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How Physical Climate Risks Impact the Risk Linkage of the Electricity Industrial Chain

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Abstract

The physical risks of climate change are transmitting shocks along the entire electricity industrial chain, disrupting the cross-sectoral interdependencies between them. This study measures dynamic risk linkage across the upstream, midstream, and downstream segments of China's electricity industry chain using the DCC-GARCH model. Then, the MF-VAR model is used to investigate the impact of physical climate risk on the electricity power industry chain. The results reveal that the risk linkage network of China's electricity power industry chain exhibits significant heterogeneity. Upstream-midstream and upstream-downstream linkages are primarily characterized by negative risk hedging, whereas midstream-downstream connectedness displays positive risk synergy. Furthermore, different types of physical climate risks affect risk linkage within the power industry chain through distinct short-term impact pathways. Specifically, extreme temperatures and droughts influence upstream-midstream linkages by altering the power generation mix, whereas extreme rainfall directly disrupts midstream-downstream linkages through physical grid failures. In contrast, when these individual physical risks are aggregated into a comprehensive index, a rise in that index enhances overall risk co-movement. Moreover, the impacts of climate risk on segment returns are asymmetrical, with the midstream generation segment as the core value-loss zone and main vulnerability. These findings provide policy guidance to enhance climate adaptability and prevent cross-segment risk transmission.

Keywords

climate change, physical climate risk, electric power industry chain, DCC-GARCH model, MF-VAR model

1. Introduction

Promoting a green energy transition and optimizing the energy structure are not only the core pathways to achieving carbon neutrality but also vital cornerstones for ensuring national energy security and maintaining stable economic and social operations. As a pillar industry of the national economy, the stable and healthy development of the electricity power industry chain is key to fulfilling this foundational role. However, as global climate change intensifies, climate risk is becoming a major challenge threatening the stable operation of the power system. In February 2021, Texas experienced a once-in-a-century extreme cold storm, leaving approximately 4 million households without power for several days. In the summer of 2022, the Yangtze River basin in China endured the most severe meteorological drought since 1961, causing a sharp decline in hydropower generation. These extreme events clearly demonstrate that physical climate risks are exerting dual pressure on the power system from both supply and demand sides, posing a severe and complex security challenge.

Existing literature has primarily focused on the impact of climate risks on energy price volatility and power market operation. For example, Li et al. (2024) [1] employ an ARDL/NARDL model to examine the effect of climate risks on the dirty-clean energy stock price dynamic conditional correlations. However, few studies have systematically examined, from a holistic perspective of the electricity industry chain, how climate risks, particularly physical climate risks, influence risk interdependencies across its various segments. In fact, the upstream and downstream segments of the electricity industry chain are highly interdependent. Once a particular segment is impacted by extreme weather, the resulting supply shortages, price fluctuations, or facility shutdowns can easily propagate upstream and downstream along the industry chain, creating a multiplier effect that ultimately leads to systemic risk.

The impact of physical climate risks on the electricity sector is multifaceted and multi-path. Heavy rainfall can directly damage power plants and transmission and distribution facilities, triggering power outages and equipment scrappage. High temperatures and drought reduce river runoff, lowering hydropower output. Shortages of cooling water also restrict the operation of thermal and nuclear power units, resulting in tight power supply during summer peak demand periods. In addition, extreme cold, on the other hand, can cause ice accumulation on transmission lines, leading to failures such as broken wires and toppled towers. Moreover, these physical impacts can disrupt fuel transportation routes, interrupting the supply of coal and natural gas, thereby further jeopardizing power generation capacity and the normal functioning of society as a whole. It is evident that physical climate risks do not strike a single point in isolation but simultaneously affect multiple links in the chain, including power generation, fuel supply, and transmission and distribution.

For this reason, it is necessary to view the electricity industry chain as a complete risk transmission system. Climate risks often trigger a chain reaction through technical interdependencies and cost pass-through between upstream and downstream segments. Abdullah et al. (2023) [2] point out that during times of crisis, significant tail risk contagion exists within the electricity market, providing direct evidence for cross-segment risk diffusion under extreme climate events. A study by Apergis et al. (2015) [3] on the Australian market also shows that climate policy uncertainty can lead to structural breaks in electricity prices and generates risks across various segments of the entire industrial chain. The operational disruptions in the real economy caused by physical or policy shocks can rapidly spread to capital markets through channels such as corporate earnings expectations and investor sentiment, resulting in sharp fluctuations in stock prices within the power sector. For example, during the surge in coal prices in 2021, the total market capitalization of China's thermal power sector contracted sharply, while the coal mining index rose against the trend during the same period. Such cross-segment and cross-market risk linkages are sufficient to drag the entire electricity industry chain into crisis, directly threatening the stability of the entire industry chain. This gap highlights the urgency of treating the industry chain as a unified entity for risk transmission and of thoroughly exploring how physical climate risks influence internal risk correlations within it.

In light of this, this study focuses on China's electricity industry chain, dividing it into upstream, midstream, and downstream segments. First, the DCC-GARCH model is employed to measure the dynamic risk correlations among these segments. Subsequently, the Mixed-Frequency Vector Autoregression (MF-VAR) model is introduced to identify the differentiated impacts of physical climate risks on risk correlations within the industry chain and their transmission characteristics.

The contributions of this study are as follows: First, it expands the scope of research on the relationship between climate risks and energy markets from a holistic industry chain perspective; second, it quantifies the asymmetric effects of physical climate risks in risk transmission across different segments; and third, it provides decision-making guidance for enhancing the climate resilience of the electricity industry chain and preventing cross-segment risk transmission.

2. Literature Review

2.1 Climate Risk

Early research focused primarily on physical climate risks, including the direct economic and social impacts of extreme weather events. Mideksa et al. (2010) [4] pointed out that rising temperatures would alter cooling demand and affect power generation efficiency. Golombek et al. (2011) [5] narrowed their analysis to Western European markets and confirmed the multi-dimensional impacts of climate change on power systems. Emanuel

(2005) [6] showed that the destructive power of tropical cyclones had increased markedly over the previous three decades. Anna et al. (2014) [7] examined the immediate effects of heatwaves on power markets and found that extreme heat significantly increased electricity price volatility. As research progressed, scholars began to quantitatively assess climate impacts. Diaz et al. (2017) [8] quantified the economic risks associated with climate change, and Stern et al. (2016) [9] called for a more scientific decision-making framework that encompasses climate and energy issues. Recently, the literature has further classified climate risks into physical risks and transition risks.

