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# Research on the Impact of Climate Policy Uncertainty on Corporate Green Technology Innovation: An Empirical Study from China

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## Abstract

Faced with growing climate change, government policies aimed at fixing market failures have also created significant regulatory and economic uncertainty. This uncertainty influences corporate strategic decisions. Green technological innovation has become a key ability for firms to adapt and compete in a global environment that values sustainability. This study examines how climate policy uncertainty affects corporate green technological innovation. It uses Prospect Theory , Information Asymmetry Theory and data from China's A-share listed companies between 2013 and 2023. The main explanatory variable, climate policy uncertainty, is built by multiplying a city-level index—based on analyzing mainstream newspaper reports with a deep learning algorithm—by how often green transition keywords appear in firms' annual reports. The dependent variable, green technological innovation, is measured as the logarithm of a firm's total yearly green patent applications plus one. The analysis uses a two-way fixed effects model. To address endogeneity, an instrumental variable approach is applied. We use the mayor's remaining years in office and the interaction between the city-level climate physical risk index and industry energy intensity as the instrument for climate policy uncertainty.A mediation model tests two mechanisms: managerial foresight, measured by keyword frequency in annual reports, and analyst coverage, sourced from the CSMAR database. Regional differences are also examined. The results show that: (1) climate policy uncertainty significantly promotes corporate green innovation, with an economic effect of approximately 3.4%. This finding holds across various robustness checks; (2) the positive effect operates through two pathways—stimulating managerial foresight and mitigating information asymmetry; and (3) the effect is stronger for firms in non-eastern regions of China.

**Keywords:** Climate change challenges, Manager foresight, Prospect theory,Text Analysis

# 1. Introduction

In recent years, in the face of increasingly severe climate change challenges, governments around the world have actively formulated and implemented policies to address climate change. As a responsible major country, China has clearly set the goals of "peak carbon emissions and carbon neutrality", elevating the promotion of these goals and active participation in global climate governance to a national strategic level. Green technology innovation is key to addressing climate challenges and achieving sustainable development. Many scholars have explored how to promote green technology innovation. Corporate strategic pace has a positive impact on green innovation (Zhou et al., 2025). Digital transformation has a positive effect on corporate green innovation(Xu et al., 2025). External fund holdings have a positive role in promoting green innovation in heavily polluting enterprises(Fu et al., 2025). The carbon emission trading system promotes corporate green technology innovation(Lan et al., 2024). Climate risk disclosure by Chinese A-share listed companies significantly enhances their green innovation capabilities(Han et al., 2025). Government fiscal reforms, by reducing financing constraints and effectively allocating resources, significantly promote green innovation(Li & Qi, 2025).

In the current context, climate issues require governments to correct market failures and optimize resource allocation through climate policies. The resulting uncertainty in climate policies will become a significant factor affecting corporate green technology innovation. Climate policy uncertainty has different impacts on corporate innovation (Liu et al., 2024)(Niu et al., 2023). Climate policy uncertainty negatively affects physical investment (Wang & Hu, 2024). Climate policy uncertainty facilitates the transition to a green economy(You et al., 2025). When climate policy uncertainty increases, corporate investment decreases(Zhao et al., 2025). While CPU has a positive impact on research investment for general enterprises, it has a significant negative effect on R&D investment for heavily emitting companies(Hoang, 2022). This paper aims to define an index of climate policy uncertainty at the firm level and provide insights into how climate policy uncertainty affects corporate green technology innovation, thereby offering recommendations for management decisions and sustainable development strategy under climate change. The empirical research results enhance understanding of how companies can identify and manage climate policy risks, which is a critical aspect of the business environment.

This study explores the relationship between climate policy uncertainty and green technology innovation in Chinese enterprises from 2013 to 2023. A two-way fixed effects model is used for empirical testing, and instrumental variable methods are used to further test endogeneity, and prospect theory,information asymmetry theory is used to empirically test the impact mechanism.

