variables. NET is the net spillover index, which is the result of TO minus FROM. TOTAL stands for the total spillover index, which indicates the connectedness of the entire system.

by Baruník and Křehlík (2018), we estimate a 10-variable VAR model and calculate the spillover effects among three climate risks and seven European electricity markets based on the model estimation results. The selection of the one lag order for the VAR model is determined by the BIC information criterion. To further analyze the heterogeneity of spillover effects at different frequency intervals, we identify three frequency bands. The first frequency band is 1–2 weeks (roughly corresponding to half a month), the second is 3–12 weeks (one quarter), and the third is more than 12 weeks or more than one quarter. As explained by Baruník and Křehlík (2018), these frequency bands can respectively capture the spillover effects of the system under different time horizons. This section presents the static spillover effects of different types of climate risks and extreme risks in the electricity markets in the time and frequency domains.

Table 4 shows the connectedness table among climate risk shocks and extreme risks in the electricity markets over the full sample in the time domain. The values in row *j*, column *k* represent the strength of the shocks from node *k* to the variance of node *j*; that is, the spillover effect

Table 5
Spillover results in different frequency intervals (%).

Panel A: Short-term spillover table (half a month)											
	CPU	CPR	CCI	Germany	France	UK	Netherlands	Norway	Italy	Spain	FROM
CPU	73.50	0.56	1.59	1.48	0.01	0.14	3.23	0.56	0.08	0.06	7.71
CPR	0.14	57.54	3.12	0.36	0.13	0.17	0.41	0.29	0.67	0.02	5.32
CCI	0.11	4.20	68.90	0.22	0.09	0.04	0.03	1.40	0.04	0.16	6.29
Germany	0.14	0.62	0.10	24.57	2.13	0.01	4.16	0.02	0.12	1.03	8.32
France	0.27	0.58	0.02	2.54	35.04	0.07	1.77	0.00	0.19	0.95	6.40
UK	0.03	0.01	0.01	0.00	0.02	11.51	0.43	0.01	0.21	0.00	0.73
Netherlands	0.23	0.07	0.02	1.35	0.50	0.23	9.50	0.02	0.18	0.21	2.80
Norway	0.04	0.04	0.05	0.00	0.00	0.00	0.00	1.93	0.02	0.01	0.17
Italy	0.02	0.29	0.27	0.13	0.12	0.35	0.45	0.14	19.26	0.58	2.35
Spain	0.15	0.00	0.04	0.36	0.32	0.01	0.18	0.06	0.51	11.84	1.64
TO	1.12	6.39	5.22	6.45	3.33	1.01	10.66	2.50	2.02	3.01	TOTAL
NET	−6.59	1.07	−1.06	−1.87	−3.06	0.28	7.86	2.34	−0.33	1.37	4.17
Panel B: Medium-term spillover table (one quarter)											
	CPU	CPR	CCI	Germany	France	UK	Netherlands	Norway	Italy	Spain	FROM
CPU	14.69	0.24	0.26	0.22	0.01	0.04	0.33	0.17	0.03	0.05	1.36
CPR	0.16	26.86	2.44	0.43	0.23	0.20	0.18	0.25	0.23	0.01	4.14
CCI	0.05	1.40	18.34	0.47	0.02	0.03	0.08	0.44	0.01	0.07	2.55
Germany	0.30	0.13	0.12	35.93	3.78	0.09	4.94	0.17	1.84	1.43	12.80
France	0.06	0.06	0.02	4.12	34.02	0.14	2.94	0.01	0.65	1.96	9.97
UK	0.07	0.06	0.07	0.06	0.20	35.48	2.44	0.61	1.17	0.02	4.71
Netherlands	0.66	0.10	0.04	4.07	2.39	3.36	23.62	1.08	1.72	0.52	13.94
Norway	0.17	0.02	0.17	0.28	0.03	0.25	0.57	10.03	0.14	0.02	1.64
Italy	0.06	1.34	0.15	0.89	1.14	1.43	2.35	0.26	43.09	1.30	8.92
Spain	0.01	0.09	0.15	2.11	3.30	0.03	0.60	0.22	0.83	41.30	7.33
TO	1.55	3.42	3.43	12.65	11.09	5.58	14.44	3.19	6.62	5.39	TOTAL
NET	0.19	−0.71	0.88	−0.15	1.12	0.87	0.50	1.55	−2.30	−1.95	6.74
Panel C: Long-term spillover table (more than one quarter)											
	CPU	CPR	CCI	Germany	France	UK	Netherlands	Norway	Italy	Spain	FROM
CPU	2.54	0.06	0.05	0.02	0.00	0.00	0.01	0.05	0.01	0.01	0.20
CPR	0.04	5.23	0.49	0.11	0.04	0.12	0.01	0.07	0.03	0.01	0.91
CCI	0.01	0.26	3.37	0.10	0.00	0.02	0.07	0.08	0.00	0.01	0.56
Germany	0.06	0.08	0.10	11.75	1.26	0.23	1.95	1.41	1.33	0.20	6.63
France	0.01	0.00	0.02	1.73	9.63	0.23	1.50	0.12	0.48	0.85	4.94
UK	0.06	0.13	0.29	0.62	0.36	29.29	5.32	9.49	1.78	0.22	18.28
Netherlands	0.23	0.23	0.31	3.91	1.70	7.01	19.57	14.28	2.60	0.30	30.56
Norway	0.67	0.19	1.23	2.90	0.39	4.84	7.69	67.08	0.73	0.51	19.15
Italy	0.03	0.70	0.07	0.67	0.67	1.46	2.00	0.32	20.17	0.27	6.20
Spain	0.02	0.09	0.15	1.95	2.84	0.12	0.51	0.63	0.16	31.42	6.47
TO	1.13	1.74	2.72	12.02	7.27	14.04	19.06	26.44	7.11	2.39	TOTAL
NET	0.92	0.82	2.16	5.39	2.33	−4.24	−11.51	7.29	0.91	−4.08	9.39