Regarding physical risks, Pokhrel et al. (2021) [10] reveal the growing drought risks from a global water resource perspective. Vliet et al. (2016) [11] analyze the vulnerability of power generation infrastructure and point out that water shortages severely limit the cooling capacity of thermal and nuclear power plants. Concerning transition risks, Dupont et al. (2023) [12] systematically review thirty years of climate policy evolution in the European Union and illustrate the far-reaching impacts of policy uncertainty on energy markets. Oberthür et al. (2016) [13] analyze the EU's positioning under the Paris Agreement and offer approaches for understanding climate policy coordination. Ma et al. (2023) [14] construct a news-based climate policy uncertainty index for China, which serves as a vital tool for the quantitative measurement of transition risks. Several studies examine the interaction between the two types of risks simultaneously. For instance, Rao et al. (2023) [15] find that climate risks and carbon emissions exert heterogeneous shocks on energy markets through asymmetric spillover effects. Collectively, these studies demonstrate that climate risks extend beyond environmental issues and have become core economic variables driving financial market volatility and industrial chain restructuring.

2.2 The Impact of Climate Risk on Power Markets

Existing literature has confirmed the significant impacts of climate risks on power markets from multiple dimensions. Regarding prices and volatility, Ciarreta & Zarraga (2015) [16, 17] analyzed the price transmission mechanism of spot power markets in the Iberian Peninsula and Central Europe and established volatility models for the Spanish power market. Ioannidis et al. (2021) [18] used a periodic GARCH model with conditional skewness and kurtosis components to capture the complex volatility characteristics of electricity prices. Using data from the power market of England and Wales, Tashpulatov (2013) [19] provided empirical evidence on volatility. Employing the event study method, Mosquera-Lopez et al. (2018) [20] identified the causal effect of a specific supply shock, namely suspended hydropower generation, on electricity price dynamics.

In terms of market connectedness and risk spillovers, methodological advancements have been substantial. Diebold & Yilmaz (2009) [21, 22] proposed a spillover index framework based on variance decomposition and subsequently developed it into a predictive directional measurement approach, which has become a standard tool for risk spillover research. This method has been widely applied to power market studies. Pen Y L et al. (2010) [23] conducted an early analysis of volatility transmission mechanisms across European power forward markets. Diebold et al. (2019) [24] adopted a network topology approach based on variance decomposition to measure the connectedness structure of European power markets. Furthermore, research has expanded to cross-market linkages. Ding Qian et al. (2022) [25] investigated spillover effects among carbon, fossil energy, and clean energy markets from both time and frequency domains. Their results show that attention to climate change acts as a key factor driving cross-market risk spillovers. Focusing on China's carbon market, Yan et al. (2023) [26] tested the dynamic spillover effects of climate policy uncertainty and coal prices on carbon prices. From the perspective of information efficiency, Ren et al. (2024) [27] uncovered asymmetric spillover patterns between fossil energy and green markets.

2.3 Risk Linkages Within the Electricity Industry Chain

Most existing literature focuses on price spillovers and volatility transmission within a single market or across different markets, and can be categorized into three main lines of research. The first line of research centers on horizontal risk linkages among electricity markets. Sæther & Neumann (2024) [28] analyzed the impacts of the 2022 energy crisis on the North Sea power market and found that crisis shocks spread rapidly to neighboring markets through electricity prices. Ly et al. (2022) [29] adopted Copula-GARCH and dynamic state-space models to explore multi-dimensional dependence structures among European power markets. Hellwig et al. (2020) [30] provided a measurement framework for market integration. Uribe et al. (2020) [31]

quantified the integration features of the North Sea power market. These findings have greatly enhanced our understanding of horizontal risk spillovers between markets; however, their analytical units inherently sever the vertical linkages between electricity generation, transmission, and consumption, making it difficult to directly apply them to vertical risk analysis within the industrial chain.

The second line of research begins to address the internal structure of the power system. Do et al. (2020) [32] analyzed dynamic volatility linkages between the Irish and Great Britain markets, and their research implicitly addressed cross-border co-movement within the power industry chain. Erdogdu (2016) [33] identified asymmetric volatility features in European power markets, while Rao et al. (2023) [34] further verified the asymmetric transmission of climate shocks across energy markets. However, these studies still treat the electricity market as a "black box" and do not delve deeply into the heterogeneous responses and amplification mechanisms of shocks across various stages within the industrial chain.

The third research strand extends to the broad impacts of climate risks on energy firms. Fuss et al. (2008) [35] were among the earliest scholars to examine how climate policy uncertainty shapes energy investment decisions. Ma Rufei et al. (2022) [36] investigated how economic policy uncertainty drives volatility spillovers in power markets. From the firm performance perspective, Pham et al. (2024) [37] revealed the correlation between energy consumption and external shocks. Cepni et al. (2022) [38] discussed the feasibility of hedging climate risks through green assets. Although these studies are becoming increasingly numerous, most treat the industrial chain as a homogeneous whole, overlooking the possibility that climate risks may generate heterogeneous shocks through the interdependent structures between upstream and downstream segments of the chain, thereby altering the risk landscape of the entire chain.

In summary, the existing literature has established a comprehensive framework covering risk identification, quantitative measurement, and analysis of transmission mechanisms. However, significant shortcomings remain in the following areas: First, few studies treat the upstream, midstream, and downstream segments of the power industry chain as an integrated risk system and directly measure the vertical risk correlations within it. Second, there is a lack of empirical testing from a time-varying perspective on how physical climate risks, by altering the degree of these vertical linkages, lead to the amplification or buffering of risks across different segments of the industry chain. Third, the microfoundations of how climate risks exert heterogeneous shocks on the revenues of various segments through industry chain linkages have not been sufficiently elucidated.

3. Research Design

3.1 DCC-GARCH Model

To scientifically measure the level of dynamic risk linkage within the power industrial chain, this paper adopts the DCC-GARCH model proposed by Engle (2002).

First, to depict the volatility clustering inherent in the return rate series of the upstream, midstream, and downstream segments of the power industrial chain, univariate GARCH models are constructed for each series, respectively. Since the GARCH(1,1) model has been widely verified to effectively capture the volatility characteristics of most financial time series, this paper adopts this baseline model, and its conditional variance equation is specified as follows:

$$\sigma_{i,t}^2 = w + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2 \tag{1}$$

The coefficients ω, α and β are estimated via the maximum likelihood method. ω refers to the constant term; α is the coefficient of the lagged squared residual; β is the coefficient of the lagged conditional variance itself. The sum $\alpha + \beta$ reflects the persistence of residual volatility. A larger value of this sum implies that current volatility is strongly affected by historical shocks, and the magnitude of future volatility decays slowly; the opposite holds true for a smaller value.