This paper makes contributions to the existing literature in two main aspects. First, it establishes an analytical framework for the impact transmission mechanism of climate policy uncertainty on green technology innovation based on prospect theory and information asymmetry theory. Most existing studies focus on financing constraints, risk-taking levels, and operational risks (Zhang et al., 2024) . In dynamic, uncertain, ambiguous and complex environments, teams need to adapt effectively to changes in order to maintain efficient operation, but the mechanism by which leaders exert influence is not clear(Wei et al., 2024). This paper studies the uncertainty of climate policy and the vision of managers, and discusses the impact of management on enterprise innovation.Meanwhile, it also examines the role of analyst coverage as an information intermediary, which mitigates information asymmetry between firms and external investors, thereby facilitating green innovation.

Secondly, existing climate policy uncertainty only quantifies indicators by considering regional-level climate policy uncertainty, while ignoring the specific circumstances of individual companies(Wang et al., 2024)(Sun et al., 2024)(Zhang et al., 2024). Different companies face varying impacts from climate policy uncertainty. This paper extends the measurement of climate policy uncertainty to the company level, using regional climate policy data and corporate green transition data for a more accurate assessment.

## 2. Theoretical Analysis and Hypothesis Development

### 2.1 Climate Policy Uncertainty and Green Technology Innovation

Climate policy uncertainty is both a challenge for corporate transformation and a strategic opportunity to reshape competitiveness. Although green technology innovation requires substantial initial investment, the irreversible damage caused by climate change and the compounded impact of policy fluctuations impose new demands on companies, compelling them to upgrade green technology innovation from a reactive measure to a necessity for survival. In the short term, resource allocation for green technology research and development increases operating costs. However, it plays a crucial role in long-term corporate development, and these early investments will gradually transform into unique competitive advantages. At the same time, the corporate green image created by green technology is more likely to win consumer favor.

At the same time, external pressure plays an indispensable role in driving corporate innovation and transformation. In the industry, some companies take the lead in green transition and green technology innovation. When these pioneering enterprises gain significant advantages such as enhanced brand reputation and expanded emerging markets through green technology innovation, other companies feel intense competitive pressure and are forced to break away from their previously conservative business strategies(Zhu et al., 2026). To cope with policy changes, companies must proactively engage in green technology innovation, enhancing their technical capabilities and management levels. By doing so, they can transform the challenges posed by policy uncertainties into valuable opportunities for their own transformation and upgrading, finding new paths for survival and development in the ever-changing market and policy environment.

Therefore, the hypothesis is proposed:

H1:Climate policy uncertainty can prompt companies to engage in green technological innovation.

### 2.2 Mechanism Analysis

1. Prospect theory

Prospect theory posits that individual decisions are based on comparisons of potential gains and losses. When facing losses, individuals exhibit risk aversion; to avoid certain losses, they may take risky actions. It is precisely because of the risk-averse nature of business managers that companies actively engage in innovative investment activities(Xu & Zhou, 2021). Companies often subjectively estimate the probability of events occurring, converting their perceptions into subjective probabilities. When transforming objective probabilities into subjective ones, for rare events, companies tend to overestimate the likelihood of these events occurring(Zhang et al., 2022).

In the face of today's severe global climate change challenges, companies view not taking green actions as a potential loss. To avoid greater losses in the future, they are now willing to take risks for green technology innovation. This not only reduces potential risks associated with climate policies but also lowers future carbon emission costs. The first-mover advantages that green technology innovation can bring, such as market share and brand image enhancement, may be amplified, encouraging companies to invest.

When government policy directions are unclear, the risk-averse function of green technology innovation, investing in green technologies such as clean energy and low-carbon processes, is seen as an "insurance strategy" to avoid future policy risks. Even if current policies are ambiguous, companies will still take preemptive action due to loss aversion to avoid compliance costs or market competitiveness declines caused by sudden policy changes in the future.

Green actions by leading companies in the industry will create new social norms that force other companies to adjust their reference points and see "non-innovation" as a loss from deviating from industry standards. If competitors have already laid out green technologies, companies may accelerate innovation for fear of losing market share, even if the policy environment is not clear.

