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# Time-varying Impact Mechanisms of China's Environmental Governance Policy Uncertainty on New Energy Enterprises: A Frequency Domain Perspective

**Abstract.** *This paper employed the TVP-VAR frequency connectedness method to analyse the dynamic spillover effects between China's environmental governance policy uncertainty (EGPU) and new energy stock markets. Drawing on high-frequency data from 2015 to 2023, the study reveals that significant risk contagion effects exist within new energy markets, which primarily operate through short-term channels. Static connectedness analysis confirms the dominant role of short-term spillover effects. Environmental governance policy uncertainty functions as a net spillover receiver during most periods, suggesting that new energy market development conditions inversely influence policy uncertainty perceptions. Different new energy sub-sectors play differentiated roles within the system: power equipment manufacturing enterprises primarily transmit risk, whilst emerging technology enterprises predominantly absorb system shocks. Dynamic analysis reveals significant time-varying characteristics of spillover effects, with the Total Connectedness Index (TCI) reaching a peak of 65% during the COVID-19 period in 2020, reflecting the amplification effect of extreme events on systemic risk. The research findings provide important reference points for investors' risk management and asset allocation strategies, as well as for policymakers' green finance policy design.*

**Keywords**: *environmental governance policy uncertainty, frequency domain connectedness, new energy stocks, TVP-VAR.*

**JEL Classification:** G11, G12, Q48, Q58, C32.

| Received: 6 July 2025 | Revised: 11 December 2025 | Accepted: 13 December 2025 |
|---|---|---|

DOI: 10.24818/18423264/59.4.25.08

## 1. Introduction

As global climate change issues have intensified and the concept of sustainable development has gained a deeper acceptance, the new energy industry has emerged as a crucial strategic pillar for economic transition and green development worldwide (Androniceanu and Sabie, 2022). Simultaneously, as the world's second-largest economy and the largest carbon emitter, China assumes significant responsibility in driving the necessary energy structure transformation and achieving its carbon peak and carbon neutrality targets (Liu et al., 2022). Moreover, China's renewable energy market represents the world's largest in terms of installed capacity and investment scale, with its policy framework serving as a reference model for numerous developing economies pursuing green transitions. Examining the Chinese context thus provides valuable insights with broader applicability to understanding policy-market interactions in rapidly evolving renewable energy sectors globally (Zhao et al., 2022). Since the 2006 promulgation of the Renewable Energy Law, the Chinese government has successively introduced a series of environmental and new energy development policies. These policies, which include renewable energy development plans, the construction of a carbon emissions trading system, new energy vehicle promotion policies, and green finance policies, have greatly accelerated the rapid development of China's new energy industry (Guilhot, 2022; Sawin, 2012).

From an industry development perspective, China’s new energy sector has achieved remarkable accomplishments under concerted policy guidance. By 2024, projections suggest that China's new renewable energy capacity additions will account for an estimated 86% of the nation’s total new power capacity additions, with the cumulative renewable energy capacity representing 56% of the national total (Xinhua, 2025). Furthermore, new energy vehicle production and sales have consistently maintained global leadership for several consecutive years, and the power battery industry chain has become increasingly sophisticated. However, whilst the industry has experienced this rapid development, new energy enterprises simultaneously face unprecedented challenges stemming from policy uncertainty (Dong et al., 2022).

This policy uncertainty manifests itself across multiple critical dimensions. Firstly, the dynamic adjustment of policy targets is evident. Renewable energy development goals, carbon emission peak timetables, and new energy vehicle promotion targets, for instance, undergo regular adjustments and optimisation over different periods (Zhang and Qin, 2018). Secondly, the policy instruments demonstrate diversity and complexity, involving the combined use and dynamic modification of various policy tools such as fiscal subsidies, tax incentives, carbon trading schemes, and green bonds. Thirdly, regional variations exist in policy implementation, where significant differences are observed across distinct regions regarding the intensity, standards, and timing of environmental policy execution. Finally, the international policy environment exerts a notable influence, which includes the impacts of international carbon neutrality commitments, trade policy shifts, and the coordination of technology standards.

As policy-sensitive entities, the development trajectories of new energy enterprises are intimately linked to policy changes. The presence of policy uncertainty affects enterprise behaviour through several channels. Regarding investment decisions, policy uncertainty elevates enterprises' anticipated risk concerning future returns, frequently leading to delayed or insufficient investment (Li et al., 2023). For technological innovation, uncertainty in policy standards and directional mandates influences enterprises' research and development investment and subsequent technology pathway choices (Hao et al., 2021). Within market positioning, regional policy disparities impact enterprises' capacity allocation and market expansion strategies. Finally, concerning financial performance, policy changes directly affect enterprises' profitability and overall cash flow conditions (Yu et al., 2024).

Crucially, China's new energy industry is currently undergoing a critical transition from a policy-driven to a market-driven development model. With the gradual phase-out of subsidy policies, the advent of the grid parity era, and intensifying market competition, new energy enterprises confront increasingly complex operating environments (Hoang et al., 2021; Wang and Liu, 2024). Against this backdrop, conducting an in-depth study of the impact mechanisms of environmental policy uncertainty on new energy enterprises will not only assist enterprises in better navigating policy risks and formulating scientific business strategies, but will also provide vital reference material for policymakers aiming to optimise policy design and enhance policy effectiveness.

Through a systematic review of existing literature, several gaps and deficiencies were identified in the research on the impact of policy uncertainty on new energy enterprises. (1) In terms of research content, the existing literature mainly concentrated on macroeconomic levels and traditional industry sectors, with relatively limited research specifically targeting policy uncertainty in the new energy industry. Most studies focused on general policy uncertainty or economic policy uncertainty, lacking in-depth analysis of environmental policy uncertainty as a specific domain. Even when few studies involved the new energy industry, they mostly employed industry-level aggregated data, lacking micro-level analysis of specific enterprises. (2) In terms of research methods, existing studies primarily adopted static analysis methods, unable to effectively capture the time-varying characteristics and dynamic evolution processes of policy uncertainty impacts on enterprises. Traditional panel data regression models and event study methods, whilst able to identify average effects of policy uncertainty, were difficult to reveal the variation patterns and transmission mechanisms of such impacts across different periods. Additionally, existing research often treated policy uncertainty as an exogenous variable, lacking in-depth analysis of the interactive mechanisms between policy uncertainty and enterprise performance. (3) In terms of sample selection, existing research mostly employed industry average data or single enterprise cases, lacking comparative analysis and differentiated research on different types of new energy enterprises. Significant heterogeneity existed within the new energy industry, with enterprises in different sub-sectors such as hydropower, nuclear power, solar energy, wind energy, and energy storage demonstrating significant differences in technical characteristics, market environments, and policy sensitivity. However, existing research often ignored this heterogeneity. (4) In terms of impact mechanism analysis, existing research mainly focused on the direct impact of policy uncertainty on enterprise financial performance, lacking in-depth analysis of impact transmission pathways and temporal dimensions. In particular in frequency domain analysis, existing research rarely distinguished between short-term, medium-term, and long-term effects of policy uncertainty and lacked systematic analysis of transmission mechanisms of policy uncertainty shocks between different new energy enterprises.

The existence of these research gaps not only limited academic understanding of policy uncertainty impact mechanisms, but also made it difficult to provide targeted policy recommendations and management insights for policymakers and enterprise decision-makers. Therefore, conducting systematic research on the impact of China's environmental policy uncertainty on new energy enterprises possessed significant theoretical and practical value.