After obtaining the conditional variances and standardized residuals of the return rate series for each segment, a dynamic conditional correlation structure is constructed. As a multivariate extension of the GARCH model, this model first establishes a GARCH model for each variable to generate standard deviations and obtain standardized residuals. These standardized residuals are then used to estimate the correlation coefficient matrix in the form of a GARCH-type specification.

3.2 MF-VAR Model

Traditional VAR models cannot directly estimate parameters when they contain variables with different data frequencies; all variables must be converted to a uniform frequency, which may result in the loss of sample information. As a type of model capable of direct estimation using mixed-frequency data, the MF-VAR effectively addresses this limitation of standard VAR models. For the estimation of missing values, the Kalman filter approach or Bayesian mixed-frequency data method is predominantly adopted. Data iteratively generated from these two approaches can efficiently supplement the sample information embedded in low-frequency data without sacrificing information contained in high-frequency series. This paper employs the second method to estimate the MF-VAR model.

According to relevant literature, the general form of the MF-VAR(p) model can be derived by modifying the standard VAR model. This paper assumes that the high-frequency data are monthly series:

$$x_t = \phi_c + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \mu_t, \quad \mu_t \sim \mathrm{iidN}(0, \Sigma) \tag{2}$$

Equation (1) is converted into matrix form as follows. Let $X_t = [x_t', \dots, x_{t-p+1}']$ and $\Phi = [\phi_1, \dots, \phi_p, \phi_c]'$. The matrix representation of the MF-VAR model is presented below, which also serves as the state transition equation of the MF-VAR model.

$$X_t = F_1(\Phi) X_{t-1} + F_c(\Phi) + v_t, v_t \sim \mathrm{iidN}(0, \Omega(\Sigma)) \tag{3}$$

where $F_1(\Phi)$ denotes the coefficient matrix of the MF-VAR model in matrix form, and $F_c(\Phi)$ stands for its constant term. v_t represents the stochastic error term of the MF-VAR model, which follows an independently and identically distributed normal distribution with a mean of zero and variance $\Omega(\Sigma)$. $\Omega(\Sigma)$ is an $n \times n$ matrix whose upper-right block equals Σ, while all other elements are zero.

4. Data and Descriptive Statistics

4.1 Data

To examine the impacts of climate risks on risk linkages within the power industry chain, this paper constructs stock return series covering the upstream, midstream, and downstream segments based on the actual structure of the industry chain. The detailed classification is as follows: the upstream segment includes coal mining, thermal power equipment, photovoltaic equipment, and wind power equipment; the midstream segment covers thermal power generation, hydropower generation, wind power generation, and photovoltaic power generation; the downstream segment consists of power supply equipment and power grid equipment. Considering industrial representativeness, market capitalization, and data availability, this paper selects listed companies with typical industry characteristics from each segment, totaling 26 firms. The sample period runs from January 2011 to December 2023, and all data are recorded at a monthly frequency. The original stock price data are obtained from the CSMAR database, and returns are calculated based on prices adjusted for stock splits and dividends.

For each listed company, this paper calculates its monthly logarithmic return. To further capture the systematic volatility characteristics of each segment in the industry chain, principal component analysis (PCA) is applied to the stock return series of firms within the upstream, midstream, and downstream segments separately. The first principal component is extracted as the representative return series for each segment. This method retains most of the original information while effectively reducing data dimensions and highlighting common trends.

To investigate the impacts of physical climate risks, this paper selects the following annual climate indices: extreme heat index, extreme cold index, extreme precipitation index, extreme drought index, and a composite index measuring the overall level of physical climate risks. These climate indices are sourced from the ISETS Energy-Finance Network.

4.2 Descriptive Statistics

Table 1 illustrates the descriptive statistics of return series for the electricity industry chain. As demonstrated in Table 1, the mean values of all series are close to zero, which is consistent with the typical characteristics of financial return series. In terms of variance, the midstream return series exhibits the highest volatility, followed by the upstream series, while the downstream series has the lowest volatility, indicating that the power generation segment in the midstream faces the greatest market uncertainty. Furthermore, the Jarque-Bera test rejects the null hypothesis of normality at the 1% level for all samples, confirming that the return series follow a typical leptokurtic and fat-tailed distribution. Unit root tests confirm that all series are stationary.

Table 1: Descriptive Statistics

	Mean	Variance	Skewness	Kurtosis	JB	ADF	Q(10)	$Q^2(10)$
upstream	0	3.497	0.473**	1.403***	20.050***	-4.897**	4.766	11.249***
midstream	0	6.434	0.182	3.490***	86.167***	-4.487**	7.169	43.013***
downstream	0	2.587	0.540***	3.445***	91.210***	-5.409**	14.165	41.337***

*Notes: ***, ** and * are statistically significant at 1%, 5% and 10%, respectively.*

5. Results and Discussion

5.1 Estimation of Univariate Volatility Models

To estimate the GARCH model, 10 GARCH family models, including the GARCH, IGARCH, and GJR-GARCH models with Student's t distribution, the skewed Student's t distribution, and normal distribution, were utilized to fit the stock market return series. The selected models were chosen based on the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HQIC). Table 2 shows the GARCH model fitting results for each segment of the electricity industry chain. For the Upstream return series (Panel A), the optimal model is IGARCH (1,1) with Student's t distribution. The sum of the ARCH coefficient and the GARCH coefficient equals one, which is consistent with the IGARCH model. The Ljung-Box test and ARCH-LM test on the standardized residuals after model estimation are both insignificant, confirming that the model fully captures the volatility clustering effect of the series. As for the Midstream return series (Panel B), the optimal model is GJR-GARCH(1,1) with Student's t distribution. This model introduces an asymmetric coefficient γ as its core parameter. The estimation results show that γ is -0.34904, which implies a strong leverage effect exists in the midstream power generation segment. For the Downstream return series (Panel C), the best model is GARCH (1,1) with a skewed Student's t distribution. The skewness parameter estimated from the model is greater than 1, indicating that the return distribution is right-skewed. In other words, the probability of extreme positive returns is slightly higher than that of extreme negative returns.

