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The Time-Varying Impact of Climate Policy Uncertainty on the Volatility of China's New Energy Stock Market

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Abstract. This paper systematically examines the differential time-varying impacts of Chinese and U.S. climate policy uncertainty (CPU) on the volatility of China's new energy stock market. Utilizing a Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model, this study conducts a comparative analysis of the mechanisms through which CPU from both countries influences the volatility across different time horizons. The results indicate that the impacts of both Chinese and U.S. CPU on the volatility of China's new energy stocks are time-varying. Specifically, Chinese CPU suppresses stock price volatility in the short run, with its effect gradually diminishing to zero in the long run. In contrast, shocks from U.S. CPU persistently amplify market volatility without showing significant decay. Furthermore, the study finds that the influences of these shocks exhibited significant divergence during extreme events, such as China's accession to the Paris Agreement in 2016 and the COVID-19 pandemic in 2020. Based on these findings, this paper proposes corresponding policy recommendations pertaining to international policy coordination and the construction of market stabilization mechanisms.

Keywords: Climate Policy Uncertainty; New Energy Stock Market Volatility; TVP-SV-VAR Model.

1. Introduction

In recent years, increased volatility in international energy markets and rising climate policy uncertainty have profoundly impacted investment, financing behaviors, and market stability within the new energy industry. Against the backdrop of global energy transition and deepening climate governance, the Chinese government has elevated the new energy industry to a strategic level concerning national energy security and green development through the top-level design of the "Dual Carbon" goals, industrial planning, and fiscal support systems, thereby fostering the industry's scale expansion and technological advancement. However, as a capital-intensive industry, the development of the new energy sector heavily relies on financial market support. Fluctuations in its stock prices not only directly affect corporate financing costs and investment confidence but also pose potential risks to the industry's stable development. Crucially, as the climate policy orientations of China and the United States have become core variables influencing the global new energy landscape, the uncertainties arising from their policy formulation and adjustment processes may trigger abnormal volatility in China's new energy stock market through multiple channels such as international trade, technological barriers, and capital flows. In this context, systematically uncovering the differences in the time-varying impacts of Chinese and U.S. climate policy uncertainty holds significant theoretical and practical importance. Therefore, based on the TVP-SV-VAR model, this paper investigates the dynamic impact mechanisms of Chinese and U.S. climate policy uncertainty on the volatility of China's new energy stock market. It focuses on identifying their heterogeneous responses in the short and long term, as well as their divergent characteristics during special events, to fill research gaps in existing literature regarding cross-country comparison and time-varying characterization, and to provide empirical evidence for policymaking.

Climate Policy Uncertainty refers to the uncertainty arising from government adjustments in policy objectives, changes in enforcement intensity, or fluctuations in the international situation during the formulation and implementation of climate-related regulations, carbon pricing mechanisms, and energy transition policies. This makes it difficult for businesses and investors to accurately predict future policy directions. Regarding the quantitative research on CPU, academia has developed various measurement methods. Early studies, such as Gavriilidis, constructed an international CPU index by analyzing climate policy-related word frequencies in mainstream American newspapers, providing an important reference for subsequent research. In recent years, with advancements in text analysis technology, machine learning methods have been widely applied to CPU measurement. For instance, Ma et al. utilized deep learning algorithms to process news reports from six authoritative Chinese newspapers, constructing a more precise Chinese CPU index. They found that this index effectively captures the impact of policy fluctuations on the green bond and treasury bond markets. Domestic scholars Guo Jing and Yong Zhiting employed word frequency analysis to study the inhibitory effect of CPU on Chinese enterprises' green innovation. In summary, the measurement methods for CPU have evolved from early media word frequency analysis to text mining techniques incorporating deep learning, providing methodological support for accurately quantifying policy uncertainty and its economic and financial impacts.

Climate Policy Uncertainty exerts profound impacts on both corporate performance and financial markets, yet its mechanisms of action exhibit multi-dimensional differences. At the corporate level, the influence of CPU on green innovation behavior is academically contested: some studies, such as Niu et al. and Sun et al., indicate that CPU suppresses corporate technology R&D by exacerbating funding constraints and reducing risk tolerance. This conclusion aligns with Huang's findings regarding CPU reducing green patent output. Conversely, Bai et al. propose the opposite view, suggesting that moderate policy pressure may compel enterprises to increase R&D investment to cope with future regulations. Additionally, CPU has been proven to increase corporate debt issuance costs, further constraining corporate financing capacity. Recent research, such as Raza et al., further indicates that CPU amplifies financial market volatility, thereby exerting a non-linear impact on the performance of financial products like green stocks and bonds. This suggests that policymakers need to focus on constructing market stabilization mechanisms while promoting the energy transition.

At the financial market level, CPU primarily functions through channels such as asset pricing, volatility transmission, and industry heterogeneity: Engle et al. found that CPU lowers investors' expectations for returns on green technologies, thereby increasing financing costs; Ilhan et al. further pointed out that CPU increases the cost of option protection for high-carbon enterprises, highlighting its impact on derivatives pricing. The stock market, as a core carrier of risk transmission, exhibits particularly significant reactions to CPU. Based on Chinese market data, Shuaibu et al. found that the impact of CPU is asymmetric, with stronger negative effects during bear markets; Chen Jie et al., using network models, showed that industries such as industrials and materials become net risk exporters, while the financial sector is vulnerable to shocks; Jia Shanghui et al. and Iqbal et al. both emphasized industry heterogeneity, finding the energy sector to be the most sensitive, while responses of ESG stocks and carbon allowance prices differ between short and long terms. At the mechanism level, scholars from Tianjin University of Finance revealed that the risk spillover between CPU and the stock market is time-varying, with investor perception amplifying the contagion effect; Wang Jing et al. indicated that CPU is superior to traditional economic policy indicators in predicting ESG volatility. The existing research consensus holds that CPU affects the market through expectation adjustment, cost structure, and risk premium channels, but its intensity and direction are moderated by market conditions, industry attributes, and policy stages. Future research needs to further capture its dynamic transmission paths by combining high-frequency data and machine learning methods.

As the new energy industry has become the core of the national energy strategy transformation, an increasing number of researchers are focusing on exploration in this field. However, the deep embedding of the industry's development within the context of global climate governance inevitably exposes it to the impacts of climate risks. Existing research gradually reveals that climate risks affecting the new energy industry mainly concentrate on two categories: physical risks and transition risks. These two types of risks profoundly impact the supply chain security, technology iteration paths, investment and financing environment, and market valuation of China's new energy industry through multiple channels such as resource endowment, policy environment, financial markets, and international trade, constituting key challenges for the sustainable development of the industry.