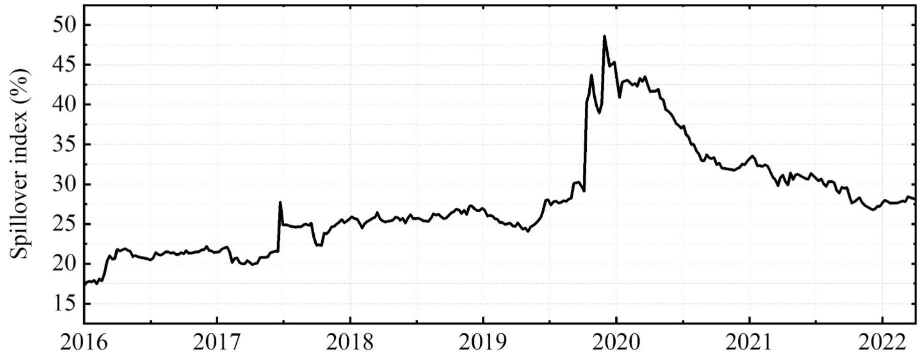

Fig. 3. Dynamic total spillover index in the time domain.

of variable *j* caused by *k*. The diagonal values represent the influence of each variable's own changes on its variation process, describing the self-correlations of each variable in this model. The non-diagonal part is the focus of this study, reflecting the interactions between variables within the system.

Table 4 shows that the total spillover index is much greater than zero, indicating spillover effects between different variables. Specifically, the total spillover index is 20.30%, which means that 20.30% of the variance of the system's total forecast-error variance comes from the information spillover between all variables, indicating a significant spillover effect between climate risk shocks and extreme risks in the electricity markets. In this study, climate risks mainly include climate physical risks, climate policy uncertainty, and climate concern shocks. From the perspective of climate physical risks, the electricity markets could be affected by climate change through demand or supply (Mideksa and Kallbekken, 2010). First, electricity demand is affected by temperature changes. Second, the hydroelectric power supply is also affected by water inflow caused by changes in precipitation and temperature. Third, the power generation efficiency of the power plants decreases with the increase in temperature of the water used to cool the equipment (Golombek et al., 2012). From the perspective of climate transition risk, climate-related policy uncertainty (such as carbon reduction policy uncertainty) can affect investment in the power industry and amplify the anxiety of risk-averse investors toward electricity investment, creating an impact on electricity market prices (Apergis and Lau, 2015). Table 4 also shows that the spillover strength from one node to other nodes is significantly different from the spillover strength of other nodes to themselves, indicating the directed and asymmetric nature of the directional spillover index. For example, the value of spillovers from climate policy uncertainty to all extreme risks in the electricity market is 3.28%, whereas the value of spillovers from extreme risks in the electricity market on climate policy uncertainty is 6.51%, indicating that climate policy uncertainty is the net receiver of extreme risks in electricity markets (−3.23%). This may be explained by the fact that fluctuations in electricity market prices can stimulate government departments to actively adjust various climate policies to mitigate risks, thereby exacerbating the level of climate policy uncertainty (Ozturk et al., 2022).

Some interesting conclusions can also be drawn from the net spillover results. Among them, the net spillover effects of climate physical risk shocks and climate concern shocks on extreme risks in the electricity markets are positive, indicating that these two kinds of climate risk shocks play the role of a spillover transmitter in the spillover system. Overall, climate change could lead to increases in average temperatures, changes in the intensity and pattern of extreme weather events, and rising sea levels in most regions around the world, directly or indirectly affecting global energy supply and demand. One of the most immediate effects is that higher temperatures mean a spike in cooling demand and a decrease in heating demand. In addition, electricity conversion and transportation are also highly susceptible to extreme weather events (Mideksa and Kallbekken, 2010). Therefore, such climate risks have a greater impact on energy markets, such as the electricity markets.

Following Baruník and Křehlík (2018), we further extend the results to the frequency domain, as shown in Table 5. Table 5 includes three sub-tables, from top to bottom, showing the results of three different frequency bands (1–2 weeks, 3–12 weeks, 12 weeks or more). Consistent with the spillover table in the time domain, in each sub-table, the values in row *j*, column *k* represent the spillovers from variable *k* to the variable *j*.