Table 2: GARCH Model fitting results for the Upstream Return Series

Model	AIC	BIC	SIC	HQIC
Panel A: Upstream Return Series				
IGARCH(1,1)-t	4.103877	4.178257	4.102778	4.134064
GARCH(1,1)-t	4.115038	4.208013	4.113333	4.152771
GARCH(1,1)-sstd	4.119916	4.231486	4.11748	4.165196
GJR-GARCH(1,1)-t	4.122769	4.234339	4.120333	4.16805
GARCH(1,2)-t	4.127042	4.238612	4.124606	4.172322
GARCH(1,1)-norm	4.129988	4.204368	4.128889	4.160175
GARCH(1,2)-sstd	4.131839	4.262004	4.128548	4.184666
GARCH(1,2)-norm	4.141851	4.234826	4.140147	4.179585
GARCH(2,1)-norm	4.142094	4.235069	4.14039	4.179828
GARCH(2,2)-norm	4.153779	4.265349	4.151343	4.199059
Panel B: Midstream Return Series				
GJR-GARCH(1,1)-t	4.392406	4.503976	4.38997	4.437686
IGARCH(1,1)-t	4.44206	4.51644	4.440961	4.472247
GARCH(1,1)-t	4.442367	4.535342	4.440662	4.4801
GARCH(1,1)-sstd	4.444599	4.556169	4.442163	4.48988
GARCH(1,2)-sstd	4.448865	4.57903	4.445574	4.501692
GARCH(1,2)-t	4.457838	4.569408	4.455403	4.503119
GARCH(1,1)-norm	4.522751	4.597131	4.521652	4.552938
GARCH(2,1)-norm	4.535026	4.628001	4.533322	4.57276
GARCH(1,2)-norm	4.535405	4.62838	4.533701	4.573139
GARCH(2,2)-norm	4.547579	4.659149	4.545143	4.592859
Panel C: Downstream Return Series				
GARCH(1,1)-sstd	3.679437	3.753817	3.678338	3.709624

Model	AIC	BIC	SIC	HQIC
IGARCH(1,1)-t	3.682076	3.793647	3.679641	3.727357
GARCH(1,1)-t	3.685464	3.778439	3.683759	3.723197
GJR-GARCH(1,1)-t	3.701526	3.813096	3.699091	3.746807
GARCH(1,2)-t	3.741848	3.853419	3.739413	3.787129
GARCH(1,2)-sstd	3.755642	3.885808	3.752352	3.80847
GARCH(2,2)-norm	3.756095	3.867665	3.753659	3.801375
GARCH(1,1)-norm	3.768673	3.843053	3.767574	3.79886
GARCH(2,1)-norm	3.784435	3.87741	3.782731	3.822169
GARCH(1,2)-norm	3.831791	3.924766	3.830086	3.869524

5.2 Estimation of DCC-GARCH Model

After obtaining robust univariate volatility models, this paper adopts the DCC-GARCH model to estimate the time-varying correlation coefficients for each pair of segments among the upstream, midstream, and downstream. The estimation results of the DCC parameters are presented in Table 3.

As described in Table 3, both parameters θ_1 and θ_2 are significantly positive at the 1% level, and their sum is less than one, satisfying the model's stability condition. To test the overall goodness-of-fit of the DCC-GARCH model, joint diagnostic tests are performed on the multivariate standardized residual series obtained from the model estimation. The Ljung-Box Q test shows no significant autocorrelation in any of the standardized residual series or their squared counterparts, suggesting that the model has fully captured both linear and nonlinear dependence within the return series.

Table 3: Estimation Results of DCC-GARCH Parameters

	μ	ω	α	β	shape	γ	skew
upstream	0.0000	0.0003	0.0001	0.9999	9.4092*		
midstream	0.0000	0.4697**	0.3290***	0.7593***	5.8003***	-0.3490***	
downstream	0.0000	0.4056**	0.1468*	0.6985***	6.2081		1.0210***
	θ_1	θ_2	AKaike	Bayes	shibata	Hannan-Quinn	
DCC estimates	0.0383	0.8239***	11.485	11.894	11.455	11.651	

Based on the above optimal DCC-GARCH model for each segment of the electricity industry chain, this paper extracts three sets of dynamic conditional correlation coefficient series: upstream-midstream, upstream-downstream, and midstream-downstream. The descriptive statistics are presented in Table 4, which clearly reveal the structural characteristics of internal risk connectedness within the electric power industry chain.

As described in Table 4, the average correlation coefficient between upstream and midstream is -0.629 and remains negative throughout the full sample period. This reveals a persistent, strong risk-hedging effect within the traditional energy value chain centered on coal and thermal power. Rising upstream raw material and equipment costs directly squeeze the profits of midstream power generators, resulting in a stable negative correlation between their returns. As for the upstream and downstream pair, the average correlation coefficient is -0.345, indicating an overall negative relationship and significant risk hedging between the upstream and downstream segments of the power industry chain. Turning to the Midstream and downstream pair, the average correlation coefficient is 0.397 and remains predominantly positive over the entire sample period, demonstrating a prominent risk synergy between midstream power generation and downstream equipment sectors.

Table 4: Descriptive Statistics of Dynamic Correlation Coefficients

	Mean	standard	minimum	maximum	median
upstream–midstream	-0.629298186	0.049659114	-0.736310115	-0.510187466	-0.632071917
upstream–downstream	-0.344806006	0.059473032	-0.470133111	-0.163083685	-0.34867761
midstream–downstream	0.39690847	0.067369572	0.17390101	0.509480533	0.412156872

Next, we will analyze the dynamic correlation among various segment pairs in the electricity industry chain. Figure 1 shows that the correlation between the upstream and midstream segments remains strongly negative in the long run, with fluctuations primarily driven by cost shocks to the coal-power value chain. From 2011 to 2013, the correlation coefficient hovered around -0.75. During 2014-2015, hydropower output rebounded, and coal prices entered a downward cycle. In 2020-2021, the combined impacts of extreme weather and the global energy crisis triggered a coal price surge. It was not until 2022-2023 that policies to secure coal supply and stabilize coal prices took effect, alongside advances in electricity pricing marketization reform, gradually reverting the correlation coefficient back to its long-term average.

