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On the Effects of Physical Climate Risks on the Chinese Energy Sector

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Abstract: We examine the impact of physical climate risks on energy markets in China, distinguishing between traditional energy and new energy stock markets, and the energy commodity market, utilizing a time-varying parameter vector autoregressive model with stochastic volatility (TVP-SV-VAR). Specifically, we investigate the dynamic effects of five specific subtypes of physical climate risks, namely waterlogging by rain, drought, typhoon, cryogenic freezing, and high temperature, on WTI oil prices and coal prices. The findings reveal that these physical climate risks exhibit time-varying similar effects on the returns of traditional energy and new energy stocks, but heterogeneous effects on the returns of WTI oil prices and coal prices. Finally, we categorize and examine the impact of both acute and chronic physical risks on the energy commodity market.

Keywords: climate risk; energy markets; commodities; TVP-SV-VAR model

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1. Introduction

Profound and persisting changes in the climate represent the foremost global risk in the upcoming decade. (IPCC 2023), while the energy sector is one of the most crucial components of most nations' economy. Climate change risks have shown varying effects on the energy industry, which is very sensitive and susceptible to climate variations (Perera et al. 2020), the compassing fossil fuel industry (Zhu et al. 2023), and the new energy industry (Huo et al. 2023). Recently, extreme weather events and abnormal climate change have challenged energy systems (Ren et al. 2023), which has garnered significant attention from scholars, investors, and policymakers globally.

Recently, China experienced an onset of climate change, marked by record-breaking temperatures, windfall, and flooding, to an extent that threatened the economy (Ma et al. 2024). China is the world's largest coal consumer, with a carbon dioxide (CO_2) emissions intensity per unit of energy consumption 30% higher than the global average. As China works toward its carbon neutrality goals, the challenging task of optimizing its energy structure will significantly impact its energy sectors (Zhu et al. 2023). Consequently, China's dual carbon goals were introduced into climate policy as long-run perspectives, the National Strategy for Climate Change Adaptation was established, and an Action plan for carbon dioxide peaking was issued, seeking a stable energy transition.

Climate change has a profound impact on the Chinese energy system, which is highly sensitive to climate conditions and susceptible to vulnerabilities (Vafadarnikjoo et al. 2022; Sun et al. 2023). The physical risks associated with climate change directly influence various facets of the energy system. For instance, the potential and demand for power generation may change due to global warming, consequently affecting the transmission and distribution of electricity. Additionally, extreme climate events like floods and heatwaves pose a significant threat by causing physical damage to energy infrastructure (IEA 2020).

For example, rainstorms in Zhengzhou, Henan Province, and high temperatures and heat waves, drought, and flood disasters in many cities all result in the disruption of the energy system. On the other hand, climate-related disclosure guidance in China remains at an early, preliminary framework stage. According to an announcement from China's Ministry of Finance in 2024, climate-related disclosures by Chinese companies, like energy companies, are currently mostly voluntary and lack standardized guidelines. Moreover, China aims to have introduced climate-related disclosure standards by 2027.

The existing body of literature investigates the nexus between climate risks and energy markets, including new and traditional energy markets, with a primary emphasis on green transition risks and climate policy uncertainty (Kettner and Kletzan-Slamanig 2020; Reboredo and Ugolini 2022; Yang et al. 2022; Yao et al. 2023; Zhou et al. 2023). Furthermore, other studies probed into the impacts of physical climate risks on the energy market (Saunders 1993; Chang et al. 2008; Gu et al. 2023; Ding et al. 2024). In addition, most papers utilize indices for measuring physical climate risk, predominantly relying on data established by Faccini et al. (2021) and Lee and Cho (2023). Nevertheless, the dynamic and nonlinear effects of physical climate risks on the returns in the energy sector so far have obtained less scrutiny, particularly relevant to the Chinese market. The reasons may be embedded in the complexity of China's energy market structure, the evolving nature of climate-related risks, and the challenges in accurately quantifying the impact of climate events on energy market dynamics over time (Sun et al. 2023). Additionally, inconsistencies in data availability and the relatively recent focus on climate change in financial analysis further contribute to the lack of clarity in this area.

This paper examines the effects of physical climate risks on China's energy stock markets, differentiating between traditional energy, new energy stock markets, and the energy commodity market. Nevertheless, do climate change risks significantly, time-varyingly affect the returns of the new and traditional energy industries in China? Do physical climate risks affect the energy market differently under different periods? Is there heterogeneity in the impact of different types of physical climate risks on energy commodity markets? Thus, we collected monthly data on China's stock indices and energy commodity prices from January 2009 to September 2023. In addition, the Climate Risk Index for China and five subtypes of physical climate risk indices were utilized from the Beijing Climate Centre[1]. Then, a time-varying parameter vector autoregressive model with stochastic volatility (TVP-SV-VAR) is employed to assess the impacts. Finally, this study enriches the existing literature in related fields and offers valuable insights for formulating relevant policy.

Our research contributes to the literature on climate change risks and the energy sector in three different ways. Firstly, we provide empirical evidence examining the relationship between physical climate risk, the new energy stock market, and the traditional energy stock market. Secondly, we explore the dynamic relationship between physical climate risks and energy commodity markets. Additionally, we employed robust quantitative climate risk measurement, including the overall Climate Risk Index for China and five subtypes of indices for waterlogging by rain, drought, typhoons, cryogenic freezing, and high temperatures, provided by the Beijing Climate Centre, which has been scarcely utilized in the prior literature. However, previous studies focus on climate risk measurements (Engle et al. 2020; Gavriilidis 2021; Zhu et al. 2023; Lee and Cho 2023) based on news articles. Thirdly, our paper classifies and explores how acute and chronic physical risks affect the energy commodity market.

The remainder of the paper is structured as follows: Section 2 provides an overview of the empirical literature on climate risks and Chinese energy market. Section 3 introduces the data employed in the analysis and the TVP-VAR model with stochastic volatility. Section 4 presents the TVP-VAR and time-varying impulse response results for the impacts of physical climate risks on energy markets. Section 5 showcases the discussion of the findings. Finally, Section 6 provides the concluding remarks, and Section 7 includes

limitations and further study. Appendix A lists the detailed TVP-VAR model results, and Appendix B lists the data sources.