Based on the above research background and existing research gaps, this study aimed to deeply explore the specific impact mechanisms and dynamic characteristics of China's environmental policy uncertainty on major new energy enterprises. Specifically, this research focused on the following core questions: First, did environmental policy uncertainty significantly impact stock price volatility of new energy enterprises? This question aimed to verify whether significant statistical relationships existed between environmental policy uncertainty and new energy enterprise market performance, and to determine the direction and intensity of such relationships. Second, did different types of new energy enterprises demonstrate varying sensitivity levels to environmental policy uncertainty? Considering the heterogeneity within the new energy industry, this study conducted a comparative analysis of response differences to policy uncertainty among enterprises in different sub-sectors including hydropower, nuclear power, solar energy, wind energy, and energy storage. Third, what were the time-varying characteristics of environmental policy uncertainty impacts on new energy enterprises? This study analysed the variation patterns of policy uncertainty impact effects across different periods, identifying cyclical and structural changes in impact intensity. Fourth, what were the transmission mechanisms of policy uncertainty shocks between different new energy enterprises? This study analysed how policy uncertainty shocks propagated between different enterprises and the differences in such transmission effects across different time scales. Fifth, what were the frequency characteristics of environmental policy uncertainty impacts on new energy enterprises? This study distinguished between short-term, medium-term, and long-term effects of policy uncertainty, analysing differences in impact mechanisms across different frequency domains.

To deeply analyse these questions, this study selected representative new energy listed enterprises in China as research subjects. These enterprises covered major sub-sectors of the new energy industry including hydropower, nuclear power, solar energy, wind energy, and energy storage, possessing good representativeness and typicality that could comprehensively reflect the development status and policy sensitivity characteristics of China's new energy industry.

This study contributes significantly to the existing literature in several key areas. Firstly, regarding the scope of the research, we conducted the first systematic investigation into how China's environmental policy uncertainty affects a representative selection of new energy companies. This effectively closes a gap in policy uncertainty research specific to the new energy sector. By selecting seven market-leading companies that span various new energy sub-sectors, we could comprehensively reflect the patterns of impact and the mechanisms of transmission for policy uncertainty across the entire industry. Secondly, on a theoretical level, this study enhances understanding of the mechanisms through which policy uncertainty operates. In particular, we reveal the time-varying and frequency characteristics of policy uncertainty's impact on new energy companies. Analysing the effects of policy uncertainty across different time scales allows us to offer new theoretical perspectives for grasping the transmission mechanisms of policy uncertainty. Thirdly, in the empirical domain, this study establishes a systematic quantitative assessment framework for the impact of policy uncertainty on new energy companies. This framework offers significant practical guidance for policymakers seeking to evaluate the market effects of environmental policies. Furthermore, through a comparative analysis of the varying sensitivities to policy uncertainty among different types of new energy companies, we provide essential foundations for investors' risk management and investment choices.

This work employs the Time-varying Parameter Vector Autoregression-Frequency Connectedness (TVP-VAR Frequency Connectedness) method, which offers substantial advantages over conventional analytical approaches. Firstly, the TVP-VAR model permits the parameters to evolve over time, which allows us to effectively capture the time-varying nature of how policy uncertainty affects new energy companies. This capability holds major importance for analysing corporate responses within rapidly shifting policy environments. Secondly, the frequency connectedness technique allows us to decompose the associations between variables into distinct frequency domains. This enables us to identify the short-term, medium-term, and long-term effects of policy impacts, which is invaluable for understanding the multi-level impact mechanisms of policy uncertainty. In addition, this method effectively addresses endogeneity issues within multivariate systems. By constructing impulse response functions and variance decomposition, we can deeply analyse the transmission pathways and the intensity of impact stemming from policy uncertainty shocks between various new energy companies. The innovative deployment of this methodological framework not only elevates the reliability and precision of the research findings but also offers crucial methodological references for subsequent research in cognate fields. By applying this advanced econometric method, this study can more accurately identify and quantify the dynamic impacts of environmental policy uncertainty on new energy companies, thus providing robust empirical evidence for an in-depth understanding of the economic effects of policy uncertainty (Zeng et al., 2023).

## 2. Methodology and data

### *2.1 TVP-VAR connectedness*

Through the implementation of a time-varying methodology, connectedness dynamics could be examined and analysed. We utilised a time-varying parametric vector autoregressive (TVP-VAR) connectedness framework grounded in the work established by Diebold and Yilmaz (2014; 2012) for measuring return spillovers amongst variables (Antonakakis et al., 2020). The analysis commenced with the subsequent standard equations:

$$Yt = \beta_t Y_{t-1} + \varepsilon_t,\ \varepsilon_t \tilde{} N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu_t,\ \nu_t \tilde{} N(0, R_t) \tag{2}$$

$$Yt = A_t \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

Where, $Yt$,$\varepsilon_t$and $\nu_t$ is $N \times 1$ vector; $\beta_t$ rely on $\beta_{t-1}$ and is an error matrix of $N \times N_p$ ; $Y_{t-1}$ is an error matrix of $N_p \times 1$. $A_t$, $S_t$ and $R_t$are $N \times N$ matrix; $p$ is the chosen lag length. $Yt = A_t \varepsilon_{t-1} + \varepsilon_t$ is the Wold representation. Diebold and Yilmaz (2012) developed a new function of spillover index method via using the impulse response function introduced by Koop et al. (1996) and generalised forecast error variance (GFEV) introduced by Pesaran and Shin (1998), then we will estimate the $H$-step-ahead GFEV decomposition (GFEVD), is estimated as:

$$\tilde{\theta}^{g}_{ij,t}(H) = \frac{\sum_{t=1}^{h-1} \psi^{2,g}_{ij,t}}{\sum_{i=1}^{N} \sum_{t=1}^{h-1} \psi^{2,g}_{ij,t}} \tag{4}$$

As $\psi^{2,g}_{ij,t}(H) = S^{-\frac{1}{2}}_{ij,t} A_{h,t} \sum_t \varepsilon_{ij,t}$, $\sum_t$ is a covariance matrix of errors term $\varepsilon_{ij,t}$and $\sum_{j=1}^{N} \tilde{\theta}^{g}_{i,t}(H) = 1, \sum_{i,j=1}^{N} \tilde{\theta}^{N}_{ij,t}(H) = N$. We calculate total connectedness index (TCI) as:

$$C^{g}_{t}(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}^{g}_{ij,t}(H)}{\sum_{j=1}^{N} \tilde{\theta}^{g}_{ij,t}(H)} \times 100 \tag{5}$$

The directed connectedness from index *i* to index *j* can be estimated as:

$$C^{g}_{i \to j,t}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}^{g}_{j,t}(H)}{\sum_{j=1}^{N} \tilde{\theta}^{g}_{ji,t}(H)} \times 100 \tag{6}$$

Then, the directed connectedness received by index *i* from system as:

$$C^{g}_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}^{g}_{ij,t}(H)}{\sum_{i=1}^{N} \tilde{\theta}^{g}_{ij,t}(H)} \times 100 \tag{7}$$

The net connectedness of index *i* to system can be calculated from the difference between the connectedness via received from all other indices:

$$C_{i,t}^{g}(H) = C_{i\to j,t}^{g}(H) - C_{i\leftarrow j,t}^{g}(H) \tag{8}$$

Then the net pairwise directional connectedness (NPDC) as:

$$NPDC_{ij}(H) = \frac{\tilde{\theta}_{ji,t}^{g}(H) - \tilde{\theta}_{ij,t}^{g}(H)}{N} \times 100 \tag{9}$$