At the level of physical risks, extreme weather events and long-term climate pattern changes triggered by climate change directly threaten the stable operation and resource base of the industry. Research shows that China, as a global leader in installed wind and solar capacity, is significantly affected by climate change in terms of the geographical distribution and temporal stability of its wind and solar resources. Specifically, long-term trends in average wind speed changes, the suppression of photovoltaic module efficiency by extreme high-temperature events, and the weakening of hydropower peak-shaving capacity by droughts all directly reduce the expected power generation and operational efficiency of new energy projects. Furthermore, the increased frequency and intensity of extreme climate events such as hurricanes, hail, and sandstorms pose direct threats to the physical security of infrastructure like wind farms and photovoltaic power stations, not only increasing operation and maintenance costs but also potentially causing unexpected power generation interruptions, affecting grid security.

At the level of transition risks, the ongoing adjustments in energy policies and technological advancements pursued to address climate change bring enormous opportunities but are also accompanied by significant uncertainties. This type of risk is centrally manifested as Climate Policy Uncertainty. Scholars, by constructing text-based indices, have found that increased Climate Policy Uncertainty in China significantly exacerbates the financing constraints faced by new energy enterprises. Due to the long investment cycles and high capital intensity of new energy projects, ambiguity in policy signals elevates the risk perception of financial institutions, leading to increased debt financing costs and suppressed corporate R&D innovation investment. This impact is manifested in the capital market as a significant positive correlation between the stock price volatility of listed new energy companies and the Climate Policy Uncertainty index, particularly during sensitive windows of policy adjustment, where market sentiment amplifies such shocks. It is noteworthy that the international climate governance landscape, particularly the game theory surrounding trade policies like carbon border adjustment mechanisms among China, the US, and Europe, as an external transition risk, also profoundly impacts the international market environment and competitive landscape of China's new energy industry by affecting the global supply chain of new energy equipment and product trade.

In summary, existing research has gradually constructed an analytical framework for the impact of climate risks on China's new energy industry from the two dimensions of physical exposure and policy transition. The research consensus indicates that climate risks are no longer distant externalities but core operational and strategic risks directly affecting all links of the industrial value chain. Future research needs to further analyze the impact of climate risks on China's new energy industry and explore the construction of a more resilient industrial climate risk management system.

The impact of Climate Policy Uncertainty on the green financial market exhibits significant cross-country heterogeneity, with the differences between China and the United States being particularly pronounced. Under the global climate change governance framework, the fundamental differences in political systems and governance models between China and the US have led to distinct management paths for climate policy uncertainty. Researchers argue that the decentralized structure under the US federal system results in highly fragmented policies, where natural disaster shocks and political polarization exacerbate cyclical adjustments in emission reduction targets. This creates challenges for enterprises, such as prolonged legal adaptation cycles and intermittent subsidies. Such institutional friction is particularly evident in the energy transition, forcing companies to rely on short-term arbitrage rather than technological accumulation. In stark contrast, China leverages the administrative efficiency of a unitary state to achieve vertical control, connecting its Nationally Determined Contributions with Five-Year Plans and enhancing policy operability through quantified targets. Non-state-owned enterprises, under the pressure of environmental inspections, actually increase their green R&D investment, thereby effectively driving innovation. Communication studies indicate that the reporting framework of Chinese official media, which focuses on collective action achievements, effectively fosters social consensus. Conversely, the emphasis on partisan conflict in US media exacerbates the crisis of trust in policies. This divergence in public discourse directly influences cross-border capital flows – when US political deadlock causes fluctuations in its international negotiation stance; China's stable policy expectations become a key factor in attracting green investment.

Although the existing literature on the economic impacts of climate policy uncertainty has made significant progress, it suffers from three key limitations. First, a substantial body of research fails to adequately account for cross-country heterogeneity, particularly the systematic differences in policy frameworks, market structures, and transition pathways between China and the US, the world's two largest economies, casting doubt on the universality of their conclusions. Studies focusing on the US market show that climate policy uncertainty is a key driver of volatility in its domestic energy market. However, in-depth research in the Chinese context reveals more complex transmission mechanisms. Studies find that China's climate policy uncertainty exerts unique asymmetric shock effects on domestic asset prices and heterogeneously impacts the stock market through a multi-layer network structure across industries. This mechanism of influence differs significantly from that in the US market. Neglecting these differences in impact mechanisms makes it difficult to fully characterize the true economic consequences of global climate policy uncertainty.

The neglect of national heterogeneity in existing literature extends not only to the macro level but also to the realm of micro-level corporate behavior. Research demonstrates that climate policy uncertainty significantly affects the bond issuance costs and credit spreads of Chinese enterprises and suppresses their green R&D investment. In contrast, studies on US firms focus more on the impact of climate policy uncertainty on their financing decisions, or address the stranded asset risks for fossil fuels that may result from stringent climate policies. This difference in research focus itself reflects the fundamental differences in industrial structures and policy concerns between the two economies. Furthermore, Chinese government subsidies have been shown to partially mitigate the negative impact of climate policy uncertainty on corporate green innovation, a mechanism less explored in the US context. Simply applying conclusions derived from one country's institutional context to another may lead to misleading judgments.

Second, existing studies often employ static or constant-parameter models in their methodology, which struggle to capture the dynamic time-varying characteristics inherent in climate policy uncertainty, consequently leading to biased characterization of impact mechanisms. Furthermore, traditional research rarely conducts specialized analyses of specific time points, resulting in insufficient granularity and prompting subsequent researchers to explore this gap. The impact of climate policy shocks on financial markets has been proven to exhibit non-linear changes depending on market conditions, with their negative effects on green industry stock returns being particularly significant and asymmetric during bear markets. This finding challenges the assumptions of linear constant-parameter models.

To accurately describe such time-varying relationships, the Time-Varying Parameter Vector Autoregression model combined with stochastic volatility has become a necessary methodological choice. This model framework can simultaneously capture the time-varying nature of relationships between variables and the heteroscedasticity of stochastic disturbances, thereby providing the technical possibility to precisely quantify the dynamic effects of policy shocks. For instance, in the field of asset pricing, incorporating climate policy uncertainty into such a time-varying framework for analysis has confirmed its persistent and time-varying impact on asset returns in stochastic volatility environments. This indicates that relying on static models while ignoring the time-varying nature of impacts will fail to accurately reveal the dynamic transmission paths and evolution patterns of climate policy uncertainty within the economic system.