The interesting points and main conclusions for the decomposition results in the frequency domain are summarized below. First, the spillover effects between climate risk shocks and extreme risks in the electricity market are mostly concentrated in the long-term band. Specifically, the total spillover in the 12 weeks or more term has the highest contribution to the overall total spillovers, with a total spillover index of 9.39%, followed by the total spillovers in 3–12 weeks' term (6.74%) and the total spillovers in 1–2 weeks' term (4.17%). Second, in terms of the spillover effects of climate risk shocks on the electricity

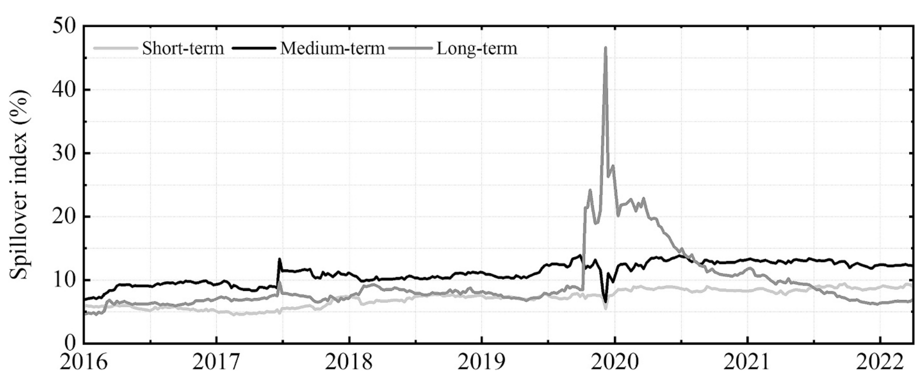

Fig. 4. Dynamic total spillover index in the frequency domain.

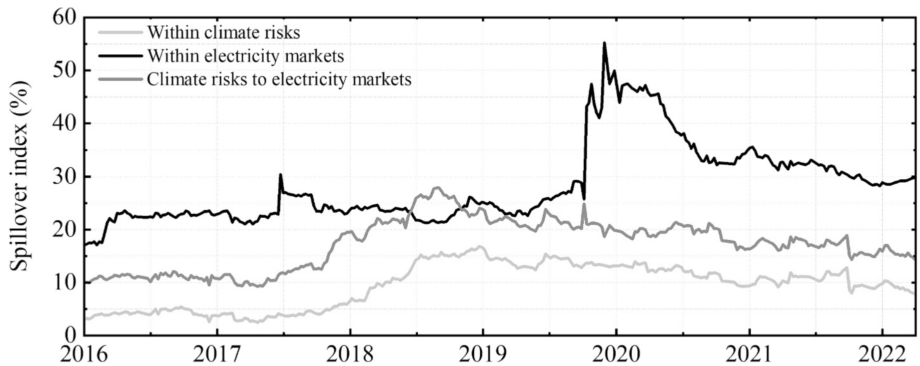

Fig. 5. Subsystem dynamic spillovers in the time domain.

markets, the short-term results indicate that climate risk is a net receiver but transforms into a net emitter of spillover effects in the medium and long term. One possible explanation is that climate-related risks mainly affect electricity demand and prices in the longer time dimension, while climate risk shocks may not respond immediately to short-term risks in the electricity markets (Ma et al., 2022).

4.2. Dynamic analysis in time–frequency spans

The full sample static spillover results show the overview of the spillover effects among climate risk shocks and extreme risks in the electricity markets. However, risk spillovers are easily affected by numerous factors, such as climate crisis events. Therefore, we use the rolling window method to make the model dynamic and estimate the model under each window, analyzing the time-varying information transmission patterns of climate risks and electricity markets from the dynamic results. Specifically, following Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), the length of the window in dynamic spillover estimation is 120 weeks and the forecast horizon is 100 weeks. In the next section, we specialize in the dynamic changes of spillover strength in the time and frequency domains from two aspects: total spillover index and directional spillover index.

4.2.1. Dynamic total spillovers

Figs. 3 and 4 plot the dynamics of the spillover effects between climate risk shocks and extreme risks in the electricity market in both time and frequency domains, respectively. The results of the time domain analysis indicate that the spillover effect within the entire system has significant time-varying characteristics, showing an overall trend of an initial increase followed by a decrease. Specifically, the total spillover index has steadily increased from July 2016 to April 2020. The reason is that the EU signed the Paris Agreement, an agreement to address global climate change, in December 2015. Since then, the EU has successively introduced a series of policies to address climate change (Oberthür and Groen, 2017). Climate policy risks and climate concern shocks can affect the energy and electricity supply policies of various countries, leading to higher uncertainty in electricity prices and extreme risk spillovers (Stern et al., 2016; Nam, 2021). From April 2020 to June 2020, the total spillover index increased significantly from 29% to 48%, mainly attributed to the COVID-19 epidemic and the European energy transition policy. The unprecedented COVID-19 has led many European countries into economic recession and reduced energy demand, especially electricity demand, resulting in price volatility and risk transmission in the electricity markets (Ma et al., 2022). For the energy transition policy, as one of the economies with the highest greenhouse gas emissions and one of the largest economies in the world, the EU has formulated detailed energy and climate-related policies to achieve the "Net-Zero Carbon Europe" goal by 2050 (Sæther and Neumann, 2024). In the *European Green Deal*, an intermediate target was set to "reduce greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels" (Steininger et al., 2022).