2. Literature Review

A growing body of literature explores the relationship between climate change risks and energy markets, encompassing both new and traditional energy sectors, with a particular focus on green transition risks and climate policy uncertainty (Kettner and Kletzan-Slamanig 2020; Yang et al. 2022; Yao et al. 2023; Zhou et al. 2023; Salisu et al. 2023; Tedeschi et al. 2024). Kettner and Kletzan-Slamanig (2020) argued that energy and climate policy are highly interconnected, given that a significant portion of greenhouse gas emissions arise from energy supply and consumption, developing a set of five output-focused indicators to assess climate policy integration: political commitment, functional overlap, policy instruments, weighting, and time perspective. Yang et al. (2022) employed OLS estimation, fixed effect, and a random effect model to demonstrate that sustainable practises, measured through environmental, social, and governance (ESG) pillars, were significantly and positively influenced by critical determinants such as green financing, clean energy, and green economic volatility, confirming their critical roles in promoting sustainable development, considering panel data from seven industries from G7 countries from 2010 to 2018. Yao et al. (2023) used a spatial autoregressive model with a production network to show that an increase in climate policy uncertainty amplifies the downside risk of the stock market, using monthly data from China and its top 10 partners from June 2001 to April 2023. Zhou et al. (2023) employed a time-varying parameter vector autoregressive model with a stochastic volatility (TVP-SV-VAR) model to dissect the time-varying relationship between U.S. climate policy uncertainty, oil prices, and five renewable energy consumption sources, collecting monthly data from January 2005 to April 2021. Climate policy uncertainty generally has a positive effect on oil prices in the short and medium term and a positive effect on total renewable energy consumption in the short and long term. Moreover, its impact on the consumption of the five different types of renewable energy varies significantly. Salisu et al. (2023) utilized a bivariate predictive model to demonstrate that transition risks, like news on international summits and climate policy uncertainty, have effects on the traditional energy markets, like crude oil, with monthly data from the U.S. from January 2000 to December 2018. Tedeschi et al. (2024) showcased that climate policy uncertainty shocks have a significant effect on the returns of clean energy and crude oil stocks, respectively, with increases and decreases in response to heightened climate risk, using the Bayesian time-varying parameter VAR model and analyzing the data from European energy stock market from March 2012 to August 2022.

Numerous papers have showcased that transition risks have effects on the energy market. Nevertheless, physical climate risks have varying impacts on the energy industry, particularly fossil fuel companies (Zhu et al. 2023). Recently, extreme weather events and abnormal climate change have challenged energy systems (Ren et al. 2023). Moreover, climate risks, including transition risk and physical risk, enhance the ability to forecast price volatility in energy markets, but physical climate risk has a lower predictive value compared to the transition climate risk (Salisu et al. 2023). VAR-type models are widely used in studies investigating the relationship between climate change and energy markets because they can capture dynamic relationships. Gu et al. (2023) revealed that increases in physical climate risks are associated with heightened energy market risk, and the positive relationship between physical climate risks and energy market risk has intensified since the Paris Agreement, utilizing the mixed frequency VAR (MF-VAR) method with meteorological monitoring data from eight global climate disasters, in addition to the West Texas Intermediate crude oil markets. Ding et al. (2024) stated that climate warming has a significant effect on renewable energy consumption using the TVP-VAR-SV model, with monthly data from the United States from August 2009 to December 2020. Guo et al. (2024) indicated that high-risk environments and all climatic factors have a pronounced

impact on the risks in China's energy market, employing a time-varying parameter vector autoregression (TVP-VAR) model and quantile models.

In addition, as for the data on climate risks, measuring climate risk is highly challenging due to the intricate nature of climate. Most researchers utilize the physical Climate Risk Index developed by Faccini et al. (2021, 2023) and Lee and Cho (2023), which has limitations. The physical Climate Risk Index developed by Faccini et al. (2021, 2023) focuses on the United States, which has deficiencies in the study of climate change in China. Numerous prior research works have constructed news-based indexes to measure physical climate risk using newspaper content (like Gavriilidis 2021; Zhu et al. 2023; Lee and Cho 2023). Our study employed physical climate risk data constructed from extreme weather and climate events from the Chinese government that have, to the best of our knowledge, only been used in one other study; Sun et al. (2023) used these data from 1995 to 2018 to explore climate risk and electric power sector.

3. Methodology and Data

3.1. Data

3.1.1. Energy Sector Stock Data

We employed data from the China Securities New Energy Sector Index (CSINE) and Shanghai Composite Energy Sector Index (SSEEN) to reflect the stock performance of Chinese new energy and fossil fuel companies, respectively. The data cover the period from January 2009 to September 2023 and were sourced from the Tonghuashun Database.

3.1.2. Energy Commodity Data

We also encompass monthly data for the West Texas Intermediate (WTI) Crude Oil Price and Coal Price Index (CI) to reflect fossil fuel commodities in the Chinese markets. These are from Datastream, spanning the period from January 2013 to September 2023.

3.1.3. Climate Risk Index (CRI) for China

We employ the monthly Climate Risk Index for China, developed by Wang et al. (2018), from the Beijing Climate Centre, covering the period from January 2009 to September 2023 to comprehensively assess climate-related risks arising from extreme weather and climate events. The index incorporates various components, including the overall Climate Risk Index and specific indices for waterlogging by rain (WLR), drought (DI), typhoons (TYI), cryogenic freezing (CFI), and high temperatures (HTIs).

3.2. TVP-VAR Model

To capture the dynamic and time-varying influence of climate risks on energy markets, including the stock and commodity markets, this study adopts a TVP-VAR model with stochastic volatility, as proposed by Primiceri (2005) and Nakajima et al. (2011). Compared to the conventional VAR model, the TVP-VAR model allows parameters to vary over time, dynamically accounting for changes in the relationships between climate change risks and energy sectors. Furthermore, disturbances are permitted to exhibit time-varying variances, enabling the model to capture effects on energy stock markets and energy commodity markets during abrupt changes in different types of climate-related risks.

The TVP-VAR model with stochastic volatility can be expressed as follows:

$$y_t = \beta_t X_t + A^{-1} \sum_t \varepsilon_t, \; t = s+1, ..., n, \tag{1}$$

where $Yt = [CSINE_t, SSEEN_t, WTI_t, CI_t, CRI_t, WLR_t, DI_t, TYI_t, CFI_t, HTI_t]^2$, X_t denotes a matrix of lags in y_t, with the time-varying coefficients β_t, A_t, and Σ_t.