Regarding research on time-varying effects, evidence shows that its influence permeates multiple levels from the macro-financial system to micro-enterprise decision-making. Studies find that climate policy uncertainty dynamically exacerbates systemic financial risk by influencing investors' perception of climate risk. Simultaneously, the predictive power of climate risk for China's stock market volatility also changes over time. At the micro-mechanism level, the inhibitory effect of climate policy uncertainty on corporate innovation performance evolves dynamically over time through the channels of financing constraints and risk aversion. Further research points out that the impact of climate policy uncertainty on China's commodity market also exhibits non-linear and asymmetric characteristics. These complex dynamic effects cannot be fully revealed within the framework of static or constant-parameter models. Therefore, adopting time-varying parameter models capable of capturing structural changes is not only a methodological improvement but also a necessary requirement for accurately understanding the dynamic economic impacts of climate policy uncertainty.

Finally, there remains a significant lack of mechanism research focused on China, the world's largest new energy market. As China's new energy industry becomes increasingly mature and receives greater strategic emphasis from the national government, research on its impact on China's new energy industry and stock prices is essential. On one hand, existing literature predominantly focuses on European and American markets or broad green financial indicators, lacking targeted analysis of the impact on Chinese new energy listed companies' stock prices, particularly neglecting the unique market structure characterized by high policy dependence. On the other hand, although some scholars suggest that CPU may affect markets through channels such as asset revaluation effects, corporate financing constraints, and investor risk preference, the transmission pathways within China's highly policy-dependent market—especially how the interaction mechanism between Chinese and U.S. CPU affects the valuation of new energy enterprises by altering investor expectations and industry financing conditions—still requires systematic empirical testing. Additionally, existing research fails to sufficiently incorporate dynamic time-varying analysis considering China's latest policy practices under the "Dual Carbon" strategy and the exogenous shocks caused by U.S. policy fluctuations.

This study aims to construct a more comprehensive analytical framework to thoroughly investigate the differential impact mechanisms of Chinese and U.S. CPU and their interaction effects on the volatility of China's new energy stock market, thereby filling the gaps in current research. Addressing the lack of systematic research on China's new energy market, particularly the comparative impact of Chinese and U.S. CPU differences, is the core issue this paper endeavors to resolve.

In summary, existing research on the economic impact of climate policy uncertainty exhibits three significant limitations: first, a lack of systematic comparison of the differential impact mechanisms between the two major economies of China and the United States, overlooking heterogeneous responses under different policy systems and market structures; second, a methodological over-reliance on static models, making it difficult to capture the dynamic characteristics of policy shocks as they evolve with economic cycles and extreme events; third, a failure to adequately account for the uniqueness of China as the world's largest new energy market, where the rapidly transitioning institutional context and financial environment provide a valuable and yet underexplored research setting. Future research urgently needs to adopt dynamic econometric methods within a cross-national comparative framework to conduct in-depth analysis of the Chinese context, aiming to build a theoretical system with greater explanatory power and practical relevance.

To address the gap in dynamic analysis in previous studies, this paper employs the TVP-SV-VAR model proposed by Primiceri and refined by Nakajima to capture the time-varying impact of Chinese and U.S. Climate Policy Uncertainty on the volatility of China's new energy stock market. By introducing time-varying parameters and stochastic volatility components, this model effectively captures structural changes in the dynamic relationships between variables and the heteroscedasticity commonly found in financial time series, making it particularly suitable for studying policy-related shocks. Compared to traditional fixed-parameter models, the TVP-SV-VAR model offers three main advantages: first, it can identify structural breaks caused by exogenous events such as financial crises or pandemics; second, it can accommodate typical stylized facts like volatility clustering and "fat tails"; third, it allows for distinguishing between short-term and medium-to-long-term effects of shocks through time-varying impulse response functions. These characteristics make it particularly effective for revealing the dynamic impact pathways of Chinese and U.S. CPU on the volatility of

China's new energy stock market across different periods, and especially suited for capturing the differentiated, time-varying transmission mechanisms of policy uncertainty from the two countries during extreme events.

2. Methodology Introduction

2.1. Measurement of Realized Volatility

In the methodology section, we first define and calculate the monthly realized volatility for China's new energy market. This study adopts the monthly realized variance as the core indicator to measure overall market volatility, a method widely recognized as a benchmark in volatility forecasting research.

The specific calculation process is as follows: The realized variance for a given month is obtained by squaring the returns of all trading days within that month and then summing them. The calculation formula is expressed as: $RV_{month} = \sum_{t=1}^{N} RV_t$, where RV_{month} represents the realized variance for month t, N denotes the total number of trading days in that month, and RV_t is the daily return on the t-th trading day. This approach essentially utilizes all the daily return data within the month to construct a more precise and robust estimate of monthly volatility, laying the foundation for subsequent modeling and forecasting.

2.2. Construction of the TVP-SV-VAR Model

Given the characteristics of China's macroeconomic structure, the relationships between economic variables may exhibit dynamic evolution features. To capture the dynamic time-varying effects induced by policy changes, this study employs the Time-Varying Parameter Vector Autoregression model with Stochastic Volatility (TVP-SV-VAR). By introducing time-varying parameters and a stochastic volatility mechanism, this model effectively characterizes the dynamic evolution patterns of the macroeconomic system. This modeling approach offers three significant advantages: 1) It captures changes in economic structure through parameter time-variation; 2) The stochastic volatility specification enhances the model's ability to adapt to heteroskedasticity; 3) The Bayesian estimation framework efficiently handles the high-dimensional parameter space. These characteristics make it particularly suitable for analyzing complex dynamic relationships in transitioning economies.