To this end, we propose the following hypothesis:

H2:Climate policy uncertainty stimulates green technology innovation by stimulating managers' foresight.

2. Information Asymmetry Theory

Information asymmetry refers to a situation in market transactions where one party possesses superior information and may exploit this advantage for undue gain, while the disadvantaged party bears additional risks due to insufficient information (Zhang, 2025). In capital markets, heightened information asymmetry distorts resource allocation and hinders firms' long-term value creation. Financial analysts, as information intermediaries in capital markets, provide decision-relevant information to investors through research reports, while simultaneously exerting significant external monitoring effects (Yu & Wei, 2026).

When climate policy uncertainty intensifies, the firm's operating environment becomes increasingly opaque, making it difficult for investors to accurately assess climate-related risks and firms' strategic responsiveness. To mitigate this information disadvantage, investor demand for firm-specific information increases substantially, attracting a larger number of analysts to follow the firm and leading to more extensive research report coverage. Greater analyst coverage implies stronger external monitoring and market expectations faced by firms. To maintain reputation and investor confidence, management is incentivized to translate green governance commitments into substantive actions. Green technological innovation serves as a visible signal of firms' long-term strategic commitment. Through strengthening external oversight and curbing managerial short-termism, analyst coverage effectively facilitates corporate green technological innovation.

Accordingly, we propose the following hypothesis:

H3: Climate policy uncertainty promotes green technological innovation by enhancing firms' analyst coverage.

## 3. Research Design

### 3.1 Data and Sample

Selecting A-share listed companies from 2013 to 2023 as the research sample. Corporate green patent data is sourced from Mark Data Network. The portrayal of macro climate policy uncertainty indicators is based on text frequency from six major newspapers in China: People's Daily, Guangming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service. The portrayal of corporate green transformation indicators is based on text frequency from corporate annual reports. Additionally, data on corporate financial characteristics and corporate governance, as well as regional factors, are derived from the CSMAR database.

This paper conducted the following cleaning of the initial sample: First, removing ST-listed companies with abnormal operating conditions; Second, removing financial and insurance samples; Third, removing samples with missing main research variables and common abnormal samples; Fourth, truncating all continuous variables by 1% . The final dataset consists of 25,182 company-year observations.

### 3.2 Variable Construction

1. Explained variable

Corporate green technology innovation (Envrpat1) is measured as the logarithm of one plus the total number of green patent applications filed by listed companies. Substantive green technology innovation (Envrpat2) is measured as the logarithm of one plus the total number of green invention patent applications, where green invention patents refer to patents whose subject matter falls within the green technology categories defined by the Green Technology Patent Classification System (CNIPA Office Regulation No. 30 [2023])—such as clean energy, energy conservation and carbon reduction, pollution control, and related fields—and that demonstrate directly evident environment-friendly or carbon-reduction effects relative to prior art, as stipulated in Article 2 of China’s Patent Law. Strategic green technology innovation (Envrpat3) is measured as the logarithm of one plus the total number of green utility model patent applications, where green utility model patents protect only the shape, structure, or combination of a product and meet the same green-technology criteria as their invention counterparts. Compared with green utility model patents, green invention patents embody greater novelty and technological creativity, and thus better reflect enterprises’ substantive green innovation capabilities. In contrast, utility model patents, which involve weaker innovativeness, may be strategically used by firms to inflate patent counts for policy subsidies or other incentives, thereby serving as a proxy for strategic green innovation behaviour (Xin et al., 2024).

2. Explanatory variable

Macro climate policy uncertainty (CPU). We extracted textual paragraphs containing climate-policy-related content from mainstream newspapers, and carried out word frequency statistics according to the method of Ma (Ma et al., 2023), and obtained the climate policy uncertainty index of national and local cities as a quantitative indicator to measure the level of climate policy uncertainty at the city level.