Let $\alpha_t = (\alpha_{21}, \alpha_{31}, \alpha_{32}, \alpha_{41}, \cdots, \alpha_{k,\,k-1})'$, and $h_t = (h_{1t}, h_{2t}, \cdots, h_{kt})'$, $h_{jt} = \log \sigma_{jt}^2$, j = 1, 2, . . ., k, $t = s + 1, \ldots, n$. Then, the parameters in Equation (1) are assumed to follow a random walk process.

$$\beta_{t+1} = \beta_t + \mu_{\beta t}, \tag{2}$$

$$\alpha_{t+1} = \alpha_t + \mu_{\alpha t}, \tag{3}$$

$$h_{t+1} = h_t + h_{ht}, \tag{4}$$

$$\begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ h_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum_{\beta} & 0 & 0 \\ 0 & 0 & \sum_{\alpha} & 0 \\ 0 & 0 & 0 & \sum_{h} \end{pmatrix}\right), \tag{5}$$

where $\beta_{s+1} \sim$ N $(\mu_{\alpha 0}, \sum_{\beta 0})$, $\alpha_{s+1} \sim$ N $(\mu_{\alpha 0}, \sum_{\alpha 0})$, $h_{s+1} \sim$ N $(\mu_{\alpha 0}, \sum_{h 0})$.

To estimate the parameters, we utilized the Markov Chain Monte Carlo (MCMC) method for addressing the problem through Bayesian inference, conducting 10,000 samplings. following Nakajima et al. (2011).

4. Empirical Results and Findings

4.1. Parameter Estimate

Table 1 presents the parameter estimates on the model employing the Climate Risk Index, traditional energy stock returns, and new energy stock returns. Table 2 documents the parameter estimates of the model utilizing the Climate Risk Index, WTI oil prices, and coal price index. The Geweke statistics, assessed at the 5% significance level, are below the critical value of 1.96, which indicates the convergence of parameters to the posterior distribution, affirming the efficiency of the estimations. Additionally, the inefficiency factors exhibit a low level. In summary, the two TVP-SV-VAR models[3] that we formulated demonstrate effectiveness.

Table 1. Parameter estimation for TVP-SV-VAR between CRI, CSINE, and SSEEN.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0226	0.0026	0.0182	0.0282	0.229	7.03
sb2	0.0230	0.0028	0.0183	0.0291	0.833	11.00
sa1	0.0678	0.0175	0.0425	0.1109	0.922	43.86
sa2	0.0231	0.0022	0.0191	0.0279	0.685	21.14
sh1	0.4044	0.0894	0.2529	0.6048	0.036	42.27
sh2	0.4399	0.1126	0.2606	0.7053	0.410	51.26

Table 2. Parameter estimation for TVP-SV-VAR between CRI, WTI, and CI.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0229	0.0026	0.0184	0.0286	0.607	8.07
sb2	0.0230	0.0027	0.0185	0.0290	0.140	6.95
sa1	0.0472	0.0098	0.0315	0.0697	0.529	19.96
sa2	0.0346	0.0052	0.0262	0.0462	0.143	15.70
sh1	0.7263	0.1473	0.4884	1.0562	0.146	32.76
sh2	0.3137	0.1084	0.1486	0.5784	0.923	59.89

4.2. Time-Varying Impulse Response Estimated Results

In this section of the paper, we identify the time-varying relationship between physical climate risk, the energy stock market, and the fossil fuel commodities market. We assess the time-varying impulse responses with different lags, 1, 2, and 3 months, representing the short, medium, and long term, respectively. Additionally, we explore three specific periods: the Paris Agreement (December 2015), the COVID-19 pandemic (January 2020), and the action plan for carbon dioxide peaking before 2030 issued in China (September 2021). Furthermore, we analyze how the Chinese energy system responds to changes in climate risk indicators (CRIs) by investigating the time-varying relationships between physical climate risk, the energy stock market, and the fossil fuel commodities market.

Time-Varying Impulse Response of Energy Stock Market to Climate Risk

We consider the time-varying relationship between the CRI, new energy stock returns, and traditional energy stock returns. Looking at the left panel in Figure 1, we can see that the impact of climate change risk will negatively affect new and traditional energy stock returns most of the time in the short term. The effects of the CRI on the returns of new and traditional energy stocks generally transition from negative to positive in the medium term. The only difference lies in the case of the new energy stock market, where it initially exhibits a positive impact before turning negative. The change in climate risk had a positive effect on both markets in recent years. In the long term, the tendency is toward a zero response.