Extending the traditional Structural Vector Autoregression model (SVAR) to a time-varying form yields the TVP-SV-VAR model. The standard SVAR model expression is:

$$A_{y_t} = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_s y_{t-s} + \mu_t, t = s + 1, \cdots, n \tag{1}$$

where y_t is a k\times 1 dimensional observation vector (this paper includes three variables: CCPU, UCPU, RV), the coefficient matrices$A, B_1, B_2, \cdots B_s$ are k \times k dimensional coefficient matrices, the structural shock $\mu_t \sim N(0, \Sigma)$, and the standard deviation is σ_k. According to Nakajima's recursive identification strategy, the structures of the lower triangular matrix A and the covariance matrix Σ are set as:

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}, A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \cdots & \cdots & \ddots & 0 \\ a_{k1} & a_{k,k-1} & & 1 \end{pmatrix} \tag{2}$$

Transforming this into the reduced-form VAR representation:

$$y_t = \omega_1 y_{t-1} + \omega_2 y_{t-2} + \cdots + \omega_s y_{t-s} + A^{-1}\Sigma_{\varepsilon_t}, \varepsilon_t \sim N(0, I_k) \tag{3}$$

Where\ $\omega_s = A^{-1}B_s$, $\beta = \begin{pmatrix} \omega_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \omega_s \end{pmatrix}$ is a k^2 s \times 1 dimensional parameter vector. Defining $X_t = I_k \otimes (y_{t-1}, \dots, y_{t-s})$, the compact form is obtained:

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t, t = s + 1, \cdots, n \tag{4}$$

To characterize structural breaks in the economy, the parameters are extended to a time-varying form:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, t = s + 1, \cdots, n \tag{5}$$

Let $\alpha 1 = (a_{21}, a_{31}, \dots, a_{k,k-1})$ be the stacked vector of lower triangular elements, and $h_{jt} = (ln\sigma_{1t}{}^2, \dots, \ln\sigma_{kt}{}^2)$and $t = \text{s} + 1, \dots, \text{n}$. The parameters evolve according to a random walk process:

$$\beta_{t+1} = \beta_t + u_{\beta t}, \alpha_{t+1} = \alpha_t + u_{\alpha t}, h_{t+1} = \alpha_t + u_{ht} \tag{6}$$

The shock terms $(\varepsilon_t, u_{\beta t}, u_{\alpha t}, u_{ht})$ follow independent normal distributions with a block diagonal covariance matrix:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{\alpha t} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right) \tag{7}$$

The model is estimated using the Markov Chain Monte Carlo (MCMC) method, performing posterior inference via Gibbs sampling. Parameter initialization is set as: $u_{\alpha 0} = u_{\beta 0} = u_{h0} = 0$, $\Sigma_{\beta 0} = \Sigma_{\alpha 0} = \Sigma_{h0} = 10 \times I_k$, with hyperparameters $\left(\Sigma_\beta\right)_t^{-2} \sim \text{Gamma}(40, 0.02)$, $(\Sigma_\alpha)_t^{-2} \sim \text{Gamma}(40, 0.02)$, $(\Sigma_h)_t^{-2} \sim \text{Gamma}(40, 0.02)$. The sampling process executes 10,000 iterations, followed by parameter estimation.

3. Data and Variable Description

This study investigates the time-varying effects of Chinese and U.S. climate policy uncertainty on the volatility of China's new energy stock prices, utilizing the following core variables:

The Chinese Climate Policy Uncertainty index data is obtained from a study published by an international research team in Scientific Data (https://www.nature.com/articles/s41597-023-02817-5). This index, constructed through textual analysis of climate policy-related keywords in major Chinese newspapers, effectively captures policy fluctuations and uncertainty during China's progress toward its carbon peak and neutrality goals. The U.S. Climate Policy Uncertainty index data is sourced directly from the Climate Policy Uncertainty project website (http://www.policyuncertainty.com/climate_uncertainty.html). Using similar textual analysis methodology applied to U.S. policy documents and mainstream media, this index reflects policy dynamics in American climate governance, with its fluctuations generating significant international spillover effects on global climate governance and new energy markets due to the U.S.'s substantial influence.

The sample period covers January 2012 to December 2023 using monthly data. The monthly realized volatility data for new energy stock prices comes from the RESSET database. Figure 1 display the time series patterns of all variables, showing that China's new energy stock volatility experienced significant fluctuations around key policy events such as the Paris Agreement signing in 2016 and China's "Dual Carbon" goals announcement in 2021, as well as during major events including the COVID-19 pandemic in 2020 and the Russia-Ukraine conflict in 2022. Both Chinese and U.S. climate policy uncertainty indices exhibited notable fluctuations during major policy adjustments - the U.S. withdrawal from the Paris Agreement in 2017 caused a sharp spike in UCPU, while China's "3060" Dual Carbon targets announcement in 2021 generated a temporary peak in CCPU. For empirical analysis, all-time series data are logarithmically transformed before conducting descriptive statistics.

From the time - series graph, China's Climate Policy Uncertainty (CCPU) was at a relatively low level from 2012 to 2014. It then rose significantly from 2015 to 2017 and reached its peak in 2017, indicating that China's climate policy underwent major adjustments or saw increased uncertainty during this period. Although it declined somewhat thereafter, it still remained at a relatively high level, reflecting the continuous fluctuations in the policy environment. The United States' Climate Policy Uncertainty (UCPU) shows a different trend. Its value was relatively stable from 2012 to 2016, but it began to rise significantly after 2017 and remained volatile at a high level in subsequent years, which may be related to changes in the U.S. political climate and the reversals in international climate policy. China's New Energy Market Volatility (RV) has shown an overall downward trend from 2012 to 2023. Especially after 2015, the fluctuation range has gradually narrowed, indicating that the market is gradually becoming stable. Despite occasional fluctuations in the interim, the risk level of the new energy market has decreased in the long run. Overall, the uncertainty of climate policies in both China and the United States has increased since 2017, while the volatility of China's new energy market has shown a long - term moderating trend, reflecting the dynamic relationship between policy adjustment and market adaptation.