Figure 1: Dynamic Correlation Coefficient between Upstream and Midstream

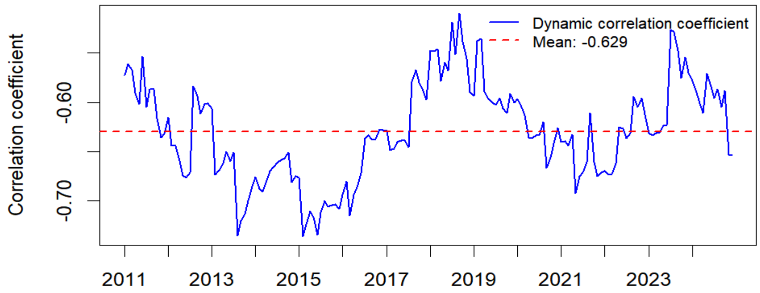
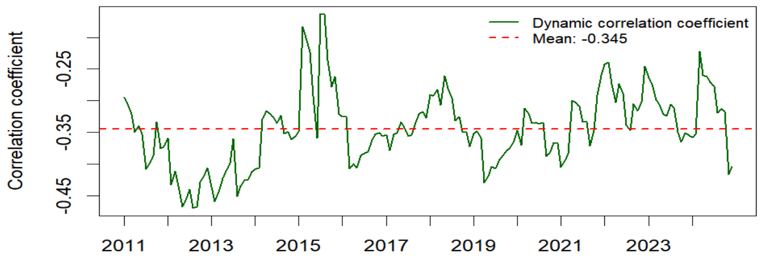


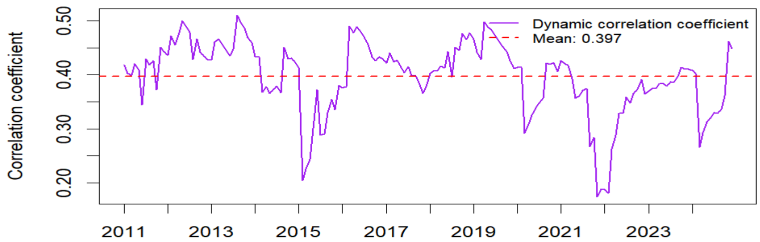
Figure 2 illustrates a moderate negative correlation between upstream and downstream segments of the electricity industry chain, whose dynamic evolution is primarily driven by the interplay of equipment investment cycles and power grid construction policies. Between 2012 and 2013, the correlation coefficient reached -0.45. During 2014-2015, increased investment in distribution grid upgrades and the implementation of policies to stabilize economic growth jointly boosted demand for power grid equipment. From 2016 to 2019, the correlation coefficient fluctuated around its mean. The extreme surge in coal prices in 2021 brought thermal power investment willingness to a record low, dragging the correlation coefficient down again.

Figure 2: Dynamic Correlation Coefficient between Upstream and Downstream



The correlation between the midstream and downstream segments exhibits stable positive co-movement in Figure 3, reflecting the inherent alignment between the expansion of power generation installed capacity and the associated demand for supporting equipment. During the 12th Five-Year Plan period (2011-2015), driven by clear capacity expansion targets, the correlation coefficient steadily climbed from 0.2 to 0.5. A sharp drop occurred in 2014-2015, mainly because abundant hydropower output curtailed thermal power investment. In 2021, widespread losses in the thermal power sector and the phase-out of new energy subsidies weighed on short-term equipment demand, triggering a pullback of the coefficient.

Figure 3: Dynamic Correlation Coefficient between Midstream and Downstream



In conclusion, using the DCC-GARCH model, this paper systematically uncovers the complex and time-varying risk linkage network within China's power industry chain, laying an empirical foundation for accurately identifying risk spillover channels and evaluating the transmission effects of external shocks.

5.3 Impact of Physical Climate Risks on Risk Linkages in the Electricity Industry Chain

The previous section accurately measured the degree of internal risk linkages. To further elucidate how exogenous climate risks affect the internal correlation structure of the electricity industry chain, we employ the Mixed-Frequency Vector Autoregression (MF-VAR) model to systematically trace the transmission channels. Impulse response functions are employed to empirically test the time-varying effects of five climate risk factors-low temperature disaster (LTD), high temperature disaster (HTD), extreme rainfall disaster (ERD), extreme drought disaster (EED), and the General Physical Climate Risk Index (GCPRI) on the three dynamic correlation coefficient series.

The impulse response results (Figure 4-8) clearly reveal the differentiated impacts of various physical climate risks on the correlation among distinct segments of the electricity industry chain, with these effects characterized by a short-lived and highly heterogeneous nature. However, owing to their distinct physical properties, different climate risks exert notably divergent influences on specific links of the power industry chain, leading to notable differences in the direction and magnitude of their shocks.

5.3.1 Effects of Low Temperature Disasters (LTD) on Risk Linkages in the Electricity Industry Chain

Figure 4 shows that extreme low temperatures exert a significant positive shock on the midstream-downstream correlation. Extreme cold greatly increases heating power demand, driving a sharp surge in load on midstream power generators. Meanwhile, peak regulation and power supply guarantee pressures mount on the downstream grid sector, which markedly strengthens their short-term coordination in coping with demand spikes.

By contrast, extreme cold triggers a notable negative shock to the upstream-downstream correlation, stemming from misaligned demand transmission. The core priority of downstream firms is real-time power supply security, focusing on stable power transmission and distribution as well as load assurance. Their demand is directly linked to midstream power generation rather than upstream equipment or raw materials, which weakens and delays demand transmission to the upstream and reduces the direct correlation. Under extremely low temperatures, the upstream fails to respond swiftly to indirect downstream demand, dampening their interactive linkage.

For the upstream-midstream correlation, the shock turns positive in the initial phase before turning negative thereafter. The short-run positive effect arises from the surge in coal consumption by thermal power units during cold weather, urgent maintenance needs for anti-freezing of wind and solar power facilities, and anti-icing inspections for hydropower equipment. These factors trigger a sharp increase in the midstream's short-term demand for coal procurement and spare parts supply from the upstream. As upstream output capacity becomes tightly tied to midstream power supply assurance, their correlation rises rapidly. Later, due to saturated upstream supply, receding midstream demand, and stabilized power supply mechanisms, the midstream's incremental reliance on the upstream fades, pulling the correlation downward.