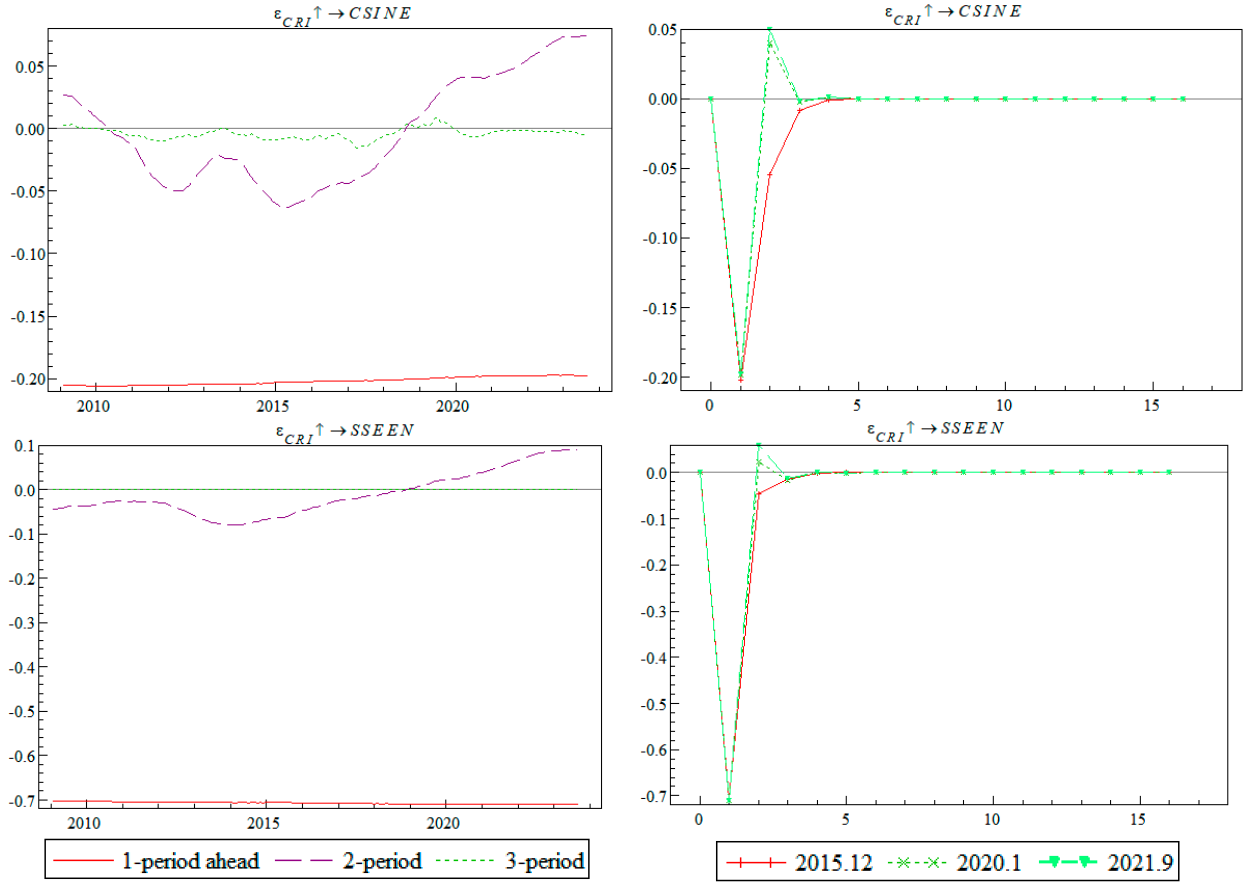

Figure 1. The impulse response of new energy stock returns and fossil fuel stock returns.

The right panel of Figure 1 presents a time-varying impulse response in three periods. The results show that the impacts of climate risk on new energy stock returns and the traditional energy market tend to increase initially and then decrease over time. Moreover, the responses of new energy and conventional stock returns to changes in climate risk are relatively similar.

4.3. The Time-Varying Impulse Response of the Energy Commodity Market to Climate Risks

In this section, we explore the time-varying relationship between the CRI, WTI oil prices, and coal prices. Figure 2 shows that the responses of WTI oil prices and coal prices to changes in climate risk are entirely opposite to each other. While climate risk has negative impacts on coal prices, it yields positive effects on WTI oil prices. The impacts are strong in the short term and tend to decrease in the medium and long term.

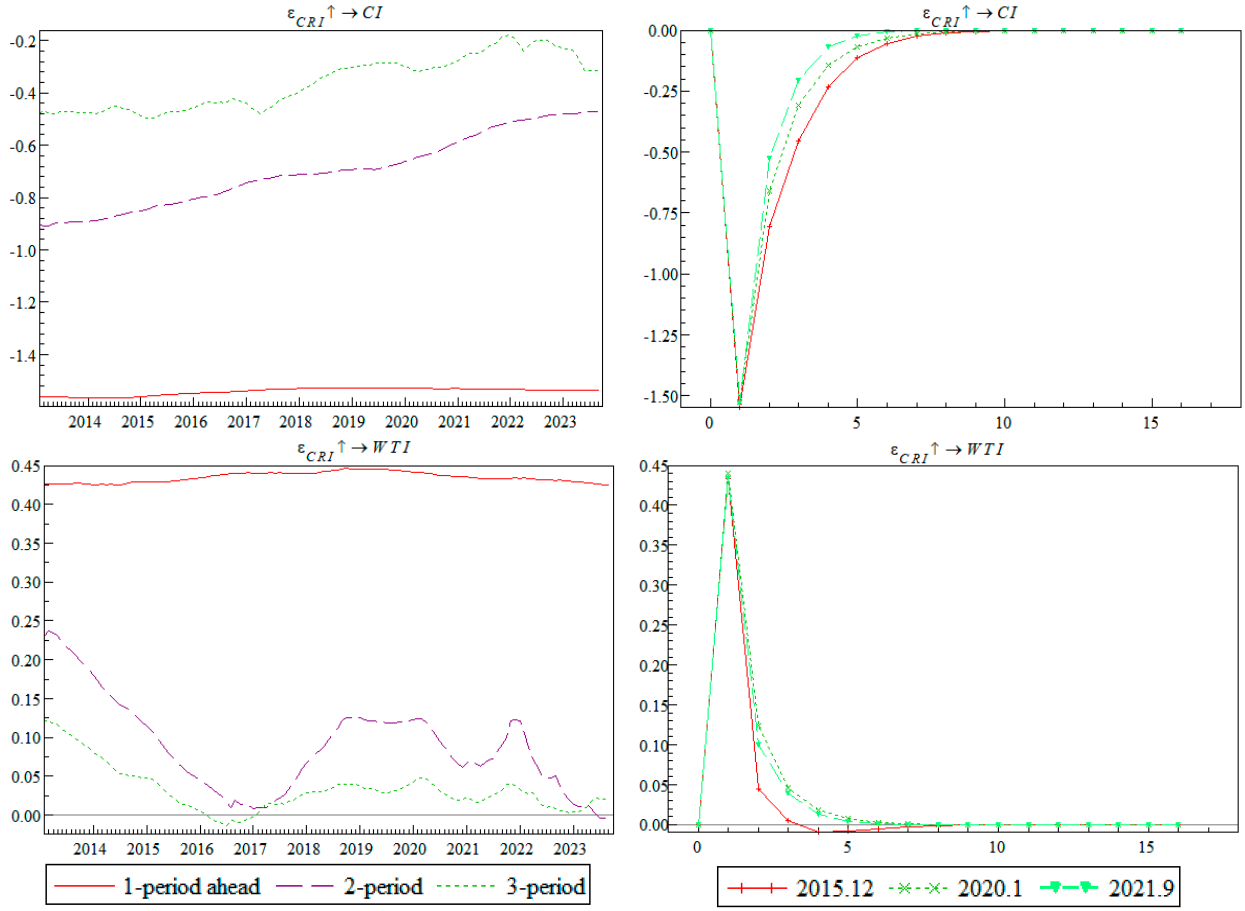

Figure 2. The impulse response of the carbon price index and WTI oil price.