## *2.2 Frequency connectedness*

Employing the Baruník and Křehlík (2018) (BK18) technique, we examined the temporal and frequency connectedness across indices. The BK18 approach expanded upon the DY12 methodology through the spectral representation of variance decomposition, which was founded on frequency response analysis to disturbances. A methodology grounded in spectral representation variance decomposition was utilised to estimate connectedness patterns within short-, medium-, and long-term financial cycles. Initially, the GFEVD at a specified frequency was defined in the following manner:

$$(f(\omega))_{jk} \equiv \frac{\sigma_{kk}^{-1}\left|\left(\Psi(e^{-i\omega})\Sigma\right)_{jk}\right|^{2}}{\left(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega})\right)_{jj}} \tag{10}$$

Where $(f(\omega))_{jk}$ is the section of the spectrum where the index with frequency $\omega$ is $j_{th}$. The GFEVD of frequency band $\mathrm{g} = (c, d): c, d \in (-\pi, \pi), c < \mathrm{d}$ as:

$$\left(\Theta_{g}\right)_{jk} = \frac{1}{2\pi}\int_{g} \Gamma_{j}(\omega)(f(\omega))_{jk} g\omega \tag{11}$$

Where $\Gamma_j(\omega)$ is the weighting structure, as:

$$\Gamma_{j}(\omega) = \frac{\left(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega})\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda})\right)_{jj} g\lambda} \tag{12}$$

The index *j*, when applied as a chosen frequency, 2π is used as a constant amount and then the amount is used to the all frequency. Applying the *g* frequency, BK18 connectedness metric as:

$$\left(\widetilde{\Theta}_{g}\right)_{jk} = \frac{\left(\Theta_{g}\right)_{jk}}{\sum_{j}\left(\Theta_{\infty}\right)_{jk}} \tag{13}$$

The connectedness in frequency *g* as:

$$C_{g}^{F} = 100 \times \left(\frac{\sum_{j\neq k}\left(\widetilde{\Theta}_{g}\right)_{jk}}{\sum\left(\widetilde{\Theta}_{\infty}\right)_{jk}} - \frac{\mathrm{Tr}\{\widetilde{\Theta}_{g}\}}{\sum\left(\widetilde{\Theta}_{\infty}\right)_{jk}}\right) \tag{14}$$

Where Tr{-} is the trace parameter. The connectedness at frequency *g* as:

$$C_g^W = 100 \times \left(1 - \frac{\mathrm{Tr}\{\widetilde{\Theta}_g\}}{\Sigma(\widetilde{\Theta}_g)_{jk}}\right) \tag{15}$$

As DY12, the pairwise spillover of the network at frequency *g* as:

$$\left(C_g^F\right)_{j,\,\mathrm{net}} = \left(C_g^F\right)_{j\rightarrow\cdot} - \left(C_g^F\right)_{j\leftarrow\cdot} \tag{16}$$

Where, *i* denoting that index *j* is a net sender (receiver) of shocks from system is showed in terms of net connectedness $\left(C_g^F\right)_{j,\,\mathrm{net}}$.

### *2.3 Data*

This study's data comprised the China Environmental Governance Policy Uncertainty Index (EGPU) and daily return data for seven new energy-related stocks, with a sample period spanning from 11 June 2015 to 29 December 2023. This timeframe was determined by the maximum available duration of the EGPU data. New energy stock data were sourced from the Wind database, including Chuantou Energy (CTNY), China XD Electric (ZGXD), Three Gorges Water Conservancy (SXSL), China National Nuclear Corporation (ZGHD), LONGi Green Energy (LJLN), EVE Energy (YWLN), and Sungrow Power Supply (YGDY). These stocks represented different segments of the new energy industry chain, covering key sectors including traditional energy, power equipment manufacturing, hydroelectric power generation, nuclear power generation, photovoltaic technology, lithium battery technology, and inverter technology. The China Environmental Governance Policy Uncertainty Index (EGPU) was sourced from http://github.com/orange-030/EGPU. This index was constructed using text mining methods, quantifying the degree of environmental policy uncertainty through analysis of uncertainty expressions in policy documents, news reports, and official statements (Wu et al., 2025). All stock price data were converted to logarithmic returns for analysis to ensure data stationarity and comparability, providing a sufficient sample foundation for subsequent TVP-VAR frequency domain connectedness analysis.

Prior to the execution of the TVP-VAR frequency connectedness analysis, researchers conducted several preliminary statistical tests to confirm data suitability and to justify the selection of nonlinear modelling approaches. First, the Elliott-Rothenberg-Stock (ERS) unit root test was employed to determine the stationarity of the return series. The ERS test offers superior power properties compared to conventional Augmented Dickey-Fuller tests, especially when examining processes close to the unit root. It achieves this enhancement through the application of generalised least squares (GLS) detrending procedures. Next, the Jarque-Bera (JB) test was utilised to assess the normality of the return distributions. This test simultaneously examines whether the skewness equals zero and the excess kurtosis equals zero. Significant JB statistics indicate a departure from normality, which forecasts the presence of fat tails and asymmetric distributions, features commonly observed in financial time series. Finally, researchers applied the Brock-Dechert-Scheinkman (BDS) test to detect nonlinear dependence structures within the data. This test assesses whether the standardised residuals are independently and identically distributed (i.i.d.). Rejecting the null hypothesis forecasts the presence of nonlinear dynamics, conditional heteroscedasticity, or chaotic behaviour that linear models cannot adequately capture.

## 3. Result analysis

**Table 1. Descriptive statistics**

| | Mean | Variance | Skewness | Kurtosis | JB | ERS |
|---|---|---|---|---|---|---|
| **EGPU** | -0.005 | 2.832 | -3.569 | 30.603 | 82869.813*** | -10.806*** |
| **CTNY** | 0.014 | 3.005 | -0.503 | 7.919 | 5347.615*** | -8.607*** |
| **ZGXD** | -0.044 | 5.941 | 0.092 | 4.938 | 2048.911*** | -18.143*** |
| **SXSL** | -0.004 | 7.591 | -0.05 | 3.819 | 1224.545*** | -4.817*** |
| **ZGHD** | 0.03 | 4.466 | 0.051 | 9.527 | 7617.855*** | -1.825* |
| **LJLN** | 0.064 | 9.819 | -0.107 | 1.899 | 306.594*** | -8.437*** |
| **YWLN** | 0.09 | 14.347 | -0.049 | 1.782 | 267.375*** | -4.559*** |
| **YGDY** | 0.029 | 14.831 | -0.032 | 3.156 | 836.426*** | -6.349*** |

Notes: Table 1 displayed the descriptive statistics results for the return rates of each variable, where ***, **, and * denoted statistical significance at the 1%, 5%, and 10% significance levels, respectively. ERS represented the Elliott-Rothenberg-Stock unit root test, and JB represented the Jarque-Bera normality test.

*Source*: Authors' own creation.

According to the descriptive statistics results in Table 1, the return rate distribution characteristics of the variables used exhibited significant heterogeneity and non-normality features. From the perspective of mean returns, YWLN demonstrated the highest average return rate (0.09), whilst ZGXD displayed the largest negative average return rate (-0.044). This return rate differentiation reflected the performance differences of different variables during the sample period and the distinct market risk pricing variations. Variance statistics revealed that YGDY and YWLN possessed the highest volatility (14.831 and 14.347, respectively), whilst EGPU exhibited the lowest variance (2.832), revealing significant risk differences amongst the variables. From the distribution form perspective, EGPU demonstrated significant negative skewness (-3.569) and extremely high kurtosis (30.603), indicating that its return rate distribution possessed obvious left-skewed and leptokurtic characteristics with fat tails. All variables' kurtosis values were significantly greater than the normal distribution kurtosis value of 3, displaying prevalent fat-tail characteristics. The JB statistic test results showed that all variables' JB statistics were significant at the 1% significance level, strongly rejecting the null hypothesis that returns followed a normal distribution. EGPU possessed the highest JB statistic (82869.813), confirming that its distribution exhibited the most severe non-normality. The ERS unit root test results indicated that all variables' return rate series were stationary time series. ZGXD displayed the strongest stationarity

(-18.143), whilst ZGHD, although having the smallest absolute statistic value (-1.825), still rejected the unit root hypothesis at the 10% significance level. These results provided a solid econometric foundation for subsequent time series analysis, ensuring the validity of model estimation and the reliability of results.