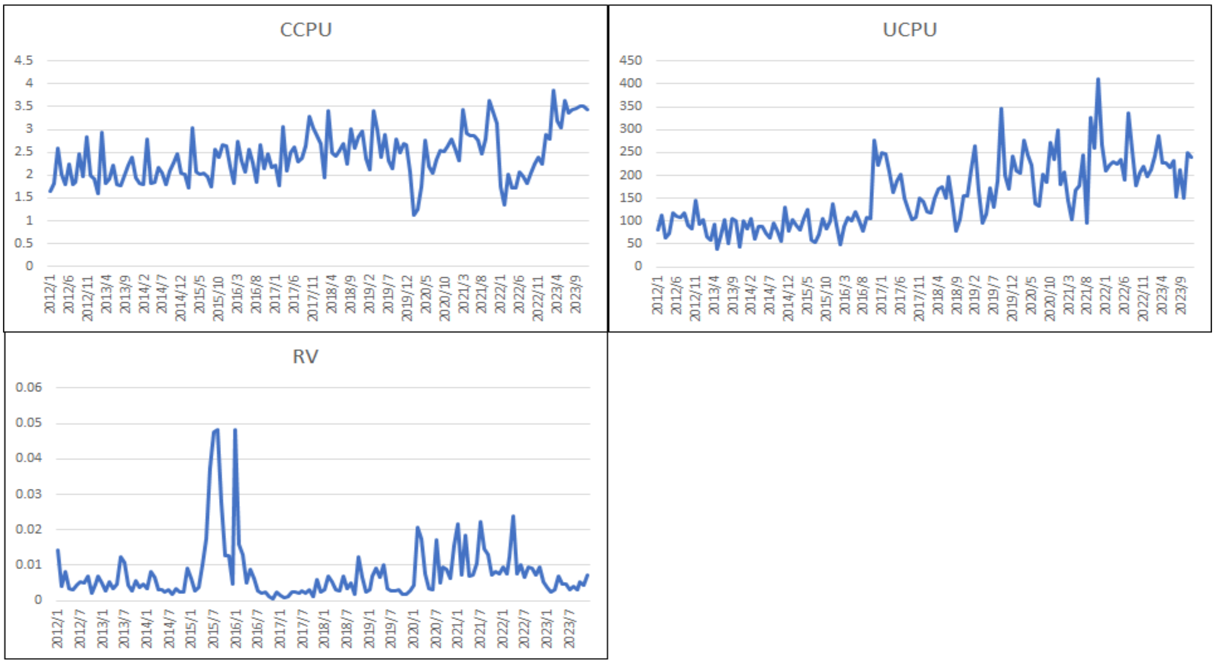

Figure 1. Timing diagram of CCPU, UCPU, and RV

Table 1. Descriptive Statistics.

	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis	ADF Test
CCPU	0.854	0.228	0.111	1.351	-0.190	0.072	-8.0636***
UCPU	4.926	0.498	3.640	6.019	-0.227	-0.669	-8.9559***
RV	-5.233	0.817	-7.482	-3.028	0.263	0.382	-6.1308***

Table 1 presents the descriptive statistics of each variable after logarithmic transformation. It can be seen that the mean value of China's Climate Policy Uncertainty (CCPU) is 0.854, with a wide fluctuation range (minimum value 0.111, maximum value 1.351) and a standard deviation of 0.228, indicating a certain degree of volatility. Its distribution is close to normal (skewness -0.190, kurtosis 0.072). The ADF test rejects the null hypothesis at the 5% significance level, indicating that the sequence is basically stationary. The mean value of the United States' Climate Policy Uncertainty (UCPU) is relatively high (4.926), with a large range (3.640~6.019) and a standard deviation of 0.498, showing significant volatility. Its distribution is left-skewed (skewness -0.227) and relatively flat (kurtosis 0.669). The ADF test rejects the null hypothesis ($p<0.001$). The mean value of China's New Energy Stock Market Volatility (RV) is -5.233 (due to logarithmic processing), with obvious differences in extreme values (-7.482~-3.028) and a standard deviation of 0.817, reflecting severe volatility. Its distribution is slightly right-skewed (skewness 0.263) and has a slightly higher peak (kurtosis 0.382). The ADF test strongly rejects the unit root ($p=0.000$), indicating that the sequence is stationary.

4. Empirical Analysis

4.1. Time-Varying Impulse Response Analysis

Table 2 consists of three rows from top to bottom, which are the sample autocorrelation coefficients, sample paths, and posterior distributions respectively. Among them, the sample autocorrelation coefficients of Σ_β, Σ_α, Σ_h all tend to zero as the number of simulations increases, indicating that 10,000 MCMC simulations can eliminate the sample autocorrelation caused by the sampling method to a certain extent. At the same time, the sample paths fluctuate around the posterior mean, showing a "white noise" fluctuation trajectory and being relatively stable overall, which indicates that the samples obtained by the MCMC algorithm are independent and valid. The MCMC estimation results show that the posterior means and confidence intervals of the model parameters have good statistical significance, indicating that the Markov chain has good convergence. Specifically, the posterior means of the smoothing parameters (sb1 and sb2) for time-varying volatility are 0.0237 and 0.0226 respectively, and their 95% confidence intervals ([0.0191, 0.0301] and [0.0183, 0.0281]) do not include zero, indicating that the model can effectively capture the persistent characteristics of volatility. In addition, the posterior means of the variance parameters (sh1 and sh2) for stochastic volatility are 0.2373 and 0.2022 respectively, but the confidence intervals are relatively wide (for example, the 95% interval of sh1 is [0.0827, 0.4800]), reflecting that there may be structural breaks or heteroscedasticity in the volatility of the new energy stock market. Overall, the model estimation results are robust, providing a reliable basis for subsequent impulse response analysis.

Table 2. Sample Autocorrelation Coefficients, Sample Paths, and Posterior Distributions

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
sb1	0.0237	0.0028	0.0191	0.0301	0.338	8.28
sb2	0.0226	0.0025	0.0183	0.0281	0.013	6.60
sa1	0.0753	0.0291	0.0399	0.1507	0.535	74.74
sa2	0.1040	0.0462	0.0460	0.2186	0.813	85.33
sh1	0.2373	0.1040	0.0827	0.4800	0.291	100.91
sh2	0.2022	0.0795	0.0827	0.3833	0.470	71.12

For the dynamic impulse response analysis among China's Climate Policy Uncertainty (CCPU), U.S. Climate Policy Uncertainty (UCPU), and the volatility of China's new energy stock market (RV), the TVP-SV-VAR model depicts the dynamic response of variables in different periods through two functions, namely the equally spaced impulse response function and the time-point impulse response function.

4.2. Analysis of Equally Spaced Impulse Response

The equally spaced impulse response is used to analyze the lag and time-varying nature of impulse responses between variables. Since the cycle of policy changes is generally long, this paper sets the time intervals as lag 1 period (one month), lag 3 periods (one quarter), and lag 6 periods (half a year) respectively, to measure the short-term, medium-term, and long-term time-varying effects.