4.4. Time-Varying Impulse Response of the Energy Commodity Market to Subtypes of Climate Risk

In order to further explore the impacts of different extreme weather events on carbon prices and WTI oil prices, we construct models[4] to probe the time-varying impulse responses of carbon prices and WTI oil prices under the impact of waterlogging by rain, drought, typhoons, cryogenic freezing, and high temperatures, separately. Furthermore, we clarify these five subtypes of climate risks into acute risks and chronic risks, following TCFD (2017).

4.4.1. Acute Risks

Acute risks involve the potential for immediate and severe negative impacts triggered by specific events or exposures. These risks include the heightened intensity of extreme weather events, such as cryogenic freezing, typhoons, and floods, which cause sudden, short-term, and significant disruptions that demand urgent response (TCFD 2017). In Figure 3, we find that the responses of WTI oil prices and coal prices to waterlogging by rain and typhoons are completely opposite to each other. While waterlogging by rain risk exerts negative impacts on coal prices, it yields positive impacts on WTI oil prices, while typhoon risks have positive effects on coal prices and negative effects on WTI oil prices. The impacts are strong in the short term and tend to be weak in the medium term and long term, which means that the trend increases initially and decreases after that. Interestingly, the cryogenic freezing risk has distinct effects on WTI crude oil prices and coal prices. It exerts a negative impact on coal prices, with a trend weakening from strong to weak. In contrast, it has a short-term negative impact on WTI oil prices, turning positive in the medium term and becoming negative again in the long term, characterized by a fluctuating trend.