The method is based on the MacBERT deep-learning model. Its dictionary construction does not rely on any manually pre-defined sentiment lexicon or rule base. Instead, it employs the pre-trained MacBERT-Base-Chinese parameters, which are initialised on large-scale Chinese corpora. Through the self-attention mechanism, the model automatically extracts contextual semantic features from complete sentences and generates dynamic vector representations, thereby effectively avoiding subjective word-selection bias. In the preprocessing stage, news articles from mainstream newspapers are denoised, split into sentences, and tokenised into subwords to preserve full linguistic information. Regarding the deep-learning implementation, the original model loads official pre-trained weights and is fine-tuned in a supervised manner using manually audited labelled samples. The classification layer employs a linear fully-connected layer followed by a Softmax function to output probabilities, with cross-entropy loss used for optimisation. The final predicted label is assigned as the category with the highest probability.

Corporate Green Transformation (Score). According to the method proposed by Zhou Kuo (Zhou et al., 2022), select keywords related to corporate green transformation, and count the frequency of each keyword in the annual reports of listed companies to form a frequency score for green transformation. The natural logarithm of this frequency score plus one is used to characterize the corporate green transformation.

The CPU index is directly used to measure the uncertainty in climate policy, where all companies face the same level of uncertainty, which does not align with reality and cannot exclude other macro-policy disturbances during the same period. By introducing interaction terms, the uncertainty in climate policy is set as the product of macro climate policy uncertainty and corporate green transition, denoted as CPU_Score. This approach distinguishes different responses of companies to the same macro shock, indicating that the impact of climate uncertainty on companies depends both on the macro level and the direct influence of the company itself, taking into account both macro and corporate dimensions.

The definition of relevant variables is shown in Table 1 below.

*Table 1: Variable Definition*

| **Variable category** | **Symbol** | **Paraphrase** | **Data processing** |
|---|---|---|---|
| Explained variables | Envrpat1 | Green technology innovation | Ln(Number of green patent applications+1) |
| | Envrpat2 | Substantive green technology innovation | Ln(Number of green invention patent applications+1) |
| | Envrpat3 | Strategic green technology innovation | ln(Number of green utility model patent applications+1) |
| Explanatory variable | CPU_Score | Climate policy uncertainty | Macro CPU index × Enterprise green transformation score |
| Control variables | Size | Company size | Ln(Total assets ) |
| | Roa | Return on assets | Net profit/Total assets |
| | Lev | Asset-liability ratio | Total liabilities /Total assets |
| | Fixed | Fixed assets ratio | Fixed assets/Total assets |
| | Cash | Cash ratio | Monetary resources/Total assets |
| | First | Shareholding ratio of the largest shareholder | The ratio of the largest shareholder to the total share capital |
| | Inc_GDP | Regional economic growth level | The annual GDP growth rate of the city where the company is located |
| | Tobinq | Growth | Tobin Q index |

| Variable category | Symbol | Paraphrase | Data processing |
|---|---|---|---|
| | Dual | Dual appointments | Virtual variable, the value of the enterprise where the chairman and general manager are concurrently employed is 1, otherwise it is 0 |
| | Soe | Property rights | Virtual variable, the value is 1 for state-owned enterprises and 0 for non-state-owned enterprises |

### 3.3 Empirical Model

In order to test the impact of climate policy uncertainty on enterprises' green technology innovation, the following model is constructed:

$$Envrpat_{i,t}=\beta_0+\beta_1 CPU\_Score_{i,t}+\beta_k\ Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (1)$$

$$CPU\_Score_{i,t}=\beta_0+\beta_1 Remterm_{i,t}+\beta_2 CPRI\_Energy_{i,t}+\beta_k\ Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (2)$$

$$Envrpat_{i,t}=\beta_0+\beta_1 CPU\_Score\_Fitted_{i,t}+\beta_k\ Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (3)$$

$$Mediator_{i,t}=\beta_0+\beta_1 CPU\_Score_{i,t}+\beta_k\ Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (4)$$

$$Envrpat_{i,t}=\beta_0+\beta_1 CPU\_Score_{i,t}+\beta_2 Mediator_{i,t}+\beta_k\ Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (5)$$