Although the EU is at the forefront of renewable energy development, coal-fired and nuclear power still occupy a high proportion of its power generation structure. Faced with increasing pressure to reduce emissions and the safety issues of nuclear energy, the EU needs to consider future plans for the transformation of coal-fired and nuclear power. To achieve the 55% emission reduction target set in the *European Green Deal*, the EU needs to gradually achieve the withdrawal of coal-fired power by 2030, but there is still no consensus among the member states. These uncertain energy and climate policies have deepened the price risk of the electricity market.

The decomposition of the spillover effects in the frequency domain indicates that the spillover effects between climate risk shocks and extreme risks in the electricity market are mainly concentrated in the medium and long term, while they are relatively small in quantity but rather stable in the short term. Fig. 4 shows that the spillover effect in the long-term frequency domain dominates, fluctuating between 4.6% and 46%, close to the trend shape of the total spillover index Fig. 3. These findings indicate that risk spillovers within the entire system are difficult to absorb in a short period. The implications for market investors and risk managers lie in the need to pay attention to the persistence of risk transmission between climate shocks and the electricity market.

Furthermore, we subdivide each rolling window in the dynamic analysis into two subsystems: climate risks and electricity markets. Fig. 5 depicts the dynamics in the spillover effects between the different types of climate risks, cross-market risk spillovers in the electricity system, and spillover effects between climate risks and the electricity markets. The key findings can be summarized as follows.

First, the strength of the risk spillover within the electricity market subsystem is the highest, ranging from 18% to 55%. The spillover index shows an overall upward trend. In particular, the sharp rise in April 2020 is mainly due to the superposition of the COVID-19 pandemic and the energy crisis (Abdullah et al., 2023). On the one hand, the COVID-19 pandemic has a serious influence on economic development, affecting the uncertainty of energy demand and amplifying the spillovers between extreme downside risks in the electricity markets (Ma et al., 2022). In addition, the frequent occurrence of extreme climate crisis events has increased energy demand. However, the shift in EU climate change policies has led to the premature withdrawal of traditional energy supply, while the supply of clean energy remains unstable. The imbalance between supply and demand has caused a significant boost in the extreme risk level in the electricity market and has driven up the spillover effect of extreme risks across markets (Yang, 2022).

Second, the spillover effect from climate risks to extreme risks in the electricity market varies within the range of 9% to 27% and shows a trend of initial increase followed by a decrease. This is due to the strong signal for global governance on climate change initiated by the adoption of the Paris Agreement in December 2015, where a series of climate policies were introduced to restrain greenhouse gas emissions generated