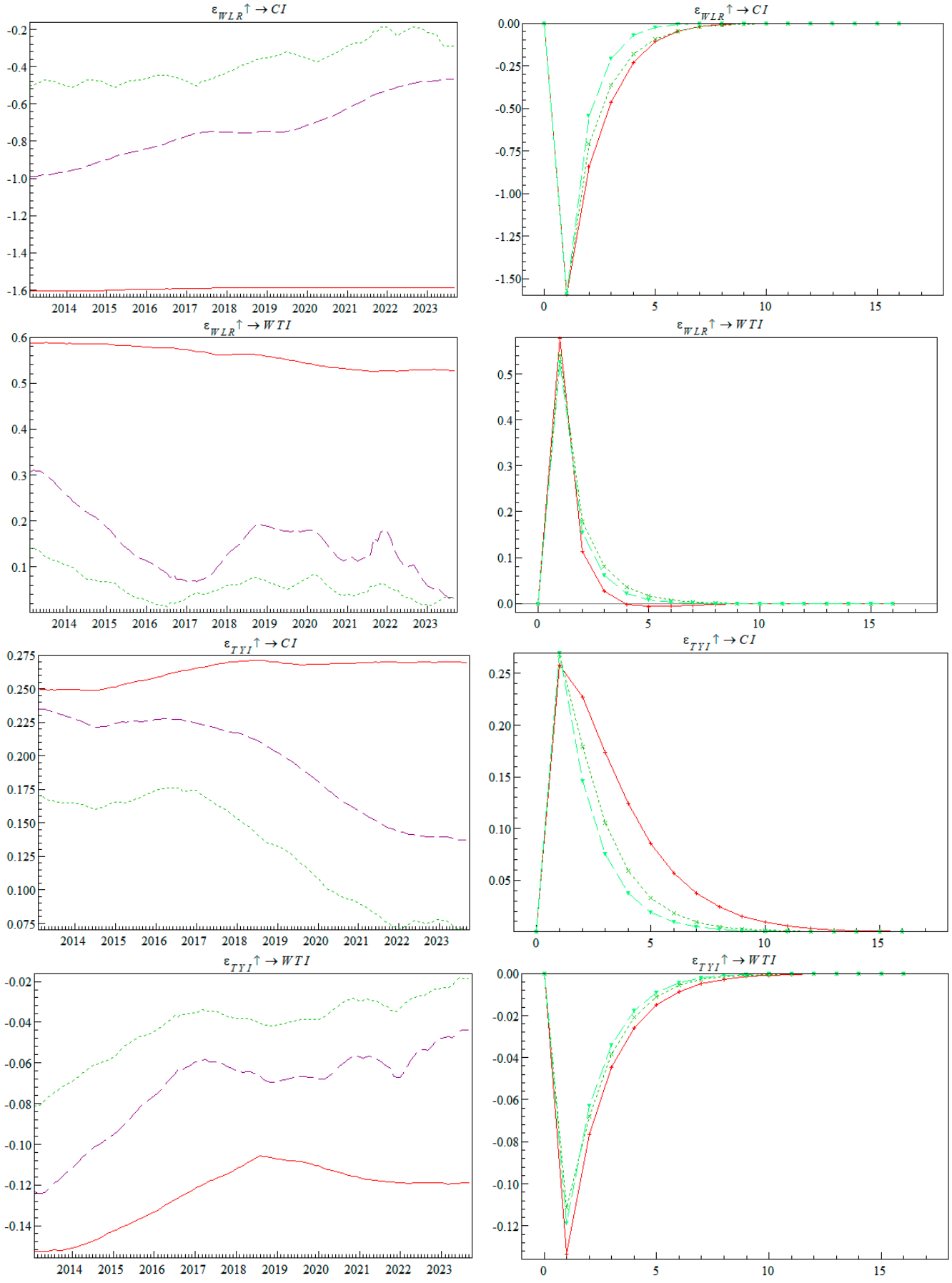

Figure 3. *Cont.*

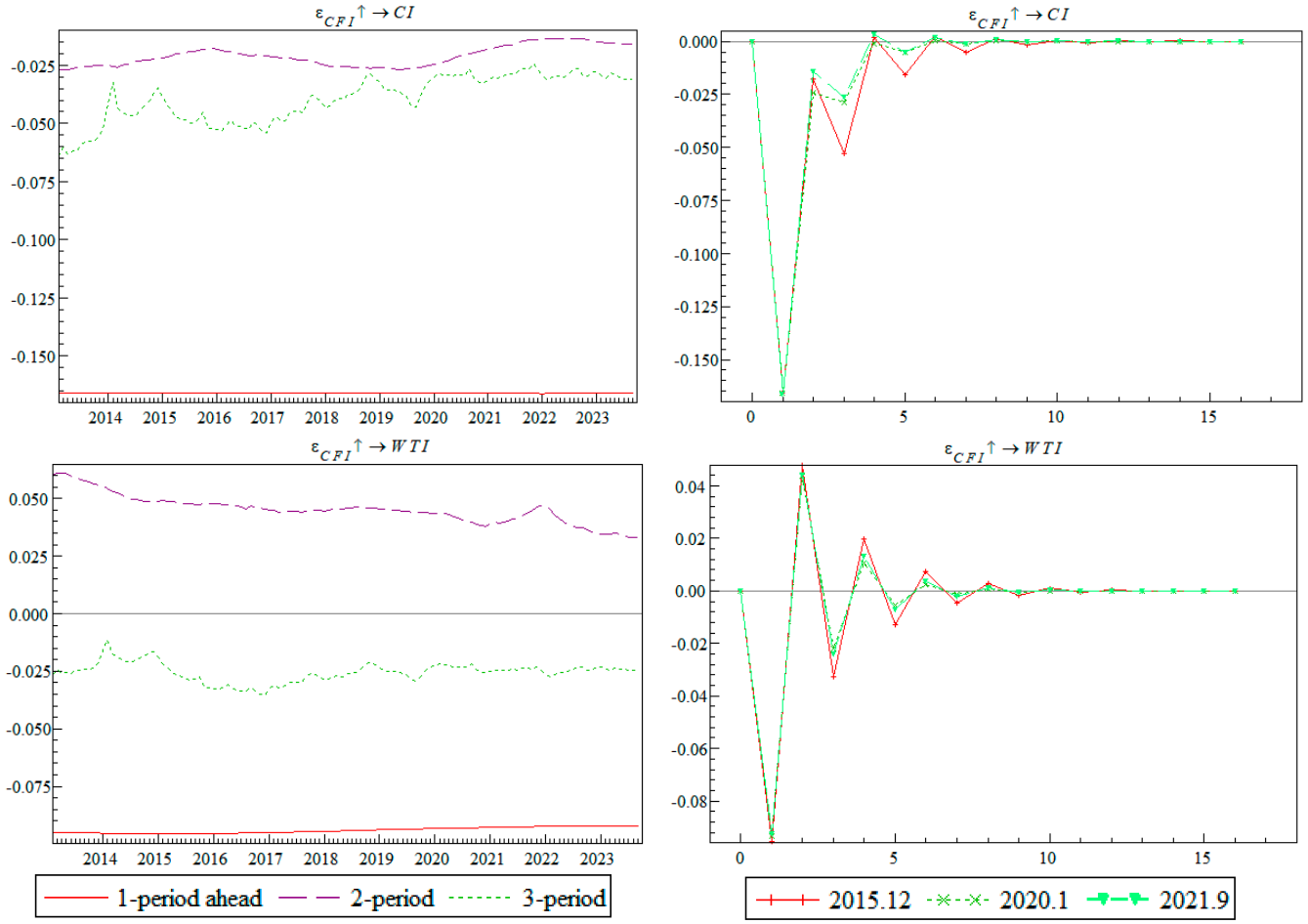

Figure 3. The impulse response of the carbon price index and WTI oil price to acute risk.

4.4.2. Chronic Risks

Unlike acute risks, chronic risks relate to long-term shifts in climate patterns and the potential for prolonged negative impacts, which develop gradually over time and require continuous management and prevention strategies. In Figure 4, chronic risks, including drought risks and high-temperature risks, have a similar impulse response to WTI crude oil prices and coal prices. The results showcase that the drought risks have consistent negative impacts on WTI crude oil prices and coal prices. Nevertheless, the trend in impact on coal prices strengthens from weak to strong, whereas the trend in impact on WTI oil prices weakens from strong to weak in the short term, medium term, and long term, respectively. On the other hand, high-temperature risks have similar nonlinear impacts on WTI crude oil prices and coal prices, while having a negative impulse in the short-term and positive impulse in the medium term and long term.