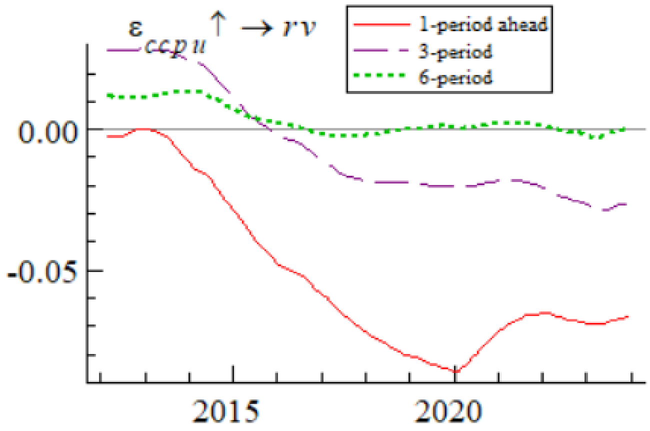

Figure 2. Equally Spaced Impulse Response of China's Climate Policy Uncertainty to the Volatility of New Energy Stock Market

Figure 2 presents the results of the equally spaced impulse response of China's climate policy uncertainty to the volatility of the new energy stock market. Overall, the impact of China's CPU shock on the volatility of the new energy market is negative, indicating that it has played a role in curbing volatility and stabilizing the market to a certain extent. From the time-varying path perspective, the mitigating effect of China's CPU continued to strengthen between 2015 and 2020, with the impulse curve deepening negatively; although it remained negative after 2020, the curve showed a slow upward trend, and the mitigating effect weakened. From the perspective of time-varying effects in different cycles, the peak of the short-term (lag 1 period) impulse response is approximately -0.10, the response amplitude in the 3rd lag period narrows and there is a positive-negative alternation phenomenon, with the highest peak and lowest peak being approximately 0.02 and -0.03 respectively. The impact of the 6th lag period gradually weakens to zero, indicating that the shock effect gradually fades over time. From 2012 to 2016, the short-term impulse curve only showed a weak negative impulse, while the medium- and long-term impulses were positive, which is basically consistent with the static VAR results mentioned earlier. In general, the impulse impact of China's climate policy uncertainty on the volatility of new energy stocks is mainly concentrated in the short term, and the medium- and long-term impulse effects are not obvious.

This empirical result can be reasonably explained from the perspective of the evolution of China's new energy industry policies and market maturity. First, the sustained negative impulse response reflects the inherent stability of China's climate policy system. Although uncertainty arises during policy discussions, the top-level design of the "dual carbon" goals provides a clear long-term orientation for the market. This makes policy uncertainty instead prompt investors to pay more attention to fundamentals and reduce speculative transactions, thereby curbing market volatility. Second, the time-varying characteristic of the inhibitory effect is highly consistent with the policy evolution stage: The period from 2015 to 2018 was just the adjustment period of China's new energy subsidy policy. The market was highly sensitive to policy signals, and any policy movement would trigger investors to re-evaluate asset values, leading to an enhanced inhibitory effect. After 2018, as the industry entered the grid parity stage, the market's dependence on policies decreased, making the inhibitory effect weaken accordingly. Finally, the short-term nature of the impact is consistent with the theory of financial market information efficiency. New policy signals will be quickly digested and priced by the market, while medium- and long-term fluctuations are more driven by fundamental factors. In summary, China's climate policy uncertainty has effectively curbed the volatility of new energy stocks in the short term through a stable expectation mechanism, and this effect gradually weakens as the industry matures, reflecting the dynamic evolution process of the relationship between policy and the market.

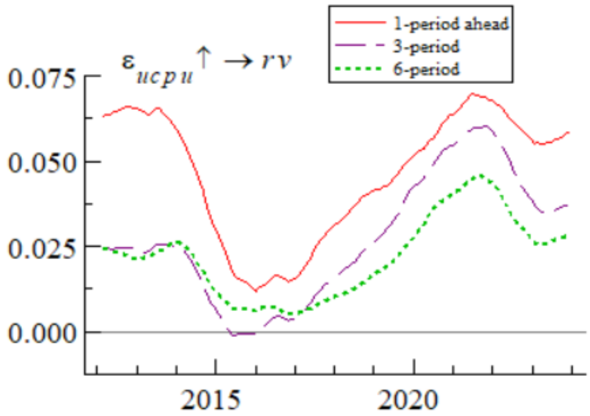

Figure 3. Impulse Response of U.S. Climate Policy Uncertainty to the Volatility of China's New Energy Stock Market

Overall, the impact of UCPU shock on the volatility of the new energy stock market is sustainably positive, indicating that it significantly exacerbates market volatility, forming a sharp contrast with the stabilizing effect of China's CPU on the market. From the time-varying path perspective, the impulse response shows a fluctuating pattern of "decline—rise—fall—rise again": it showed a downward trend before 2015 and turned negative temporarily in the mid-2016; it continued to rise between 2016 and 2022 and reached its peak in 2021–2022; it fell briefly after 2022 and rose again after 2024. From the perspective of time-varying effects in different cycles, the peak of the short-term impulse response is about +0.075, the peak after 3 periods still remains at about +0.050 without obvious weakening, and the peak at the 6th lag period is about +0.040, with only a slight decrease, indicating that the U.S. policy shock has a relatively strong sustainability.

This empirical result can be reasonably explained from the perspective of the U.S. political and economic environment and its global market status. First, the sustained positive impulse response reflects the characteristic that U.S. climate policy is highly influenced by political cycles. The partisan divisions on climate issues have led to a lack of policy continuity. In particular, actions such as the Trump administration's announcement of withdrawing from the Paris Agreement in 2017 sent strong negative signals to the market, exacerbating investors' concerns about the prospects of the global clean energy transition and thus amplifying market volatility. Second, the time-varying path is closely related to the policy shifts in the United States: The period from 2017 to 2020 was a period of drastic adjustment of U.S. energy policy, and policy reversals significantly increased market uncertainty. After the Biden administration took office in 2020 and rejoined the Paris Agreement and launched the Inflation Reduction Act, although the policy direction tended to stabilize, the policy uncertainty accumulated in the early stage still continued to affect the market. Finally, there is no obvious short-term dominance in the impact, because U.S. climate policy as a whole still has strong variability, so there is no significant hierarchical effect in the short, medium and long-term curves of the United States. The differentiated impacts of China's and the U.S.'s CPU reveal that policy institutional design plays a key role in market stability. China maintains policy consistency and transparency through top-level design and gradual reform, enabling CPU to play a role in curbing volatility. U.S. policies lack consistency due to political cycles and regime changes, which not only exacerbate volatility in its domestic market, but also spill over to emerging markets through international capital flows and supply chain channels. This indicates that in the process of global climate governance, establishing a predictable and cross-partisan consensus policy framework is more important than simply increasing financial investment. The uncertainty of a country's policy may become an external source of market volatility in other countries. Therefore, strengthening international policy coordination and building a more resilient energy supply chain are of practical urgency for stabilizing global new energy market volatility.