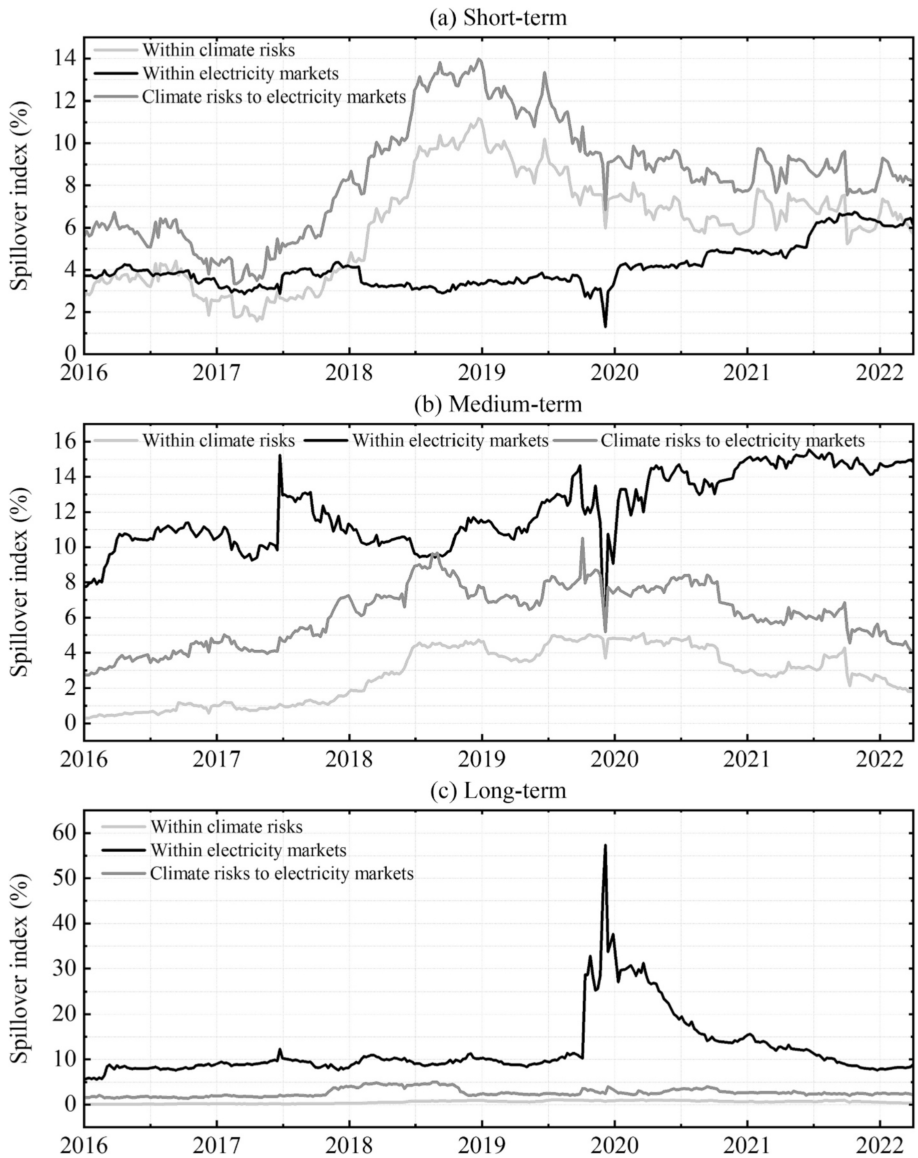

Fig. 6. Subsystem dynamic spillovers in the frequency domain.

by fossil energy consumption (Tanaka and O'Neill, 2018). By affecting the supply-demand relationship of energy, it further increases the risk in electricity prices and its spillover effects (Semieniuk et al., 2021). Subsequently, the extreme climate change in 2018 led to the highest growth rate in energy consumption since 2011. On October 8, 2018, the United Nations Intergovernmental Panel on Climate Change (IPCC) released a special report analyzing how to achieve the target of controlling global warming by 1.5 °C and the impact of warming. Mitigating climate change requires a large-scale and rapid transformation of the energy system, which exacerbates the level of risk linkage between electricity markets. Therefore, the spillover strength of climate risk shocks on extreme risks in the electricity system cannot be ignored.

Third, the spillover effect between different types of climate risks is the lowest, ranging from 4% to 15%, but shows an overall upward trend. The EU plays a very active role internationally in combating climate change. As early as November 2018, the EU first proposed the goal of achieving carbon neutrality by 2050. In December 2019, the European Commission published the *European Green Deal*, an ambitious plan to develop Europe into the first continent to achieve carbon neutrality by 2050. In June 2021, the European Climate Law was officially passed. This is the first time that the carbon neutrality goal has been incorporated into the legal system, transforming political commitments into legal obligations and investment incentives to ensure that all levels of society work toward this goal (Dupont et al., 2024). While these climate policies increase the feasibility of addressing climate change, they also increase the linkage between climate policy uncertainty and climate concerns.

The results in Fig. 6 indicate that in the short term, climate risk shocks have the greatest spillover effect on extreme risks in the electricity market, followed by climate risk subsystems, whereas the spillover effect within the electricity market subsystem is the smallest. In the medium and long term, the spillover effect within the electricity market subsystem is the greatest, followed by the extreme risk spillover effect of climate risk shocks on the electricity markets. Notably, the spillover effect within the climate risk subsystem is the smallest.

4.2.2. *Dynamic directional spillovers*

Although the total spillover index displays the trends and dynamic changes of spillover strengths between climate risk shocks and extreme risks in the electricity markets within the entire system and different subsystems during the sample period, it cannot reflect the directionality of spillover effects within the system. Hence, we further calculate the

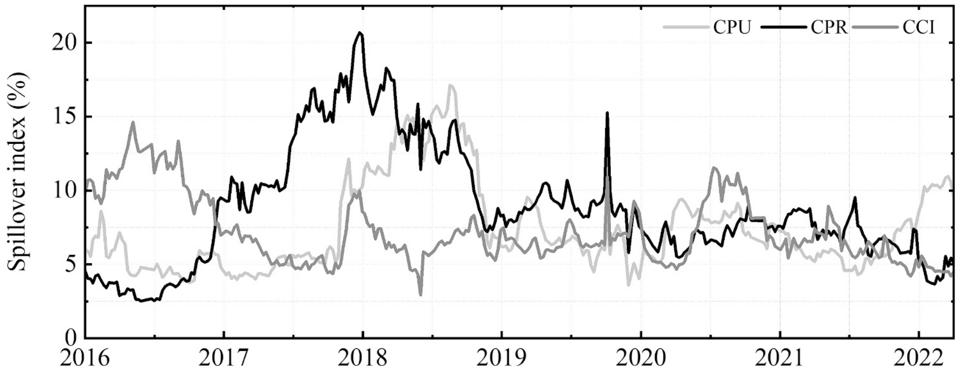

Fig. 7. Dynamic spillovers from climate risk shocks to the electricity markets in the time domain.

directional spillover effects from different types of climate risk shocks to the electricity markets in both time and frequency domains.

The dynamics of spillovers from climate risk shocks to extreme risks in the electricity markets in the time domain are revealed in Fig. 7. Among them, the spillover effect of CPR shocks is the largest, ranging from 2.5% to 20.5%, followed by CPU shocks, ranging from 3.6% to 17%. The spillover effect of CCI shocks is the smallest, ranging from 2.9% to 14.6%. The spillover trends of climate physical risk shocks and climate policy uncertainty shocks are similar, both showing an upward trend followed by a downward trend. By contrast, the spillover index of climate concern shocks shows a fluctuating downward trend.