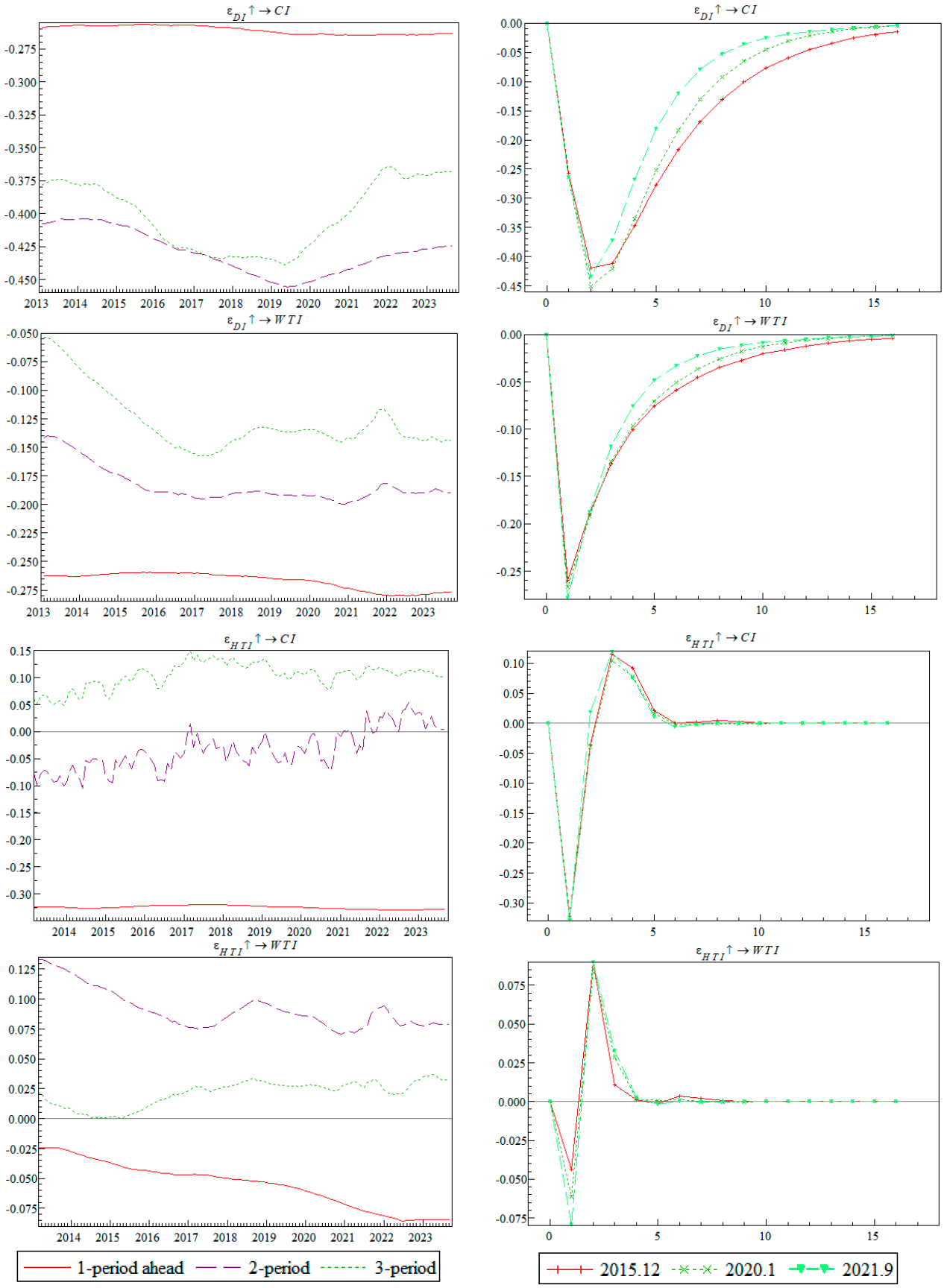

Figure 4. The impulse response of carbon price index and WTI oil price to chronic risk.

5. Discussion

In this study, we aimed to explore the dynamic relationship between physical climate risks, energy stock markets, and commodity markets. To achieve this, monthly data on the climate policy uncertainty index, traditional energy stock returns, new energy stock returns, WTI oil prices, and coal price index from January 2013 to September 2023 were gathered, and a TVP-SV-VAR model was developed. Additionally, the overall Climate Risk Index and five subtype indices for waterlogging by rain, drought, typhoons, cryogenic freezing, and high temperatures were collected, and the impact of different physical climate risks on energy markets was explored. The findings of this study offer valuable insights and a foundation for investors, energy companies, and policymakers to develop strategies and policies that promote investment and ensure stability in the energy market.

The empirical analysis is organized into four sections: parameter estimation, the impulse response of the energy stock market to climate risk, the impulse response of the energy commodity market to climate risks, and the impulse response of the energy commodity market to subtypes of climate risk. The parameter estimation results indicate that none of the parameters in our TVP-SV-VAR model reject the null hypothesis of convergence to the posterior distribution at the 95% confidence interval, affirming the efficiency of the estimations. Furthermore, the inefficiency factors are notably low. Therefore, the TVP-SV-VAR models we developed demonstrate robustness and effectiveness. To represent short-, medium-, and long-term effects in time-varying impulse responses, we used lags of one month, two months, and three months, respectively. For the impulse response of the energy stock market to climate risk, the results revealed that the relationship between physical climate risks, energy stock markets, and new energy stock is time-varying. In particular, climate risk typically negatively impacts new and traditional energy stock returns in the short term, with a tendency toward a neutral response in the long term. The findings of some related studies showcase a negative relationship between physical climate risks and energy stock markets. The reason for this may be that the energy firms' performance reflects their exposure to physical climate risks, which are influenced by climate-related shocks impacting cash-flow expectations and investor preferences (Pástor et al. 2021; Zhu et al. 2023). For the impulse response of the energy commodity market to climate risk, the results showed that physical climate risks negatively affect coal prices while positively influencing WTI oil prices, with these impacts being strong in the short term but diminishing over the medium and long term. As for the crude oil commodity, the reason for this may be that climate change has increased trading and volatility in crude oil (i.e., those with a positive impact) (Tumala et al. 2023). As for coal, coal prices may be affected by climate change, which impacts coal production and transportation, thus influencing supply and prices (Sun et al. 2023). Additionally, the global trend toward energy transition, particularly the shift to renewable energy sources, may reduce the demand for coal, leading to a decline in prices. Nick and Thoenes (2014) predicted that fluctuations in the global climate would impact fossil fuel prices in the short term, which is consistent with our study. Ultimately, the impacts of different physical climate risks on the energy markets are heterogeneous.

In addition to the time-varying impulse response analysis, three key events were selected to examine impulse responses at specific points in time: the Paris Agreement in December 2015, the COVID-19 pandemic in January 2020, and the action plan for carbon dioxide peaking before 2030 issued in China in September 2021. The results align with the time-varying impulse responses across different lags, reflecting climate-related risks from extreme weather and climate events.

6. Conclusions

This paper probes the time-varying connections between physical climate risks, the energy stock market, and the energy commodity market. Firstly, our findings declare that significant effects of returns of the new and traditional energy industry on the stock market in China are associated with comprehensive climate change risks. The impacts of climate change risks on energy stock markets are the same, with negative effects both

in the conventional and new energy stock markets in the short term, the transition from negative to positive in the medium term, and a tendency to zero. Secondly, we find that comprehensive physical climate risks have opposite effects on coal prices and WTI crude oil prices. Climate change risks have negative impacts on the coal commodity market in the short, medium, and long term, while having positive effects on the WTI oil price market in the short term. Finally, we explore how acute and chronic risks effect the energy commodity market. We find that extreme weather or climate events have varying impacts on energy commodity markets, with the strongest effects occurring in the short term, while the impacts weaken in the medium and long term. Waterlogging by rain and typhoons exhibit contrasting effects on WTI oil prices (positive effects from waterlogging by rain and negative effects from typhoons) and coal prices (negative effects from waterlogging by rain and positive effects from typhoons). Drought and high temperature, present similar effects on WTI oil prices and coal prices, negative effects from drought risks and nonlinear effects from high-temperature risks. Notably, the cryogenic freezing risk has distinct effects on WTI crude oil prices, with a fluctuating effect and coal prices, with negative impacts.