**Table 2. BDS test**

| Variable | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|
| **EGPU** | 3.3824*** | 3.3005*** | 3.2078** | 3.1048** | 3.0226** |
| **CTNY** | 14.2497*** | 14.2387*** | 14.2199*** | 14.1919*** | 14.2374*** |
| **ZGXD** | 16.6032*** | 16.6001*** | 16.5905*** | 16.5742*** | 16.5769*** |
| **SXSL** | 14.6728*** | 14.6534*** | 14.6532*** | 14.6273*** | 14.6270*** |
| **ZGHD** | 17.2128*** | 17.2079*** | 17.2143*** | 17.2073*** | 17.2034*** |
| **LJLN** | 9.6860*** | 9.3019*** | 9.8238*** | 9.8245*** | 9.8270*** |
| **YWLN** | 5.2393*** | 4.9891*** | 5.2781*** | 5.2878*** | 5.2783*** |
| **YGDY** | 7.2275*** | 7.1476*** | 7.3218*** | 7.3102*** | 7.2739*** |

Notes: ***, **, * denote statistically significant at 1%, 5%, 10% level of significance respectively.

*Source*: Authors’ own creation.

Table 2 presented the BDS (Brock-Dechert-Scheinkman) test results, which were used to detect nonlinear dependence and chaotic behaviour in time series data. From the test results, all variables' BDS statistics under different dimensions (M2 to M6) were significant at the 1% or 5% significance levels, strongly rejecting the null hypothesis that the data were independently and identically distributed (i.i.d.). Specifically, ZGHD exhibited the highest BDS statistics across all dimensions (ranging from 17.2128 to 17.2034), followed by ZGXD (from 16.6032 to 16.5769) and SXSL (from 14.6728 to 14.6270), while EGPU displayed relatively lower but still significant BDS statistics (from 3.3824 to 3.0226). These results indicated that all variables' return rate series possessed significant nonlinear structures and long-term dependence, violating the fundamental assumptions of traditional linear time series models. This suggested that these financial time series might contain complex nonlinear dynamic characteristics, conditional heteroscedasticity, or other forms of nonlinear dependence relationships, providing strong statistical support for adopting nonlinear modelling methods.

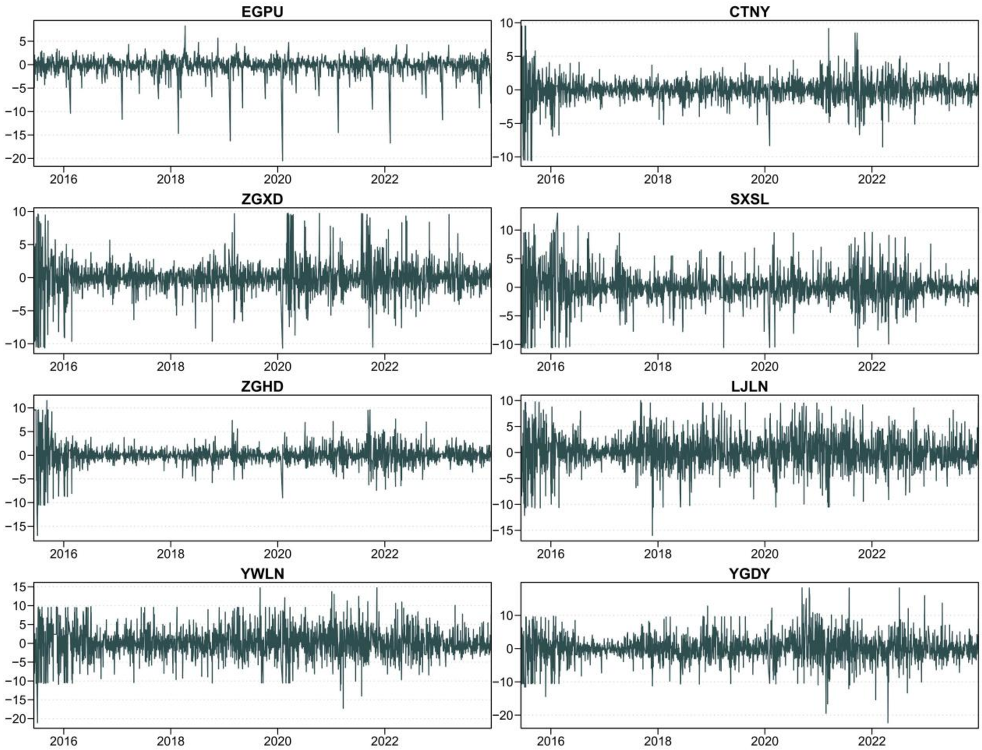


**Figure 1. Time series plot of return rates**
*Source*: Authors' own creation.

Figure 1 displays the time series plots of return rates for eight variables spanning the period from 2015 to 2023, offering an intuitive depiction of each variable's dynamic volatility characteristics and temporal evolution patterns. The figure reveals that the return rate series for all variables exhibit typical financial time series characteristics: they fluctuate around a zero mean and show clear volatility clustering, where periods of high fluctuation tend to follow one another. EGPU's volatility amplitude was relatively small, primarily concentrated between -20% and 5%, consistent with its lower variance statistics, whilst YWLN and YGDY displayed greater volatility amplitudes, with return rate changes ranging from -20% to 15%, reflecting higher market risks. Notably, around 2020, multiple variables exhibited relatively severe volatility, which might have been related to systemic risk events in global financial markets.

**Table 3. Static connectivity table**

| | EGPU | CTNY | ZGXD | SXSL | ZGHD | LJLN | YWLN | YGDY | FROM |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Panel A. Overall | | | | |
| **EGPU** | 93.23 | 1.23 | 0.98 | 0.76 | 1.12 | 0.85 | 1.05 | 0.79 | 6.77 |
| **CTNY** | 0.99 | 53.99 | 10.09 | 7.26 | 14.74 | 5.68 | 3.33 | 3.92 | 46.01 |