Fig. 8 plots the time-varying spillover effects from climate risk shocks to extreme risks in the electricity market in the frequency domain. The spillover effect from climate physical risks is more pronounced in both short and medium term. The spillover effect from climate policy uncertainty shocks is larger in the long term, whereas the spillover effect from climate concern shocks is relatively small in all frequency domains. A possible explanation is that the short-term impact of climate physical risks represented by extreme weather events not only damages electricity infrastructure in a short period but also often poses the risk of electricity supply shortage by affecting electric power charge, leading to an increase in short-term risks and spillover in the electricity markets (Nahmmacher et al., 2016; Mosquera-López et al., 2018). In the long run, the adjustment of climate policies and their consequences have the characteristics of long-term periodicity and persistence. Therefore, compared with short-term climate events, such as extremely high temperatures, climate policy uncertainty shocks are more likely to influence the risk linkages of the electricity markets in the long run (Ding et al., 2022).

In summary, this study provides evidence of the significant differences in the spillover effects of climate shock risk and extreme risk in the electricity market in different frequency domains. The spillover effects are mostly concentrated in the medium- and long-term frequency domains, indicating that the impact of climate risk shocks is persistent. Therefore, compared with existing literature on climate risk spillover effects based on time domain spillover index methods (Wang et al., 2023; Yan and Cheung, 2023), this study combines the frequency domain spillover index approach and rolling window technique, which have the advantage of directly characterizing the heterogeneity of risk spillover effects in different frequency domains, helping to deeply characterize the impact of climate risks on the electricity market. Moreover, this study reveals the heterogeneity of spillover effects from different types of climate risks to extreme risks in the electricity market, which supplements and expands existing literature on climate risk spillovers (Khalfaoui et al., 2022; Ren et al., 2023a; Tedeschi et al., 2024).

4.3. Robustness checks

To verify the reliability of our results, we test its robustness by varying the choice of extreme quantiles and the choice of rolling window size.[1]

4.3.1. Alternative extreme quantiles

To test that the choice of quantile of the extreme risk does not affect the main results, we take the total spillover index as a target and use two alternative extreme quantiles to estimate the spillover effect (0.01 and 0.1). Fig. 9 shows that the results are very close to the trend of the total spillover index estimated at 0.05% in Section 4.2.1, indicating that the spillover effect results obtained in the previous chapters of this study are robust to the selection of quantiles.

4.3.2. Alternative rolling-window sizes

To test the sensitivity of the spillover effect results to different rolling window lengths in this study, three rolling window lengths (110, 120, and 130 weeks) were selected for a robustness check. The results in Fig. 10 indicate that under different settings of rolling window sizes, the comprehensive trend of the depicted total spillover index is consistent, indicating that the results of the spillover effects are not sensitive to the selection of rolling window sizes, thereby verifying the results of our preliminary empirical results.

5. Conclusions and policy implications

In this paper, we incorporate climate risk shocks into the framework of electricity market risk spillover using the connectedness network approach. The main conclusions are as follows.

First, our empirical results highlight significant spillover effect from climate risk shocks to extreme risks in the electricity market, which varies over time. The spillover effect is easily affected by major climate-related events, such as the issues of new climate policies and the occurrence of major climate disaster events, which can cause a rapid increase in the spillover index of climate shocks. Second, the spillovers in the climate risk-electricity market nexus are mainly concentrated in the medium- and long-term frequency domains, whereas the short-term spillover effect is weak. These findings indicate that risk spillovers within the entire system are difficult to absorb in a short period. Third, the results of directional spillovers show that the spillover effects from climate physical risks to extreme risks in the electricity market are more

[1] We also implemented a robustness test on the climate physical risk index (CPR). We arbitrarily remove a keyword representing climate physical risk, recalculate the climate physical risk index, and re-estimate the dynamic DY model. The analysis shows that the climate physical risk index is also robust, and the basic conclusions remain unchanged. Detailed data are available from the authors on request.