Where$Envrpat_{i,t}$ is the explained variable, $CPU\_Score_{i,t}$ is the explanatory variable, and $Controls_{i,t}$ denotes the set of control variables. The term $\mu_i$ represents firm fixed effects, $\lambda_t$ represents year fixed effects, and $\varepsilon_{i,t}$ is the random disturbance term. Subscripts i and t index firm and year, respectively.Equation (1) is the baseline model examining the direct effect of climate policy uncertainty on corporate green technological innovation. To address potential endogeneity concerns, Equations (2) and (3) present the two-stage least squares estimation with instrumental variables, where Equation (2) is the first-stage regression of CPU_Score on the instrument RemTerm and CPRI_Energy, and Equation (3) is the second-stage regression of Envrpat on the fitted value of CPU_Score. To further investigate the underlying transmission channels, Equations (4) and (5) specify the mediation models, where Equation (4) tests the effect of CPU_Score on the mediator (either Forward or Coverage), and Equation (5) tests the direct effect of CPU_Score alongside the mediator on Envrpat. Together, these five equations constitute the core empirical framework of this study.

Beyond the core specification, we conduct a series of robustness checks and heterogeneity analyses to assess the validity and generalizability of our findings. The robustness tests—including lagged independent variable regressions, alternative fixed effects (industry-year), inclusion of additional controls (E_score), placebo tests with non-green patents, and firm-specific time trends—are all estimated as variants of the baseline model (Equation 1), with only the respective modifications applied. The heterogeneity analysis, which examines regional differences between Eastern and non-Eastern regions, follows the same baseline specification while splitting the sample accordingly. Inter-group coefficient differences are tested via the Bootstrap method (1,000 replications). These additional regressions collectively complement the empirical evidence and reinforce the reliability of our main conclusions.

To ensure the reliability of statistical inference, this paper applies clustered standard errors across all regression models. Specifically, the baseline regressions, mediation models, and robustness checks all employ firm-level clustered robust standard errors, which allow for serial correlation in the error terms across different years for the same firm, thereby mitigating the over-rejection of the null hypothesis caused by underestimated standard errors.In all regression results, clustered robust standard errors are reported in parentheses below the coefficient estimates.

# 4. Empirical Results

## 4.1 Descriptive Statistics

The descriptive statistics for the full sample are presented in Table 2. The differences in standard deviation, maximum value, and minimum value among the explanatory variables green technology innovation, substantive green technology innovation, and strategic green technology innovation—indicate that there are certain differences in green technology innovation across different firms. The standard deviation of the core explanatory variable, climate policy uncertainty, is 1.794, with a mean of 3.051, indicating significant variations in the climate policy uncertainty index among the sample firms. The statistical results for other control variables are largely consistent with existing literature.

*Table 2: Descriptive Statistics*

| VARIABLES | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Envrpat1 | 25,182 | 0.898 | 1.161 | 0 | 4.575 |
| Envrpat2 | 25,182 | 0.604 | 0.958 | 0 | 4.159 |
| Envrpat3 | 25,182 | 0.593 | 0.914 | 0 | 3.738 |
| CPU_Score | 25,182 | 3.051 | 1.794 | 0 | 8.466 |
| Size | 25,182 | 22.18 | 1.246 | 19.82 | 25.88 |
| Roa | 25,182 | 0.0350 | 0.0662 | -0.267 | 0.196 |
| Lev | 25,182 | 0.413 | 0.202 | 0.0558 | 0.894 |
| Fixed | 25,182 | 0.204 | 0.152 | 0.00199 | 0.672 |
| Cash | 25,182 | 0.181 | 0.126 | 0.0148 | 0.625 |
| First | 25,182 | 0.331 | 0.144 | 0.0860 | 0.721 |
| Inc_GDP | 25,182 | 1.017 | 5.032 | -0.912 | 38.60 |
| Tobinq | 25,182 | 2.863 | 2.168 | 0.866 | 13.40 |
| Dual | 25,182 | 0.260 | 0.439 | 0 | 1 |
| Soe | 25,182 | 0.292 | 0.455 | 0 | 1 |

## 4.2 Test of H1:Climate Policy Uncertainty and Green Technological Innovation

Table 3 presents the benchmark regression results of climate policy uncertainty and corporate green technology innovation. Model (1) shows a univariate regression result, with the CPU_Score coefficient being significantly positive at the 1% level, indicating that climate policy uncertainty significantly promotes corporate green technology innovation. Model (2) further incorporates control variables at the firm level, while Models (3), (4), and (5) include control variables at both the firm and regional levels. The coefficients of CPU_Score remain significantly positive at the 1% level in all cases. This verifies Hypothesis 1: climate policy uncertainty promotes green technology innovation.