Figure 4: Extreme Low Temperature

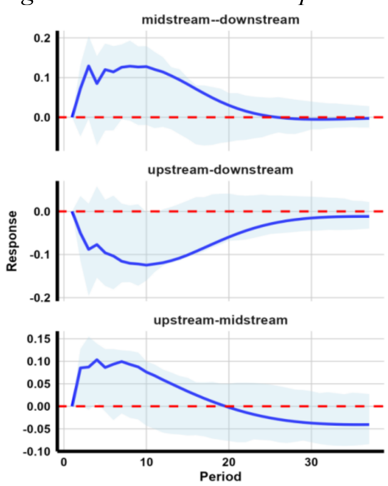
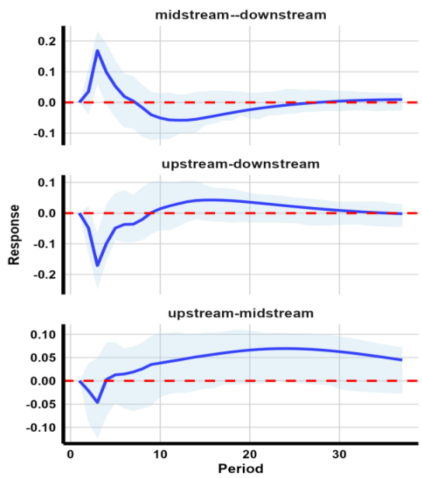


Figure 5: Extreme High Temperature



5.3.2 Effects of High Temperature Disasters (HTD) on Risk Linkages in the Electricity Industry Chain

Figure 5 indicates that extreme high temperatures generate a shock on the midstream-downstream correlation that follows an initial increase followed by a decrease. In the early stage, rising cooling loads strengthen the positive co-movement between midstream power generation returns and downstream grid returns. However, prolonged high temperatures reduce photovoltaic power generation efficiency, decrease hydropower inflows, and increase overload risks for grid equipment, placing simultaneous pressure on both power generation and transmission segments. This disrupts their coordination and drives the correlation downward.

Extreme heat delivers a strong negative shock to the upstream-downstream correlation, for reasons similar to those for extreme low temperatures: demand transmission from downstream core operations to upstream raw materials and equipment is blocked by the midstream. Meanwhile, upstream producers maintain normal output without emergency capacity adjustments, creating a supply-demand disconnect with downstream needs and pushing the correlation sharply lower.

The upstream-midstream correlation fluctuates from negative to positive. To meet surging power loads, midstream thermal power plants must procure coal immediately to run units at full capacity. At the same time, high temperatures cause power curtailment for midstream wind and solar facilities, temporarily suppressing upstream demand for new energy equipment. This mismatch between upstream supply structure and midstream generation demand pulls the correlation rapidly into negative territory.

As the heatwave persists, market forces and policy interventions gradually correct this imbalance. On the one hand, upstream coal producers ramp up supply by activating temporary production capacity and clearing transportation routes, gradually matching the fuel demand of thermal power generators. On the other hand, regulatory measures such as coal price controls and subsidies for new energy equipment purchases normalize the midstream's demand for fuels and hardware. Production coordination between upstream and midstream sectors steadily recovers, eventually lifting the correlation to a relatively high level of 0.75. Ciarreta et al. (2017) [39] study continuous electricity prices in Germany and Austria and find that extreme temperature shocks induce pronounced volatility clustering at intraday high-frequency intervals. This finding offers theoretical support for the negative-to-positive fluctuation pattern of the upstream-midstream correlation triggered by heatwaves documented in this paper.

5.3.3 Effects of Extreme Rainfall Disasters (ERD) and Extreme Drought Disasters (EED) on Risk Linkages in the Electricity Industry Chain

As two opposing extreme hydrological and climatic events, extreme rainfall and extreme drought exert opposite effects on risk linkages in Figure 6 and Figure 7.

Extreme rainfall imposes a more pronounced shock on the midstream–downstream correlation in Figure 6. Heavy rainfall leads to excess hydropower generation and water spillage, waterlogging-induced shutdowns of thermal power plants, and malfunctions of wind and photovoltaic facilities. Output from midstream power plants becomes highly unpredictable, making stable coordination with downstream transmission and distribution impossible and thereby undermining their linkage. Meanwhile, extreme rainfall may increase upstream demand for hydropower equipment maintenance and downstream demand for grid restoration, triggering a positive response in the upstream–downstream correlation.

By contrast, extreme drought significantly strengthens the upstream-midstream correlation in Figure 7. Drought immediately suppresses hydropower output, forcing thermal power units to cover baseload power and sharply increasing the short-term correlation between coal demand and power generation. In the later stage of drought, the midstream gradually optimizes its energy mix by maximizing wind and solar output to offset hydropower shortages and reduce reliance on thermal power, thereby cutting demand for upstream coal and driving the correlation down rapidly. The short-run positive shock of drought on the midstream–downstream correlation reflects the shared pressures of supply security and coordination needs faced by power generators and grid operators amid anticipated power shortages.

Figure 6: Shocks of Extreme Rainfall

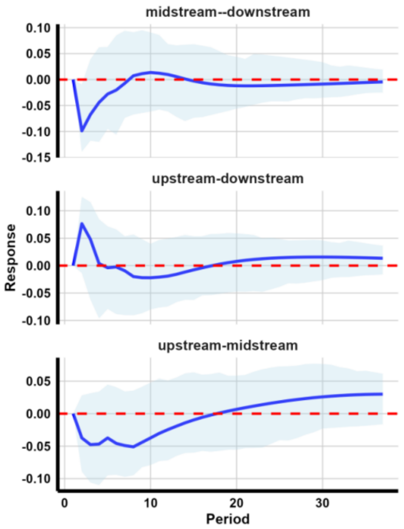
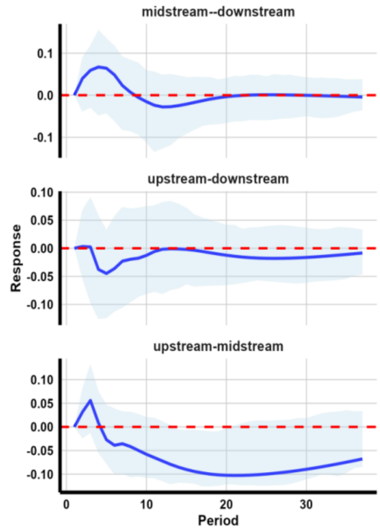