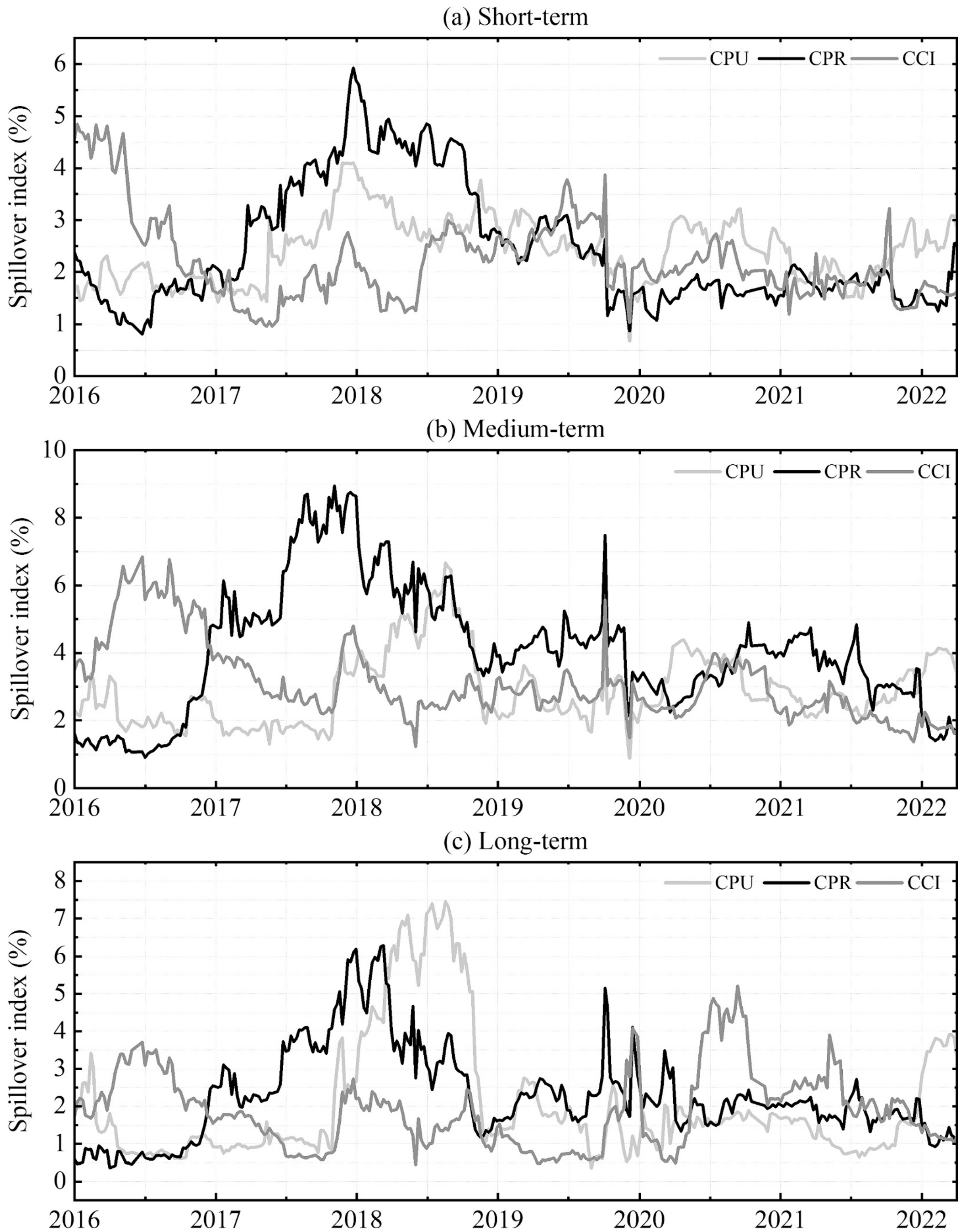

Fig. 8. Dynamic spillovers from climate risk shocks to the electricity markets in the frequency domain.

pronounced in the short and medium term, while the shocks of climate policy uncertainty to the electricity markets are more significant in the long term.

These conclusions have important implications for policymakers and risk regulators in the electricity market to avoid climate risks. First, risk regulators should include climate risk in the scope of electricity market risk regulation and improve dynamic monitoring of climate risk impacts to reduce the adverse effects of climate risk. Electricity companies should use diverse tools to manage climate risks, such as carbon 'cap-and-trade' markets (van Benthem et al., 2022). Second, it is crucial to accurately understand the dynamics of climate risk shocks to the electricity market, with a particular focus on the risk spillover effects caused by extreme climate events and important climate policies. Finally, policymakers should carefully monitor the heterogeneity of the climate risk shocks in varying scales to propose differentiated measures in different time periods and horizons. By shedding light on the spillover effects between climate risks and electricity markets, we provide important insights for practitioners in the electricity market and beyond, enabling them to make informed decisions and develop strategies to mitigate the risks arising from the climate crisis.

This study reveals that climate risks are an important driving force for exacerbating extreme risk in electricity markets. In the future, further consideration can be given to the issue of how electricity companies can hedge climate risks. Previous studies have shown that some green assets, such as green bonds, can serve as safe havens against climate risk (Cepni et al., 2022). Therefore, it would be interesting to study how to incorporate other assets into investment portfolios to manage climate risk exposures.