| | EGPU | CTNY | ZGXD | SXSL | ZGHD | LJLN | YWLN | YGDY | FROM |
|---|---|---|---|---|---|---|---|---|---|
| **ZGXD** | 0.65 | 9.4 | 50.15 | 8.98 | 12.54 | 6.79 | 5.74 | 5.75 | 49.85 |
| **SXSL** | 0.61 | 7.8 | 10.18 | 57.52 | 8.31 | 5.46 | 5.63 | 4.49 | 42.48 |
| **ZGHD** | 0.76 | 14.18 | 12.57 | 7.1 | 50.71 | 5.01 | 4.17 | 5.49 | 49.29 |
| **LJLN** | 0.56 | 5.21 | 6.68 | 4.34 | 4.98 | 49.02 | 11 | 18.21 | 50.98 |
| **YWLN** | 0.92 | 3.7 | 6.79 | 5.35 | 4.96 | 12.52 | 52.88 | 12.87 | 47.12 |
| **YGDY** | 0.65 | 3.89 | 6.26 | 3.94 | 5.61 | 19.17 | 12.14 | 48.34 | 51.66 |
| **TO** | 5.16 | 45.4 | 53.55 | 37.73 | 52.26 | 55.48 | 43.06 | 51.52 | 344.16 |
| **NET** | -1.61 | -0.61 | 3.7 | -4.75 | 2.98 | 4.5 | -4.06 | -0.14 | TCI=43.02 |
| **NPDC** | 0 | 3 | 6 | 1 | 5 | 7 | 2 | 4 | |
| | | | | **Panel B. Short-term (1-5 days)** | | | | | |
| **EGPU** | 81.38 | 1.1 | 0.84 | 0.68 | 1.01 | 0.74 | 0.94 | 0.7 | 6.01 |
| **CTNY** | 0.9 | 48.31 | 9.02 | 6.48 | 13.18 | 5 | 3.02 | 3.52 | 41.13 |
| **ZGXD** | 0.56 | 8.2 | 44.46 | 7.84 | 11.02 | 5.94 | 5.11 | 5.16 | 43.84 |
| **SXSL** | 0.53 | 6.85 | 9.02 | 50.4 | 7.35 | 4.72 | 4.91 | 3.94 | 37.34 |
| **ZGHD** | 0.69 | 12.25 | 11.09 | 6.24 | 44.55 | 4.38 | 3.76 | 4.9 | 43.31 |
| **LJLN** | 0.49 | 4.56 | 6.03 | 3.85 | 4.43 | 43.34 | 9.77 | 16.34 | 45.48 |
| **YWLN** | 0.83 | 3.25 | 6.07 | 4.72 | 4.47 | 10.96 | 46.91 | 11.54 | 41.85 |
| **YGDY** | 0.56 | 3.47 | 5.74 | 3.51 | 5.07 | 16.81 | 10.8 | 43.01 | 45.97 |
| **TO** | 4.56 | 39.7 | 47.81 | 33.32 | 46.53 | 48.56 | 38.32 | 46.1 | 304.9 |
| **NET** | -1.44 | -1.43 | 3.98 | -4.02 | 3.22 | 3.08 | -3.53 | 0.14 | TCI=38.11 |
| **NPDC** | 0 | 3 | 7 | 1 | 6 | 5 | 2 | 4 | |
| | | | | **Panel C. Long-term (5-Inf days)** | | | | | |
| **EGPU** | 11.85 | 0.13 | 0.14 | 0.08 | 0.12 | 0.1 | 0.11 | 0.08 | 0.77 |
| **CTNY** | 0.09 | 5.68 | 1.06 | 0.78 | 1.56 | 0.68 | 0.3 | 0.41 | 4.88 |
| **ZGXD** | 0.09 | 1.19 | 5.69 | 1.14 | 1.52 | 0.85 | 0.63 | 0.59 | 6.01 |
| **SXSL** | 0.08 | 0.95 | 1.15 | 7.11 | 0.96 | 0.74 | 0.72 | 0.55 | 5.15 |
| **ZGHD** | 0.08 | 1.92 | 1.48 | 0.86 | 6.16 | 0.63 | 0.41 | 0.59 | 5.98 |
| **LJLN** | 0.08 | 0.64 | 0.65 | 0.5 | 0.55 | 5.68 | 1.23 | 1.87 | 5.51 |
| **YWLN** | 0.1 | 0.45 | 0.72 | 0.63 | 0.49 | 1.56 | 5.97 | 1.33 | 5.27 |
| **YGDY** | 0.08 | 0.42 | 0.52 | 0.42 | 0.54 | 2.36 | 1.34 | 5.33 | 5.7 |
| **TO** | 0.59 | 5.7 | 5.73 | 4.41 | 5.73 | 6.93 | 4.74 | 5.42 | 39.26 |
| **NET** | -0.17 | 0.82 | -0.28 | -0.73 | -0.25 | 1.42 | -0.53 | -0.27 | TCI=4.91 |
| **NPDC** | 1 | 6 | 3 | 1 | 4 | 7 | 3 | 3 | |

Notes: Forecast horizon is 10.

*Source*: Authors' own creation.

Table 3 presented the static spillover effects analysis results under different frequency domains in the TVP-VAR model, revealing the dynamic correlations between China's environmental governance policy uncertainty (EGPU) and new energy-related stocks. From the perspective of the Total Connectedness Index (TCI), the overall frequency domain TCI was 43.02, the short-term frequency domain (1-5 days) TCI was 38.11, whilst the long-term frequency domain (over 5 days) TCI was only 4.91. These results indicated that spillover effects were mainly concentrated in the short to medium term, with the degree of mutual influence between variables significantly diminishing in the long term, reflecting the dominant role of short-term volatility contagion in financial markets.

From the net spillover effects (NET) perspective in analysing the overall frequency domain results, EGPU functioned as a net spillover receiver (NET=-1.61), indicating that new energy stock volatility inversely influenced the market perception of policy uncertainty. ZGXD served as the strongest net spillover contributor (NET=3.7), followed by LJLN (NET=4.5) and ZGHD (NET=2.98), whilst SXSL (NET=-4.75) and YWLN (NET=-4.06) were the primary net spillover receivers. This spillover pattern suggested that traditional power equipment manufacturers and emerging clean energy enterprises played the role of risk transmitters in the system, while hydroelectric power generation and lithium battery technology enterprises predominantly absorbed shocks from the system.

The short-term frequency domain analysis results displayed spillover patterns similar to the overall frequency domain. EGPU remained a net spillover receiver (NET=-1.44), with ZGXD (NET=3.98), ZGHD (NET=3.22), and LJLN (NET=3.08) maintaining net spillover contributor status, whilst SXSL (NET=-4.02) and YWLN (NET=-3.53) continued as major net receivers. Notably, YGDY transformed into a slight net spillover contributor in the short term (NET=0.14), which might have reflected the immediate impact of the photovoltaic inverter industry on other new energy sub-sectors in the short term. The short-term TCI was 38.11, comprising the vast majority of overall spillover effects, confirming the importance of short-term linkage mechanisms in new energy markets.

The long-term frequency domain presented distinctly different spillover characteristics, with the TCI dropping dramatically to 4.91, indicating that the mutual dependencies between variables weakened substantially in the long term. In the long-term frequency domain, LJLN transformed into the strongest net spillover contributor (NET=1.42), whilst CTNY also became a net contributor (NET=0.82), with other variables' net spillover effects being relatively weak. This transformation suggested that in the long term, solar technology leading enterprises and traditional energy companies might exert more sustained influence on the system, whilst the influence of power equipment manufacturers that dominated in the short term weakened in the long term.

Cross-frequency domain comparative analysis revealed several important characteristics of new energy market spillover effects. Firstly, EGPU functioned as a net spillover receiver across all frequency domains, contrasting with the traditional perception of policy uncertainty as an exogenous shock source, suggesting that new energy market development conditions might inversely influence policy-making uncertainty. Secondly, ZGXD and LJLN consistently maintained net spillover contributor status in the short to medium term, reflecting the central position of power equipment manufacturing and photovoltaic technology in the new energy ecosystem. Thirdly, the frequency structure of the spillover effects indicated that market participants primarily focused on short-term volatility contagion, with long-term fundamental linkages being relatively weak, providing important temporal dimension considerations for risk management and investment decisions. Finally, the changes in spillover positions of different new energy sub-sectors across various frequency domains reflected the complex impacts of technological progress, industrial policies, and market competition pattern evolution on inter-industry correlations.