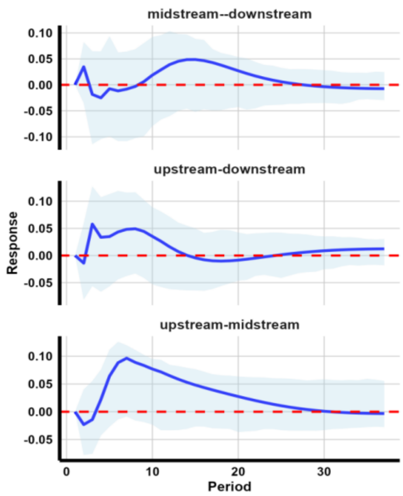
Figure 7: Shocks of Extreme Drought



5.3.4 Effects of General Physical Climate Risk Index (Gcpri) on Risk Linkages in the Electricity Industry Chain

As a comprehensive indicator, an increase in the GCPRI generates positive short-term shocks to all three correlation pairs in Figure 8. This suggests that when the overall level of climate risk rises, all segments of the power industry chain collectively face systemic pressures related to power supply security and operational safety. The upstream energy and equipment supply, midstream power generation, and downstream grid transmission sectors all need to strengthen coordination under uncertainty to cope with potential extreme weather events. Consequently, overall risk linkages across the industry chain intensify in the short run. This reflects the inherent requirement for coordinated response between power generation sources and the power grid in the face of climate risks.

Figure 8: Shocks of General Physical Climate Risk



Empirical evidence from the mixed-frequency model in this section demonstrates that physical climate risks constitute a key exogenous driver of short-term volatility and structural shifts in internal risk interdependencies within the power industry chain. This provides new micro-level evidence for understanding how climate risks propagate through financial markets and undermine the stability of energy systems.

5.4 Impacts of Physical Climate Risks on Electricity Industry Chain

To further examine the micro-level transmission channels of climate risks, this section employs MF-VAR model to investigate the direct effects of different climate Risk on the representative return series of the upstream, midstream, and downstream.

5.4.1 Effects of Extreme Low Temperatures on Electricity Industry Chain

Extreme low temperatures cause fluctuating positive shocks to upstream returns in Figure 9. Cold weather boosts coal demand, benefiting upstream coal firms in the short term. It also raises demand for equipment inspection and replacement, bringing temporary gains to upstream manufacturers. However, extreme cold exerts sustained negative shocks on midstream returns. Ice accumulation reduces wind output, photovoltaic efficiency drops, and thermal and hydropower units face higher operating costs. Extreme cold may also damage generation facilities, adding downward pressure on returns. Downstream returns also suffer. Grid companies face rising maintenance and capital costs. Equipment demand becomes unstable as thermal investment slows and new energy projects are delayed. Overall, extreme cold negatively impacts all downstream segments.

Figure 9: Extreme Low Temperature

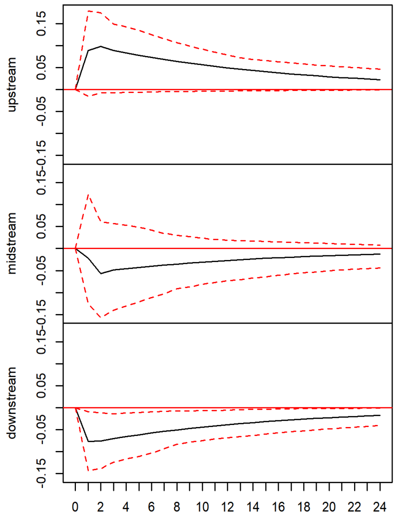
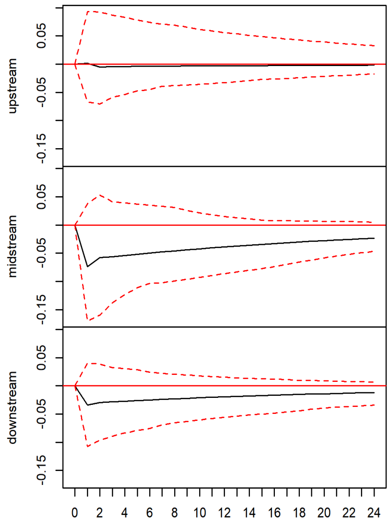


Figure 10: Extreme High Temperature



5.4.2 Effects of Extreme High Temperatures on Electricity Industry Chain

Upstream returns exhibit short-term fluctuations in response to extreme high temperatures, with little long-term impact in Figure 10. High temperatures reduce photovoltaic efficiency and thermal equipment cooling performance, temporarily hurting equipment makers. But surging air-conditioning demand boosts coal consumption, offsetting the negative effects. Thus, the overall upstream impact is limited. In contrast, extreme heat causes sustained and significant negative shocks to midstream returns. Hydropower inflows decline, photovoltaic efficiency falls, and thermal plants face cooling and emission constraints. Although total generation may rise, higher marginal costs, efficiency losses, and rationing risks erode profits, leading to persistent return declines. Downstream returns also suffer negative shocks. Heat increases line losses and reduces transmission efficiency. Grids must use costly peak-regulation resources, raising operating expenses. Hot weather also raises equipment failure risks, requiring more investment in reliability. As a result, downstream segment returns are suppressed.

5.4.3 Effects of Extreme Rainfall and Extreme Drought on Electricity Industry Chain

When hit by extreme rainfall, upstream returns experience short-term negative fluctuations in Figure 11, as post-disaster equipment demand offsets initial damage to wind and solar stations. But midstream sectors suffer sustained shocks: floods threaten hydropower dams, submerge thermal plants, and damage renewable bases, causing output losses and asset damage. Downstream grids also face heavy repair costs and revenue losses from outages. In contrast, extreme drought boosts upstream returns. Hydropower cuts raise coal demand, benefiting coal firms, while sunny weather aids solar generation, lifting equipment expectations. Midstream impacts are mixed: hydropower loses, but thermal and solar gain from tight supply and price expectations. However, power shortage risks and high operating costs pressure overall midstream returns. Downstream grids face complex, costly dispatching and public pressure from rationing.