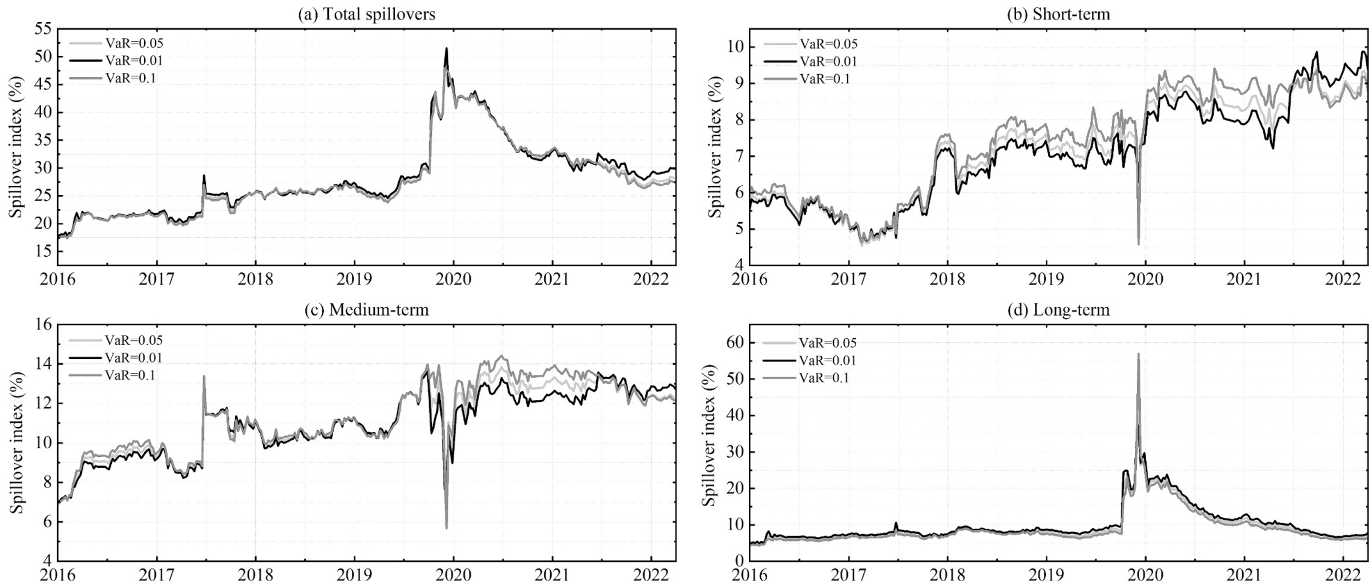

Fig. 9. Robustness check using different extreme quantiles.

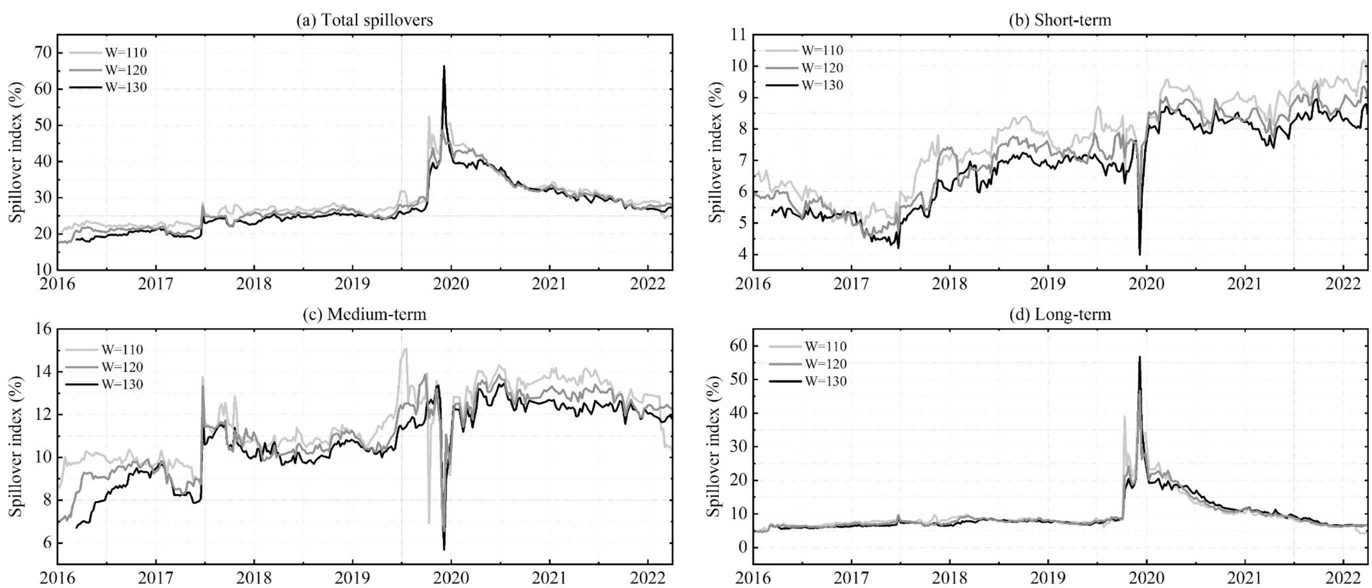

Fig. 10. Robustness check using different rolling window sizes.

CRediT authorship contribution statement

Wanli Zhao: Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Data curation, Conceptualization. **Xiangyang Zhai:** Writing – review & editing, Writing – original draft, Investigation. **Qiang Ji:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Zhenhua Liu:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgements

The support of the National Natural Science Foundation of China [Grant Nos. 72204250, 72348003]; the Humanities and Social Science Foundation of the Ministry of Education in China [No. 21YJCZH093]; the Social Science Foundation of Jiangsu Province [No. 22GLC022]; the Fundamental Research Funds for the Central Universities [Grant Nos. 2462023YJRC015, 2023SK05] are acknowledged.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107586.

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