By comparing the impulse response results of China and the United States, fundamentally different mechanisms of action can be revealed. In terms of the impact direction, China's climate policy uncertainty exhibits a volatility-inhibiting effect, while the United States shows a volatility-exacerbating effect. This reflects the essential differences between the two countries in policy system stability and market expectation-guiding capability. In terms of the time-varying path, China's impulse curve generally shows a gentle decline, as its policy formulation and implementation have a long cyclical nature. In contrast, the United States' impulse curve is more volatile, as its policies are more affected by government transitions, reflecting the policy transmission characteristics under different political systems. From the perspective of timeliness, the shocks of both countries are strongest in the short term, but the duration of the U.S. shock is relatively longer. This may be due to the United States' core position in the global financial system, which makes its policy shocks have stronger spillover sustainability. These comparison results indicate that the stability of China's new energy market relies more on the consistency and predictability of domestic policies, while U.S. policy uncertainty constitutes a significant external risk source. This finding has important implications for cross-border risk prevention and policy coordination.

4.3. Analysis of Impulse Responses at Different Time Points

In the aforementioned equally spaced impulse analysis, we found that the impulse curves of climate policy uncertainty (both from China and the United States) on the volatility of the new energy stock market share a common feature: there are turning points in the impulse curves around the two time points of 2016 and 2020. Based on this, we conduct a dedicated time-point impulse response analysis for these two time points.

The time-point impulse response is used to analyze the dynamic impact of variables on structural shocks at special time points. This paper selects two representative impulse time points based on the phased peaks of China's Climate Policy Uncertainty Index for research, namely January 2016 (China's accession to the Paris Agreement) and October 2020 (the COVID-19 pandemic), with an impulse response length of 6 periods (1 period is 1 month).

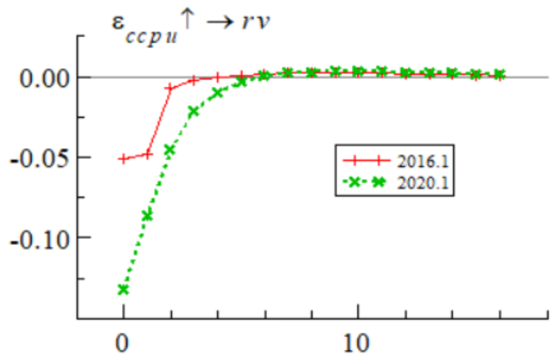

Figure 4. Time-point Impulse Response Graph of CCPU

Overall, at both time points, the impact of China's climate policy uncertainty on the volatility of the new energy stock market is negative, and the negative value at the 2020 time point is larger. This indicates that China's climate policy adjustments still have an inhibitory effect on market volatility at both time points, and the inhibitory effect is more obvious at the 2020 time point. From the perspective of time-variability, from period 0 to period 6, the impulse effects at the two time points of January 2016 and January 2020 show significant differentiation: the initial negative depth of the shock in January 2016 reaches -0.05, and then it slowly rises back to zero; while the negative impact in January 2020 reaches -0.10 in the same period and quickly returns to zero in period 6. Both time points approach zero after period 6, but the recovery speed in January 2020 is faster. Both curves first rise rapidly from negative impulses to recover to 0.00, then show weak positive impulses, and finally stabilize at the 0 axis. By comparing the two time-point impulse curves, we find that the 2016 curve is generally higher than the 2020 curve, but they basically coincide after period 6. Among them, the recovery curve at the January 2020 time point rises smoothly and rapidly, while the recovery curve at the January 2016 time point first rises slowly, then rises rapidly, and then rises slowly again, showing obvious concavity and convexity.

First, regarding the positive and negative interval characteristics of the impulse response curve, the overall negative impulse indicates that China's climate policy uncertainty has exerted a market volatility-inhibiting effect at all selected time points. This phenomenon stems from the "expectation management" mechanism in China's policy-making process. Although uncertainty arises in the initial stage of policy adjustment, the government conveys clear long-term transformation signals to the market through top-level designs such as the "dual carbon" goals, making investors regard policy discussions as a necessary process for industrial standardization and thereby reducing short-term speculative behaviors. The weak positive impulse that appears in the later stage reflects the market's normal digestion process of policy implementation. When specific policy details are clarified, differentiated expectations among enterprises due to differences in adaptation capabilities will trigger short-term price revaluation volatility. Second, the morphological characteristics of the curve trend are closely related to the policy environment in different periods. January 2016 was just the initial stage of the signing of the Paris Agreement, and China's climate policy system was still in the construction phase. The market needed more time to understand and digest the policy framework, which was manifested as a slow rebound in the impulse response. In January 2020, China's new energy industry had undergone policy baptisms such as the "531 New Policy". Market participants' ability to adapt to policy adjustments had been significantly enhanced. Coupled with the government's policy resolve to emphasize green recovery during the pandemic, the shock was digested more quickly, manifested as a smooth and rapid rebound of the recovery curve. Finally, the comparative differences between the two curves profoundly reflect the different stages of policy evolution in China's new energy industry. The 2016 curve was relatively high and recovered slowly, corresponding to the policy introduction period of industrial development, where the market mechanism was still immature and the impact of policy shocks was more lasting. The impulse curve in January 2016 showed a significant "convex" feature: initially rising slowly, accelerating in the mid-term, and gradually stabilizing in the later period. This reflects the three-stage adjustment process of the market from waiting and seeing to concentrated position adjustment and then to digestion during the policy exploration period. January 2020, on the other hand, showed a smooth "concave" recovery path. This indicates that against the background of significantly improved market depth and a mature policy framework, investors could quickly complete asset re-pricing based on clear expectations. Essentially, this difference reflects the improvement in the effectiveness of the policy transmission mechanism and the significant enhancement of market resilience during the transformation of China's new energy industry from policy-driven to market-driven. It also reflects the gradual formation of a benign interactive mechanism between policy and the market.

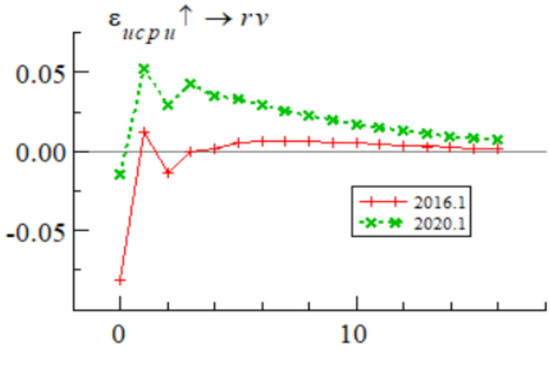

Figure 5. Time-point Impulse Response Graph of UCPU

As can be seen from Figure 5, overall, the impulse curves at the two time points both start with a brief negative value, then rise rapidly to a positive value, and finally weaken slowly to the 0 axis. The response trends of the two time points in the lag period are highly consistent, both rising rapidly first, then experiencing a brief jump down, then a jump up, and finally recovering slowly to 0.00. Both curves show obvious bulges and depressions. By comparing the two curves, we find that the time-point impulse curve in 2020 is completely above the curve in 2012. Among them, the adjustment of U.S. climate policy in 2016 once had an extremely rare mitigating effect on the volatility of the new energy market, with the initial impulse value reaching -0.08. In contrast, the UCPU's impulse on market volatility in 2020 was basically positive, and U.S. policies continued to exacerbate market volatility. Unlike China, the impact of U.S. policy adjustments on the new energy market lasts for a very long time, and the impulse curve remains positive for a long time, failing to weaken to zero even after 10 periods.