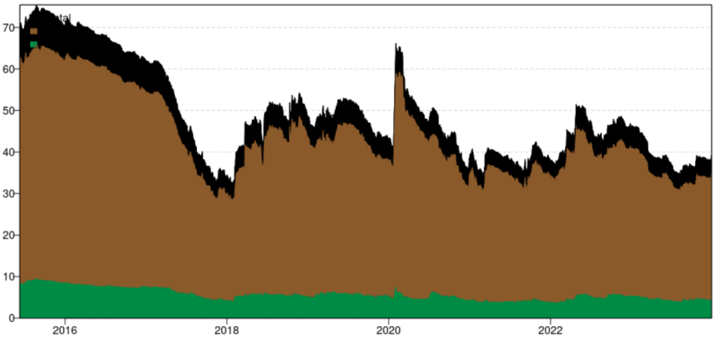


**Figure 2. Dynamic Total Connectedness Index (TCI) (Forecast horizon (H):10)**
*Source*: Authors' own creation.

Based on the dynamic Total Connectedness Index (TCI) analysis results in Figure 2, significant time-varying and cyclical characteristics of spillover effects in new energy markets across the temporal dimension could be observed. From the overall evolution trajectory, systemic spillover effects were at relatively high levels in early 2015, with the overall frequency domain TCI at approximately 70%, short-term frequency domain at around 60%, whilst the long-term frequency domain maintained a lower level of 10%. This was highly consistent with the conclusion that short-term spillover effects dominated in the static analysis. During 2015-2017, TCI across all frequency domains exhibited significant downward trends, with overall and short-term frequency domains declining from high levels to approximately 30%, possibly reflecting the mitigation of systemic risks brought about by the gradual improvement of new energy policies and the increasing maturity of market mechanisms. During 2018-2019, TCI fluctuated between 40%-50%, demonstrating market sensitivity to external uncertainty factors, whilst the COVID-19 outbreak in 2020 produced the most significant peak within the study period, with the overall frequency domain connectedness index surging to approximately 65% in the short term, fully reflecting the amplification effect of extreme events on systemic risks in financial markets.

During 2021-2023, dynamic TCI presented relatively stable but still volatile characteristics, with overall frequency domain and short-term frequency domain connectedness indices primarily fluctuating within the 35%-45% range, suggesting that new energy markets had entered a new equilibrium state after experiencing the COVID-19 shock. TCI fluctuations during this period might have been related to factors such as the accelerated carbon neutrality policy implementation and the intensified competition among the new energy technology pathways. Notably, long-term frequency domain TCI consistently maintained relatively low and stable levels of 5%-10% throughout the entire sample period, with its proportion of total spillover effects remaining consistently small. This corroborated the static analysis result where long-term TCI was only 4.91, confirming the important characteristic that new energy market risk contagion was primarily realised through short-term channels. Overall, the temporal evolution pattern of dynamic TCI not only validated the core findings of static analysis but also revealed the dynamic adjustment mechanisms of systemic risks in new energy markets in response to macroeconomic environments, policy changes, and extreme events.

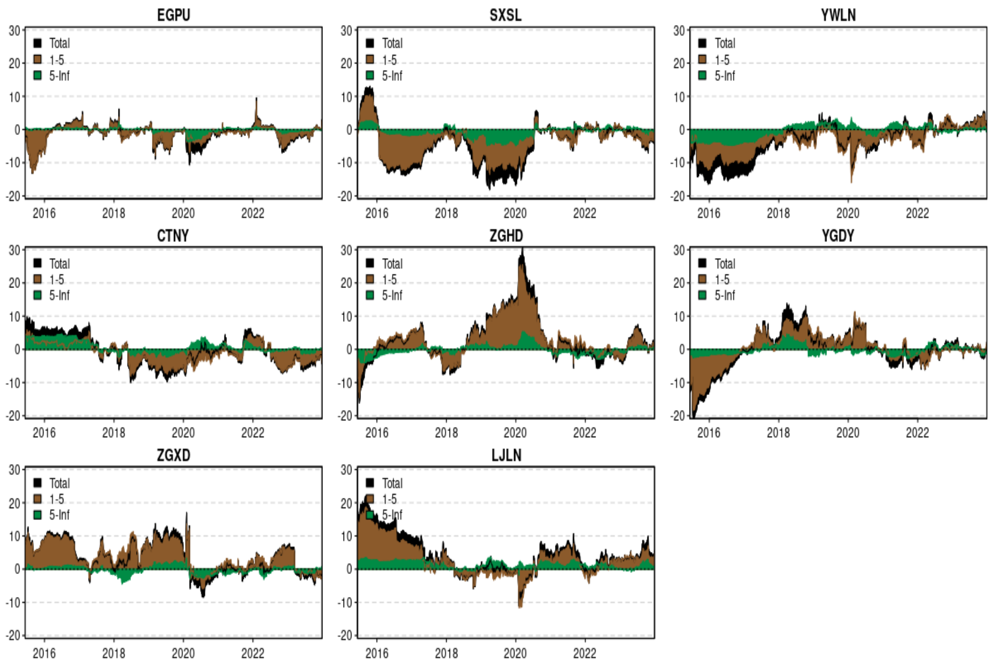


**Figure 3. Dynamic Net Spillover Effects (NET)**
*Source*: Authors' own creation.

Based on the dynamic net spillover effects (NET) analysis results in Figure 3, significant time-varying characteristics and heterogeneous performance of risk transmission roles across variables in different frequency domains could be observed. From the overall evolution pattern, EGPU, as a policy uncertainty indicator, functioned as a net spillover receiver during most periods, with NET values fluctuating primarily between -10% and 10%. This was fundamentally consistent with the conclusion that EGPU was a net receiver in static analysis, but dynamic analysis revealed the temporal characteristics of its role transitions. Particularly during the COVID-19 period in 2020, EGPU's net spillover effects exhibited obvious positive jumps, suggesting enhanced transmission effects of policy uncertainty to new energy markets under extreme market conditions. CTNY primarily functioned as a net spillover receiver throughout the entire sample period, with NET values being negative during most periods. This aligned with its slightly negative net spillover results in static analysis, but dynamic graphs showed that it briefly transformed into a net contributor during 2018-2019, possibly reflecting changes in traditional energy enterprises' market influence during specific periods.

The dynamic NET performance of new energy stocks presented more complex time-varying characteristics and obvious industry differences. SXSL functioned as a significant net spillover receiver during most periods, with NET values frequently below -10%, which was highly consistent with its -4.75 net receiver status in static analysis. Particularly during the COVID-19 period in 2020, its net reception degree deepened further, reflecting the high sensitivity of hydroelectric power generation enterprises to systemic risk shocks. YWLN similarly functioned primarily as a net spillover receiver, but its NET value fluctuation amplitude was relatively small, varying between -10% and 5% during most periods, which corresponded to its -4.06 net receiver role in static analysis. ZGXD's dynamic NET performance was most stable, maintaining long-term positive values, confirming its important status as a consistent net spillover contributor. This was highly consistent with its 3.7 positive net spillover value in static analysis. LJLN functioned as a strong net spillover contributor during 2015-2017, with NET values frequently exceeding 20%, but subsequently gradually declined and transformed into a net receiver during certain periods. This role transition might have reflected the impact of photovoltaic industry technological maturity improvement and market competition landscape changes. YGDY's NET performance exhibited cyclical characteristics, alternating between net contributor and net receiver roles across different periods, particularly showing obvious net spillover contribution peaks around 2020, suggesting dynamic changes in inverter technology enterprises' position within the new energy industry chain. Notably, each variable's NET performance maintained consistent directionality across different frequency domains, further validating the core finding that short-term spillover effects dominated in static analysis, whilst simultaneously revealing the complex dynamic characteristics of new energy market risk transmission mechanisms evolving over time.