Figure 11: Shocks of Extreme Rainfall

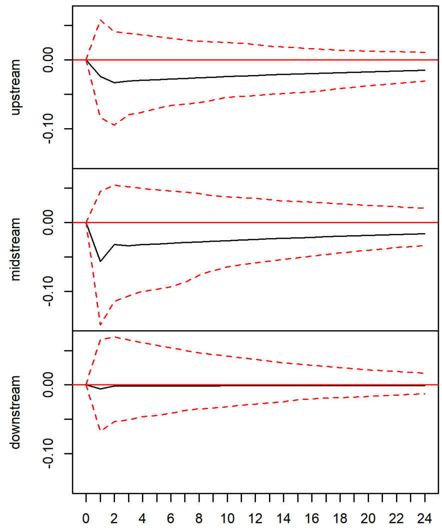
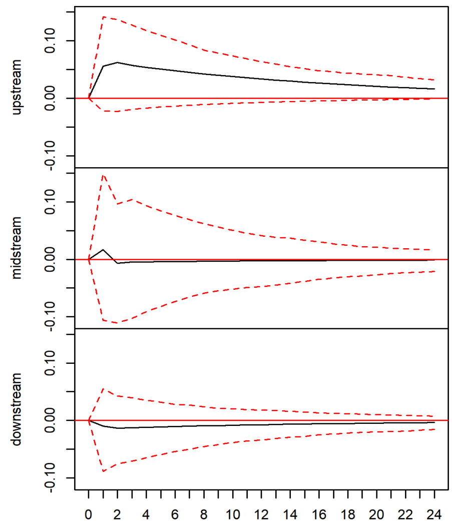


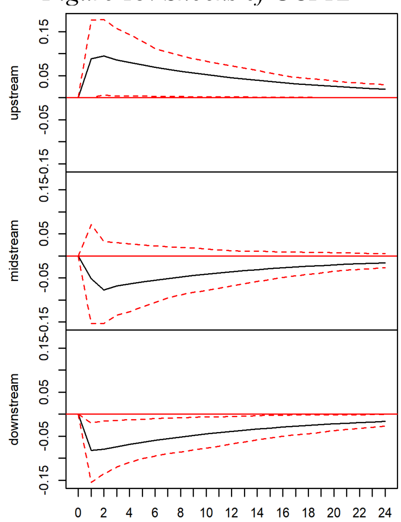
Figure 12: Shocks of Extreme Drought



5.4.4 Effects of General Physical Climate Risk on Electricity Industry Chain

General physical climate risks exert positive shocks on upstream returns while negatively affecting midstream and downstream returns in Figure 13. When climate risks intensify, energy security becomes paramount. Coal, as a reliable baseload source, gains market value, benefiting coal firms. Rising climate awareness also boosts demand for resilient grid equipment, creating opportunities for upstream manufacturers. For midstream generators, climate risks bring operational hazards—unstable output, higher costs, and asset damage—making this segment the main value-loss zone, with returns under persistent pressure. Downstream returns also decline. Grids, as the supply-demand hub, must absorb volatility and damage from climate events, increasing regulation costs and infrastructure spending. Since electricity price adjustments often lag behind these rising costs, downstream returns are suppressed.

Figure 13: Shocks of GCPRI



6. Conclusions

This paper investigates the impacts of physical climate risks on risk interlinkages and segment returns across China's electricity industry chain. Using DCC-GARCH and the MF-VAR models to construct representative return series for the upstream, midstream, and downstream segments, this study characterizes the time-varying features of risk linkages within the industry chain and identifies the heterogeneous effects of different climate risks on the interlinkage structure and returns at each segment. The main conclusions are as follows.

First, China's electricity industry chain has formed a highly heterogeneous and structurally complex network of risk interlinkages. The DCC-GARCH model reveals that there is negative risk hedging between the upstream and midstream sectors, as well as between the upstream and downstream sectors, stemming from traditional cost conflicts between coal and electricity and imbalances in the supply and demand of power equipment. Conversely, there is positive risk co-movement between the midstream and downstream sectors, reflecting phased resonance between power generation investment and equipment demand.

Second, physical climate risks, as key exogenous shocks, trigger short-term fluctuations in risk linkages within the power industry chain, and their transmission pathways exhibit significant heterogeneity. Impulse response analysis of the MF-VAR model shows that the impact effects of various extreme climate events are concentrated in the early stages and then dissipate rapidly. However, the transmission mechanisms differ markedly. Extreme heat and drought primarily disrupt the upstream–midstream linkage by altering the power generation mix, whereas extreme rainfall directly disrupts interdependencies between the midstream and downstream segments through physical failures in transmission and distribution grids. It is worth noting that when the Comprehensive Physical Climate Risk Index (GCPRI) rises, the market's consensus expectations regarding short-term coordination across all segments strengthen, which in turn amplifies the overall risk co-movement.

Third, the impacts of climate risks on the return rates of different segments of the industry chain are asymmetrically distributed, with the midstream as the core value-loss zone and risk vulnerability. Further analysis reveals that the heterogeneous transmission of these risk interactions is rooted in the differing responses of each segment's profits to climate risks. Under all climate disasters, midstream returns suffer sustained and significant negative shocks, highlighting the dual squeeze between their responsibility to ensure supply and cost pressures. The upstream segment, on the other hand, often experiences periodic positive fluctuations in returns due to the hedging properties of coal resources or the need for equipment upgrades. The downstream power grid segment generally faces downward pressure due to rising system balancing costs. These heterogeneous responses in upstream, midstream, and downstream returns collectively form the micro-foundation for the evolution of the aforementioned risk interlinkage model.

Based on these findings, this study proposes policy recommendations across three dimensions. Financial risk regulators should establish a tiered climate risk early warning system and a cross-segment emergency coordination mechanism. Corresponding industry-wide contingency plans should be activated based on the warning levels of different climate risks. For example, during high-temperature and drought warnings, energy authorities should coordinate upstream coal reserves and transportation capacity in advance, optimize the dispatch sequence of midstream power generation units, and deploy demand response plans to downstream power grids, thereby shifting emergency management from reactive response to proactive prevention.

Policymakers should increase policy support and risk buffers for the midstream power generation segment to strengthen energy supply safety. On the one hand, electricity market reforms should be deepened to provide reasonable economic compensation to power sources, such as thermal power plants, that undertake system reserve and peak-shaving tasks, thereby offsetting the soaring operating costs caused by climate disasters. On the other hand, power generation companies should be guided to use financial instruments such as green bonds, climate insurance, and carbon trading to hedge against physical risks, and they should be provided with fiscal and tax incentives or special re-lending support for upgrading their climate adaptation technologies.

Given the stable negative risk-hedging relationship between upstream and downstream segments of the industrial chain, investors could establish long-short pairing strategies or diversified allocations between upstream and midstream, as well as between upstream and downstream, to effectively hedge against volatility caused by coal-fired power cost conflicts and imbalances in equipment supply and demand. Furthermore, given the heterogeneous transmission pathways of different extreme weather events, implement differentiated sector rotation strategies.

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Conflicts of Interest

The authors declare no conflict of interest.

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