Analyzing the economic significance of climate policy uncertainty on corporate green technology innovation, after controlling for various influencing factors, the coefficient of CPU_Score in Model (3) is 0.022, with a standard deviation of 1.794, while the standard deviation of Envrpat1 is 1.161. Therefore, the economic significance of Model (3) is approximately 3.4% (0.022×1.794/1.161×100%), meaning that for every one standard deviation increase in the climate policy uncertainty indicator, corporate green technology innovation increases by about 3.4% of its standard deviation. The economic significance of Model (4) is 2.4%, and that of Model (5) is 3.3%. Comparing the sizes of the coefficients also shows that the impact of climate policy uncertainty on substantive green technology innovation is less than that on strategic green technology innovation capabilities, indicating that climate policy uncertainty promotes strategic corporate green technology innovation.

In practical terms, given the sample mean of Envrpat1 (0.898), a one-standard-deviation increase in CPU_Score (1.794 units, from approximately 3.051 to 4.845) raises Envrpat1 by 0.022 × 1.794 = 0.0395 logarithmic points, which translates into approximately 0.10 additional green patent applications per firm-year at the mean level [$e^{0.898}\times(e^{0.0395}-1) \approx 2.45\times0.040 \approx 0.10$].For substantive (Envrpat2) and strategic (Envrpat3) green innovation, the corresponding increases are approximately 0.05 and 0.07 additional patent applications per firm-year, respectively. While these magnitudes appear modest at the firm-year level, they are economically meaningful when aggregated across thousands of listed firms over multiple years.

*Table 3: Climate Policy Uncertainty and Green Technological Innovation*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **VARIABLES** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Envrpat2** | **Envrpat3** |
| CPU_Score | 0.029*** | 0.022*** | 0.022*** | 0.013*** | 0.017*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Size | | 0.391*** | 0.391*** | 0.312*** | 0.269*** |
| | | (0.02) | (0.02) | (0.02) | (0.02) |
| Roa | | -0.122 | -0.122 | -0.134 | -0.064 |
| | | (0.10) | (0.10) | (0.09) | (0.09) |
| Lev | | -0.103 | -0.103 | -0.110* | -0.031 |
| | | (0.07) | (0.07) | (0.06) | (0.06) |
| Fixed | | 0.089 | 0.088 | 0.118 | 0.088 |
| | | (0.10) | (0.10) | (0.09) | (0.09) |
| Cash | | -0.021 | -0.021 | 0.023 | 0.036 |
| | | (0.06) | (0.06) | (0.06) | (0.05) |
| First | | 0.156 | 0.156 | 0.125 | 0.162 |
| | | (0.14) | (0.14) | (0.12) | (0.12) |
| Inc_GDP | | | -0.001 | 0.000 | -0.001 |
| | | | (0.00) | (0.00) | (0.00) |

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **VARIABLES** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Envrpat2** | **Envrpat3** |
| Tobinq | | 0.018*** | 0.018*** | 0.017*** | 0.015*** |
| | | (0.00) | (0.00) | (0.00) | (0.00) |
| Dual | | -0.030 | -0.030 | -0.018 | -0.031** |
| | | (0.02) | (0.02) | (0.02) | (0.01) |
| Soe | | 0.025 | 0.026 | 0.025 | 0.018 |
| | | (0.04) | (0.04) | (0.04) | (0.04) |
| CompanyFE | YES | YES | YES | YES | YES |
| YearFE | YES | YES | YES | YES | YES |
| Constant | 0.332*** | -8.130*** | -8.129*** | -6.581*** | -5.678*** |
| | (0.02) | (0.52) | (0.52) | (0.49) | (0.43) |
| R2_a | 0.121 | 0.162 | 0.162 | 0.123 | 0.123 |