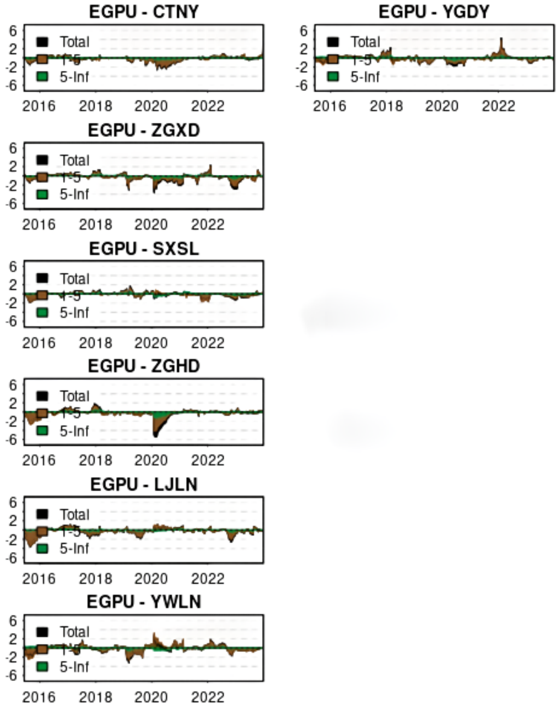


**Figure 4. Dynamic pairwise net spillover analysis results of EGPU to other variables**
*Source*: Authors' own creation.

Based on the dynamic pairwise net spillover analysis results of EGPU to other variables in Figure 4, the bilateral risk transmission mechanisms and time-varying characteristics between China's environmental governance policy uncertainty and various new energy stocks could be deeply observed. From the overall evolution pattern, pairwise net spillover effects between EGPU and new energy stocks fluctuated primarily between -2% and 4%, with relatively small amplitudes but displaying obvious time-varying and heterogeneous characteristics. In most pairwise relationships, EGPU functioned as a net spillover receiver, meaning that new energy stock volatility influenced policy uncertainty to a greater extent than policy uncertainty directly impacted stocks. This finding corroborated the conclusion that EGPU was a net receiver in the aforementioned overall NET analysis. Particularly noteworthy was that the EGPU-YGDY and EGPU-LJLN pairs exhibited relatively significant positive net spillovers during certain periods, suggesting that policy uncertainty's impact on core photovoltaic industry chain enterprises might have been more direct and intense at specific time points.

Pairwise net spillover analysis across different frequency domains revealed complex temporal structures of policy transmission mechanisms. In traditional energy infrastructure pairs such as EGPU-CTNY, EGPU-ZGXD, and EGPU-SXSL, short-term and overall frequency domain net spillover patterns were fundamentally consistent, primarily exhibiting slight negative values, indicating that these enterprises' market performance feedback effects on policy uncertainty perception were relatively stable. Long-term frequency domain net spillover effects approached zero with minimal volatility, again confirming that interactions between policy uncertainty and new energy stocks were primarily realised through short-term channels. In the EGPU-YGDY and EGPU-LJLN pairs, more obvious time-varying characteristics were observed, particularly during the COVID-19 period in 2020 and the accelerated carbon neutrality policy implementation phase in 2021-2022, where these pairs' net spillover effects exhibited significant positive jumps, reflecting the differentiated impacts of extreme market conditions and major policy changes on specific new energy sub-sectors. EGPU-YWLN and EGPU-ZGHD pairs' net spillover effects were relatively stable, fluctuating slightly within negative value ranges, suggesting that lithium battery and nuclear power enterprises maintained relatively stable negative feedback relationships with policy uncertainty, meaning that good performance by these enterprises helped reduce market uncertainty expectations regarding environmental policies. Overall, pairwise net spillover analysis not only validated the general characteristic of EGPU as a systemic net receiver but, more importantly, revealed the heterogeneity and time-varying nature of risk transmission between policy uncertainty and different new energy technology pathways, providing more refined empirical evidence for understanding the dynamic interaction mechanisms between environmental policies and new energy markets.

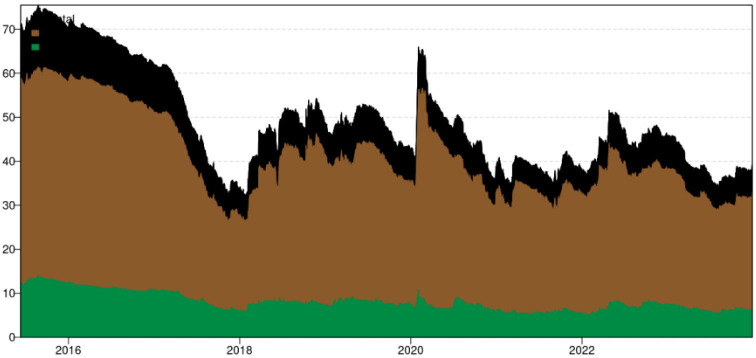


**Figure 5. Robustness test (Forecast horizon (H):20)**
*Source*: Authors' own creation.

Based on the robustness test results in Figure 5, it was observed that after adjusting the forecast horizon from H=10 to H=20, the temporal evolution pattern of the dynamic Total Connectedness Index (TCI) maintained high consistency with the baseline results in Figure 2, fully validating the robustness of the research conclusions. From the overall trend perspective, the temporal trajectories of TCI across frequency domains in Figure 5 almost perfectly overlapped with Figure 2, with key characteristics including the high levels in early 2015 (overall frequency domain approximately 70%, short-term frequency domain approximately 60%), the significant downward trend during 2015-2017, the volatility fluctuations in 2018-2019, the sharp increase during the COVID-19 period in 2020, and the relative stability in 2021-2023 all being completely preserved. This high similarity indicated that changes in forecast horizon length did not alter the fundamental time-varying patterns of spillover effects in new energy markets, confirming the reliability of TVP-VAR model estimation results and the stability of research findings.

More importantly, Figure 5 further confirmed the relative importance structure of spillover effects in different frequency domains. The long-term frequency domain TCI still maintained relatively low and stable levels of 5%-10% throughout the entire sample period, with its proportion of total spillover effects remaining consistently small, which was completely consistent with results under the H=10 setting. The short-term frequency domain continued to dominate spillover effects, with its variation amplitude and temporal patterns highly synchronised with the overall frequency domain, again confirming the core conclusion that new energy market risk contagion was primarily realised through short-term channels. Notably, at key time points such as during the COVID-19 shock in 2020, TCI peak levels under both forecast horizon settings were almost identical, further validating the measurement accuracy of extreme events' amplification effects on systemic risks. Additionally, the fluctuation patterns of TCI within the 35%-45% range during 2021-2023 maintained high consistency, confirming the assessment that new energy markets entered a new equilibrium state in the post-COVID-19 era. Overall, this robustness test not only enhanced the credibility of the research results, but, more importantly, confirmed that the identified time-varying characteristics and frequency domain differences of the new energy market spillover effects possessed inherent economic logic support, independent of specific technical parameter settings.

**Table 4. OLS regression**

| Variables | CTNY | ZGXD | SXSL | ZGHD | LJLN | YWLN | YGDY |
|---|---|---|---|---|---|---|---|
| **Coefficient** | 0.0354 | 0.0386 | 0.0236 | 0.0429 | 0.0361 | 0.0422 | 0.0177 |

*Source*: Authors' own creation.

Based on the OLS regression analysis results in Table 4, the direct impact effects of EGPU on new energy stock returns could be observed, providing important robustness test support for the aforementioned TVP-VAR frequency domain connectedness analysis. From the regression coefficients, EGPU demonstrated positive impacts on all new energy stocks, with coefficients ranging from 0.0177 to 0.0429. This result was fundamentally consistent with EGPU's role as a systemic risk transmitter in the TVP-VAR analysis. Specifically, ZGHD exhibited the highest sensitivity (coefficient 0.0429), followed by YWLN (0.0422) and ZGXD (0.0386), whilst YGDY's sensitivity was relatively lowest (0.0177). This heterogeneous pattern corroborated the differentiated response characteristics of different new energy sub-sectors to policy uncertainty shocks in the aforementioned dynamic connectedness analysis.