From the perspective of the positive and negative intervals of the impulse response curve, the shocks at both time points show a pattern of "brief negative value - sustained positive value". The brief negative impulse in the initial stage may originate from the time lag in the market's digestion of new information, and the temporary decline in trading activity leads to suppressed volatility. However, the curve subsequently remains in the positive interval, indicating that U.S. policy uncertainty mainly exerts a sustained positive impact on the Chinese market through emotional transmission and capital flow channels, reflecting its essential attribute as an external risk source. In terms of the curve trend, both time points exhibit obvious concavo-convex fluctuation characteristics. This pattern of "rapid surge - jump decline - rise again" reflects the special mechanism of U.S. policy transmission. The rapid initial rise of the curve indicates that policy shocks are quickly transmitted to China through global market linkage, triggering a sharp increase in trading activity. The subsequent jump decline corresponds to the market's initial digestion of the shock, while the subsequent rise reflects the secondary market reaction caused by multiple links in the U.S. policy-making process. Such concavo-convex changes highlight the wave-like transmission characteristics of U.S. policy shocks. When comparing the differences between the two curves, the 2020 impulse curve has shifted upward overall and has a greater degree of concavo-convexity, indicating that the impact intensity of U.S. policy uncertainty is increasing. The 2016 curve was relatively low and had a large negative impulse, which may be related to the relatively stable policy environment at that time. The 2020 curve, on the other hand, remained at a high level, reflecting the significant increase in policy uncertainty caused by the exacerbation of U.S. political polarization. This difference confirms that changes in the U.S. domestic political environment have amplified the spillover effect of its policies, leading to a continuous increase in the impact on China's new energy market and a prolonged duration of influence.

There are systematic differences in the impact of climate policy uncertainty between China and the United States on the new energy market. China's policy shocks are mainly manifested as negative impulses, and the overall curve is smooth and recovers relatively quickly, reflecting that domestic policies play a role in stabilizing the market through clear top-level design. U.S. policy shocks, on the other hand, are sustained positive, with the curve showing multiple concavo-convex fluctuations and lasting impacts, indicating that its policy reversals continuously exacerbate volatility in the Chinese market through global transmission channels. In terms of the impact mechanism, the inhibitory effect of China's policies originates from "expectation management", where the market regards policy discussions as a signal for industrial standardization. The exacerbating effect of U.S. policies stems from the repetitiveness of its legislative process, where each policy node triggers market re-pricing. From the perspective of evolutionary trends, the impact of China's policies gradually weakens over time, reflecting enhanced market adaptability. In contrast, the impact of U.S. policies increased significantly in 2020, indicating that the spillover effect caused by its political polarization continues to expand. These differences confirm that China's climate policy has become a market stabilizer, while U.S. policy constitutes a significant external risk source.

5. Conclusions and Recommendations

Against the backdrop of accelerated global energy transition in the post-pandemic era, climate policy uncertainty has become a key factor affecting the stability of the new energy market. This study uses data from January 2012 to December 2023 to analyze the dynamic relationship between China's climate policy uncertainty, U.S. climate policy uncertainty, and the volatility of China's new energy stock market. Through equally spaced impulse analysis and time-point impulse analysis using the TVP-SV-VAR model, the following main conclusions are drawn:

(1) There are differential impacts of climate policy uncertainty between China and the United States on new energy market volatility. Specifically, China's climate policy uncertainty generally inhibits new energy market volatility, while U.S. climate policy uncertainty exacerbates new energy market volatility.

(2) As time extends, the impact of both China's and U.S. climate policy uncertainty on new energy stock market volatility will gradually decrease, but the impact of U.S. climate policy uncertainty on the market is more persistent. The negative impact of China's climate policy uncertainty on new energy stock market volatility will rapidly weaken as the lag period increases, eventually tending to zero. In contrast, the positive impact of U.S. climate policy uncertainty on new energy stock market volatility does not significantly weaken with the increase of the lag period.

(3) Different political and economic events will lead to different trends in the impact of climate policy uncertainty at different time points on the stock market. For example, when China joined the Paris Agreement in 2016, China's climate policy uncertainty had a slight negative impact on new energy stock market volatility, and U.S. climate policy uncertainty had a rare negative impact on new energy stock market volatility in the same year. When the COVID-19 pandemic broke out in 2020, China's climate policy uncertainty had a relatively strong negative impact on new energy stock market volatility, while U.S. climate policy uncertainty had a significant positive impact on new energy stock market volatility in the same year.

Against the backdrop of accelerated global energy transition, climate policy uncertainty has become a key variable affecting the stability of the new energy market. Based on the empirical results of this study, to reduce the negative impact of climate policy uncertainty on new energy market volatility and promote the stable development of energy transition, policy makers can take the following targeted measures: First, China should further strengthen the continuity and transparency of climate policies. Especially at key time nodes (such as the promotion period of the "dual carbon" goals or after the signing of international agreements), by regularly releasing policy roadmaps and improving information disclosure mechanisms, the market's expectations for policy stability can be consolidated, thereby continuing and enhancing its inhibitory effect on new energy market volatility. At the same time, in view of the significant spillover effect of U.S. climate policy uncertainty on China's new energy market, China needs to establish a dynamic monitoring and early warning mechanism, and strengthen policy coordination through bilateral or multilateral dialogue platforms (such as the China-U.S. Climate Working Group) to reduce the transmission risks caused by U.S. policy swings. Second, when responding to unexpected events (such as pandemics or geopolitical conflicts), the government can offset external shocks through structural policy tools (such as green credit and tax incentives). For example, the strong inhibitory effect of China's climate policies on market volatility during the 2020 pandemic shows that timely policy intervention can effectively stabilize market sentiment. Finally, it is recommended to incorporate new energy market volatility into the macroprudential regulatory framework, regularly evaluate policy effects and dynamically adjust intervention efforts, so as to balance policy goals and market stability in the long term.

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