### 4.3 Robustness Tests

1. To mitigate endogeneity concerns, we employ two instruments for CPU_Score. The first is mayoral remaining tenure (RemTerm), calculated as years remaining to the statutory term end. The second is the interaction between the city-level climate physical risk index and industry energy intensity (CPRI_Energy). The climate risk index, sourced from CSMAR and originally constructed by Guo et al., is the equally weighted average of four normalized sub-indicators: low-temperature, high-temperature, extreme rainfall, and extreme drought days (Guo et al. ,2024). Industry energy intensity is also obtained from CSMAR.

These instruments satisfy the three core validity conditions. Relevance: mayoral tenure shapes local environmental regulations, while climate physical risks drive policy discussions. The joint first-stage F-statistic is 27.16, exceeding the 10% critical value. Exogeneity: tenure arrangements are determined by higher-level party organizations, and climate risks are purely natural phenomena—both exogenous to firm decisions. Exclusion restriction: both instruments affect green innovation only through firms' perceptions of climate policy uncertainty. Mayoral tenure operates via regulation enforcement and policy expectations, with limited scope for alternative channels. The climate–energy interaction captures exogenous physical shocks that shape policy uncertainty perceptions and, unlike mayoral tenure, is immune to budget cycles or industrial policy, as it originates from natural phenomena. The consistency of results across these conceptually distinct instruments reinforces the exclusion restriction.

Table 4 reports the results. The second-stage coefficient of fitted CPU_Score is 0.115, significant at the 10% level. Diagnostic tests confirm instrument validity: the Kleibergen-Paap rk Wald F-statistic is 27.16; the Hansen J test yields a p-value of 0.0751; and the Anderson-Rubin test returns a p-value of 0.0604. These findings confirm that, after addressing endogeneity, climate policy uncertainty continues to promote green innovation.

2. Lagged independent variable. In order to alleviate the endogeneity problem, the model uses a one-period lagged explanatory variable regression for testing. The one-period lagged climate policy uncertainty is replaced with the explanatory variable to regress on green

technological innovation in enterprises, as shown in Table 4 Model (8), and the regression results are significantly positive.

3. Change the fixed effect. By using the fixed effect of year and industry, the interference of mixed factors changing with time at the industry level is excluded from the results, as shown in Table 4 model (9), and the regression results are significantly positive.

4. Additional control variable. To address the concern that the firm-level CPU may capture the underlying "green orientation" of enterprises, this paper further incorporates the environmental pillar score (E_score) from the Huazheng ESG rating system as an additional control variable. The E_score directly measures firms' environmental performance across multiple dimensions, including climate change, resource utilization, environmental pollution, environmental friendliness, and environmental management. By controlling for firms' inherent green propensity, we aim to isolate the independent effect of climate policy uncertainty on green technological innovation. The regression results, as shown in Table 4 Model (10), remain significantly positive after controlling for E_score, confirming that our core findings are not driven by firms' green orientation.

5. Placebo test with non-green patents. To further validate that the effect of climate policy uncertainty is specific to green technological innovation rather than capturing firms' general innovative activity, we construct an alternative explained variable—total patent applications excluding green patents (i.e., Non-green patents)—and re-estimate our baseline model. As shown in Table 4 Model (11), the coefficient of CPU becomes statistically insignificant when non-green patents are used as the dependent variable. This finding suggests that our main results are not driven by a general increase in innovative output but rather reflect a genuine shift toward green innovation, consistent with the placebo-test approach adopted in prior green innovation studies.