In light of these findings, this study provides vital implications for investors and policymakers. The time-varying impulse responses indicate the significant influences of climate change risks on energy markets. Firstly, investors should incorporate the impact of physical climate risks in their risk management strategies for financial assets. At the same time, investors should also differentiate the impact of different physical climate risks on energy stock markets and commodity markets, and should implement distinct hedging strategies accordingly. Secondly, policymakers should consider these findings when formulating green policies to promote investment and ensure stability in the energy market, particularly in China's absence of climate-related disclosure guidance. Attention should be given to the varying impact of different types of physical climate risk on energy markets. Tailored policies should be developed based on the specific conditions of the energy stock market and commodity market to accelerate the energy transition. Thirdly, regulators should be mindful of shifts in market sentiment regarding climate risks, as these could trigger significant price shocks in energy markets. Such shocks may ripple through the financial system, causing market instability.

7. Limitations and Further Study

While this study provides valuable insights into the impact of physical climate risks on energy markets in China, there are several limitations. First, this study primarily focuses on WTI oil and coal prices, which may not fully represent the dynamics of all energy commodities in the market. Additionally, this study mainly explores the direct effects of physical climate risks on energy markets. Still, it does not investigate the potential mediating effects of other variables such as technological advancements, consumer behaviour changes, or international market influences. Furthermore, the scope of the study is limited to physical climate risks, potentially overlooking other relevant factors, such as transition risks.

Future research could expand the scope of this study by incorporating a broader range of energy commodities, including renewable energy sources such as solar and wind, to provide a more comprehensive understanding of the impacts of physical climate risks across the entire energy sector. Additionally, utilizing connectedness network analysis could further elucidate the interdependencies and spillover effects between different energy market sectors and physical and transition risks.

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Appendix A. TVP-VAR Model Estimation Results

Table A1. Parameter estimation for TVP-VAR between WTI, CI, and WLR.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0227	0.0025	0.0184	0.0283	0.437	5.83
sb2	0.0222	0.0024	0.0181	0.0276	0.687	5.56
sa1	0.0766	0.0271	0.0409	0.1451	0.032	51.57
sa2	0.0548	0.0134	0.0352	0.0864	0.402	44.44
sh1	0.2560	0.0866	0.1086	0.4536	0.243	47.18
sh2	0.7000	0.1492	0.4722	1.0440	0.021	39.77

Note: The lag period of the TVP-VAR model is 1, and WLR denotes waterlogging by rain index.

Table A2. Parameter estimation for TVP-VAR between WTI, CI, and TYI.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0231	0.0027	0.0185	0.0293	0.144	10.80
sb2	0.0230	0.0027	0.0185	0.0291	0.481	7.61
sa1	0.0459	0.0097	0.0316	0.0694	0.631	25.78
sa2	0.0315	0.0046	0.0241	0.0421	0.176	49.55
sh1	0.7087	0.1445	0.4743	1.0535	0.071	44.57
sh2	0.3157	0.1084	0.1499	0.5793	0.116	57.92

Note: The lag period of the TVP-VAR model is 1, and TYI denotes typhoon index.

Table A3. Parameter estimation for TVP-VAR between WTI, CI, and CFI.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0229	0.0026	0.0185	0.0285	0.074	6.45
sb2	0.0232	0.0027	0.0186	0.0293	0.695	10.11
sa1	0.0461	0.0098	0.0312	0.0683	0.589	17.94
sa2	0.0296	0.0034	0.0235	0.0369	0.013	33.13
sh1	0.6961	0.1333	0.4788	0.9994	0.598	27.92
sh2	0.2927	0.1010	0.1215	0.5139	0.069	61.16

Note: The lag period of the TVP-VAR model is 1, and CFI denotes cryogenic freezing index.

Table A4. Parameter estimation for TVP-VAR between WTI, CI, and DI.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0227	0.0025	0.0183	0.0282	0.199	8.58
sb2	0.0232	0.0028	0.0186	0.0295	0.446	8.06
sa1	0.0476	0.0106	0.0319	0.0733	0.810	15.79
sa2	0.0313	0.0040	0.0245	0.0402	0.009	11.30
sh1	0.6947	0.1334	0.4769	0.9993	0.877	21.52

Note: The lag period of the TVP-VAR model is 1, and DI denotes drought index.

Table A5. Parameter estimation for TVP-VAR between WTI, CI, and HTI.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0225	0.0026	0.0182	0.0282	0.829	5.78
sb2	0.0226	0.0025	0.0183	0.0280	0.030	5.21
sa1	0.0909	0.0419	0.0428	0.2046	0.675	63.91
sa2	0.0595	0.1100	0.0321	0.1143	0.094	67.90
sh1	0.2441	0.0852	0.0992	0.4442	0.519	58.33
sh2	0.6788	0.1307	0.4466	0.9511	0.527	46.00

Note: The lag period of the TVP-VAR model is 2, and HTI denotes high-temperature index.

Appendix B. Data Definitions

Variables	Definitions	Sources
CSINE	China Securities New Energy Sector Index	Tonghuashun Database
SSEEN	Shanghai Composite Energy Sector Index	Tonghuashun Database
WTI	West Texas Intermediate Crude Oil Price	Datastream
CI	Coal Price Index	Datastream
CRI	Climate Risk Index	Beijing Climate Centre
WLR	Waterlogging by Rain Index	Beijing Climate Centre
DI	Drought Index	Beijing Climate Centre
TYI	Typhoons Index	Beijing Climate Centre
CFI	Cryogenic Freezing Index	Beijing Climate Centre
HTI	High Temperatures Index	Beijing Climate Centre

Notes

[1] The Beijing Climate Centre (BCC) was established in 2003 under the China Meteorological Administration based on its National Climate Centre to expand its capabilities as a Regional Climate Centre (RCC) designated by the World Meteorological Organization (WMO).

[2] We individually constructed TVP-VAR models for the sets of variables ($CSINE_t$, $SSEEN_t$, CRI_t), (CI_t, WTI_t, CRI_t), (CI_t, WTI_t, WLR_t), (CI_t, WTI_t, DI_t), (CI_t, WTI_t, TYI_t), (CI_t, WTI_t, HTI_t), and (CI_t, WTI_t, CFI_t).

[3] Prior to model estimation, we assessed the stationarity of the variables. The Augmented Dickey–Fuller test indicates stationarity at first differences, thereby meeting the stationarity criterion for the TVP-VAR model. The optimal lag length, determined by the Sequential Modified LR Test (LR) or Akaike information criterion (AIC), was set at 1.

[4] The parameter estimation results for TVP-SV-VAR between the five subtypes, WTI, and coal prices refer to Appendix A.

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