The positive coefficients in OLS regression results indicated that increases in environmental governance policy uncertainty led to increases in new energy stock returns. This finding seemingly contradicted traditional negative uncertainty shock theories but actually reflected the special nature of the new energy industry. Increases in environmental policy uncertainty often accompanied the strengthening of environmental requirements and the advancement of green transformation policies, bringing more market opportunities and policy support to new energy enterprises, thereby generating positive market reactions. This explanation formed organic unity with the finding in TVP-VAR analysis that EGPU primarily functioned as a net spillover receiver, meaning that good performance in new energy markets inversely influenced market expectations and uncertainty perceptions regarding environmental policies. Notably, the differences in various stocks' sensitivity to EGPU also aligned with the different roles each variable played in the system according to frequency domain connectedness analysis, with technology-intensive enterprises such as nuclear power and lithium battery being more sensitive to policy changes, whilst traditional power equipment and renewable energy generation enterprises demonstrated relatively stable responses. Overall, OLS regression analysis not only validated the existence of the relationships between policy uncertainty and new energy stocks identified by the TVP-VAR model but, more importantly, provided supplementary information regarding impact direction and intensity, enhancing the robustness and credibility of research conclusions.

## 4. Conclusions

This work employed the TVP-VAR frequency domain connectedness methodology to conduct an in-depth analysis of the dynamic spillover effects between China's environmental governance policy uncertainty and renewable energy stock markets, providing important empirical evidence for understanding the risk transmission mechanisms of policy uncertainty within green financial systems. The research findings revealed the complex time-varying characteristics and frequency heterogeneity of risk contagion in renewable energy markets, offering significant theoretical value and practical implications for investment decision-making and policy formulation.

The principal findings of this research can be summarised in several key aspects. Firstly, significant spillover effects existed within renewable energy markets, with these effects primarily realised through short-term channels, where short-term frequency domain TCI maintained dominance whilst long-term frequency domain influences remained relatively weak. Secondly, environmental governance policy uncertainty predominantly manifested as a net spillover receiver throughout most periods, suggesting that the developmental status of renewable energy markets inversely influenced policy-making uncertainty perceptions, contrasting with traditional perspectives that view policy as an exogenous shock source. Thirdly, different renewable energy sub-sectors assumed differentiated roles within the system, with power equipment manufacturing enterprises primarily serving as risk transmitters whilst emerging technology enterprises predominantly absorbed systematic shocks. Fourthly, spillover effects exhibited pronounced time-varying characteristics, with systemic risks significantly amplified during extreme events such as the COVID-19 pandemic, whilst connectivity weakened during periods of relatively stable policy environments.

Based on these research findings, detailed investment strategy recommendations were provided to different types of investors. For short-term investors, primary attention should be directed towards short-term volatility contagion effects in renewable energy markets, as research demonstrated that spillover effects were primarily realised through short-term channels. When constructing investment portfolios, excessive concentration within the same renewable energy sub-sector should be avoided, particularly simultaneous heavy weighting in power equipment manufacturing stocks, as these stocks often served as sources of risk transmission. Conversely, allocation of certain proportions to risk-receiving stocks such as SXSL and YWLN could be considered, as these stocks, whilst absorbing systematic shocks, might also achieve greater rebound potential when market sentiment improved. Short-term investors should also closely monitor changes in policy uncertainty indicators, as OLS regression results indicated that renewable energy stocks generally benefited when environmental policy uncertainty increased, providing important timing signals for short-term trading.

For long-term investors, the research results offered more optimistic investment prospects. Due to the relatively weak and stable spillover effects in the long-term frequency domains, long-term investors need not be overly concerned about the contagion effects of short-term market volatility. Diversified investment strategies were recommended, with allocations across different segments of the renewable energy industry chain, particularly focusing on enterprises such as LJLN that might transform into net spillover contributors over the long term. Long-term investors should regard environmental policy uncertainty as investment opportunities rather than risks, as policy drivers often brought long-term developmental benefits to the renewable energy sector. Simultaneously, focus should be placed on leading enterprises with strong technological innovation capabilities and stable industry chain positions, as these enterprises often assumed risk transmitter roles within the system, possessing stronger market influence and long-term competitive advantages.

For institutional investors, the frequency domain differences discovered in this research should be fully utilised to construct multi-layered risk management systems. In short-term risk management, primary attention should be directed towards monitoring changes in systemic connectivity indicators, with timely adjustments to position allocations when TCI exhibited abnormal increases, reducing weights of high-risk contagion stocks. In long-term asset allocation, the influence of short-term volatility contagion could be relatively ignored, focusing instead on fundamental investment value within the renewable energy sector. Institutional investors should also establish dynamic portfolio rebalancing mechanisms, timely adjusting allocation weights according to the time-varying characteristics of different renewable energy stocks' roles within the system. Particularly under extreme market conditions, adequate liquidity should be prepared to address the amplification effects of systemic risks.

The research results provided important policy design and implementation guidance to environmental policy makers. Firstly, policy makers should recognise the inverse influence of renewable energy market development status on policy uncertainty perceptions, meaning that promoting healthy development of renewable energy markets could effectively reduce policy implementation uncertainty. When formulating environmental policies, market feedback mechanisms should be fully considered, establishing real-time monitoring systems for policy effectiveness and timely adjusting policy intensity and implementation pace according to renewable energy market performance. Such dynamic adjustment mechanisms would facilitate beneficial interactions between policy and markets, reducing the negative impacts of policy uncertainty on the entire green financial system.

Secondly, policy makers should emphasise risk contagion mechanisms within renewable energy markets, considering differentiated characteristics of various sub-sectors when designing industrial support policies. For power equipment manufacturing enterprises serving as risk transmitters, strengthened supervision and risk prevention should be implemented to prevent negative shocks from spreading throughout the entire renewable energy ecosystem. For risk-receiving emerging technology enterprises, more policy support and risk mitigation measures should be provided to help these enterprises resist systemic risk shocks. Establishing classified and layered policy instrument systems was recommended, formulating differentiated support measures and regulatory requirements for different types of renewable energy enterprises.

Thirdly, given that spillover effects were primarily realised through short-term channels, policy makers should fully consider short-term market reactions when releasing major environmental policies, adopting gradual and pre-announced policy implementation approaches to avoid overly concentrated and severe policy shocks. Establishing policy communication mechanisms was recommended, releasing policy signals in advance to provide markets with adequate adaptation time. Simultaneously, monitoring and intervention capabilities for short-term fluctuations in renewable energy markets should be strengthened, with timely stabilisation measures implemented during extreme market conditions to prevent further amplification of systemic risks.

Finally, policy makers should utilise the positive relationship between environmental policy uncertainty and renewable energy stock returns, releasing moderate policy uncertainty to stimulate market vitality and innovation momentum. This did not imply artificially creating policy uncertainty, but rather finding balance points amongst policy foresight, consistency, and flexibility. Establishing policy systems that combined long-term environmental policy frameworks with short-term flexible adjustment mechanisms was recommended, providing clear long-term expectations for markets whilst maintaining policy adaptability and responsiveness. Through such approaches, policy uncertainty could be transformed into positive factors promoting renewable energy industry development, achieving dual optimisation of policy objectives and market efficiency.

In future research, consideration could be given to incorporating additional uncertainty indices or more detailed renewable energy sector enterprises, such as wind and geothermal energy companies. Furthermore, extending this analytical framework to other major economies with significant renewable energy markets, such as the European Union, the United States, and emerging Asian markets, would enable cross-country comparative analyses and enhance the generalisability of findings regarding the relationship between environmental policy uncertainty and new energy markets.

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