6. Firm-specific time trends. To rule out the possibility that our results are driven by firm-specific linear trends that may be correlated with both climate policy uncertainty and green innovation, we further incorporate firm-specific linear time trends (firm * c.year) into the fixed effects specification. This specification absorbs any time-varying unobserved heterogeneity that evolves linearly at the firm level over the sample period. As shown in Table 4 Model (12), the coefficient of CPU_Score remains significantly positive, confirming that our findings are not an artifact of differential firm-level trajectories over time.

*Table 4: Robustness Tests*

| | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
|---|---|---|---|---|---|---|---|
| VARIABLES | **CPU_Score** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Non-green patents** | **Envrpat1** |
| CPU_Score | | 0.115* | | 0.067*** | 0.017*** | 0.002 | 0.019*** |
| | | (0.07) | | (0.00) | (0.00) | (0.01) | (0.00) |
| RemTerm | 0.006 | | | | | | |
| | (0.01) | | | | | | |
| CPRI_Energy | -0.002*** | | | | | | |
| | (0.00) | | | | | | |
| L.CPU_Score | | | 0.016*** | | | | |
| | | | (0.00) | | | | |
| E_score | | | | | 0.003*** | | |

| | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|
| VARIABLES | **CPU_Score** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Envrpat1** | **Non-green patents** | **Envrpat1** |
| | | | | | (0.00) | | |
| Size | 0.185*** | 0.327*** | 0.416*** | 0.424*** | 0.411*** | 0.631*** | 0.341*** |
| | (0.03) | (0.03) | (0.03) | (0.01) | (0.03) | (0.07) | (0.02) |
| Roa | 0.614*** | -0.111 | -0.194* | 0.084 | -0.193* | -0.077 | -0.351*** |
| | (0.20) | (0.13) | (0.11) | (0.10) | (0.11) | (0.33) | (0.11) |
| Lev | -0.013 | -0.021 | -0.148* | 0.321*** | -0.117 | -0.101 | -0.010 |
| | (0.11) | (0.08) | (0.08) | (0.04) | (0.08) | (0.20) | (0.07) |
| Fixed | 0.429*** | 0.012 | 0.025 | -0.840*** | 0.093 | 0.268 | -0.038 |
| | (0.15) | (0.14) | (0.12) | (0.05) | (0.11) | (0.28) | (0.10) |
| Cash | 0.162 | 0.010 | -0.103 | 0.031 | -0.025 | -0.202 | -0.120* |
| | (0.12) | (0.08) | (0.08) | (0.05) | (0.07) | (0.17) | (0.06) |
| First | 0.105 | -0.038 | 0.211 | -0.302*** | 0.090 | 0.847* | -0.253* |
| | (0.19) | (0.18) | (0.16) | (0.05) | (0.15) | (0.48) | (0.13) |
| Inc_GDP | 0.003 | -0.001 | -0.001 | -0.001 | -0.000 | 0.004* | -0.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Tobinq | 0.003 | 0.017*** | 0.025*** | 0.008** | 0.017*** | 0.010 | 0.005 |
| | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) |
| Dual | 0.018 | -0.029 | -0.028 | 0.012 | -0.030 | 0.065 | -0.024 |
| | (0.03) | (0.02) | (0.02) | (0.01) | (0.02) | (0.05) | (0.02) |
| Soe | -0.095 | -0.005 | -0.005 | 0.074*** | 0.032 | 0.000 | 0.009 |
| | (0.07) | (0.06) | (0.05) | (0.02) | (0.05) | (0.14) | (0.05) |
| CompanyFE | YES | YES | YES | | YES | YES | YES |
| YearFE | YES | YES | YES | YES | YES | YES | YES |
| IndustryFE | | | | YES | | | |
| Firm_Year trends | | | | | | | YES |
| Constant | 0.424 | -6.940*** | -8.596*** | -8.627*** | -8.720*** | -11.165*** | -6.611*** |
| | (0.80) | (0.61) | (0.57) | (0.16) | (0.58) | (1.58) | (0.55) |
| R2_a | 0.572 | 0.210 | 0.143 | 0.287 | 0.180 | 0.195 | 0.763 |

# 5. Further analysis

## 5.1 Mechanism Inspection

1. Managerial Foresight Channel

When managers perceive maintaining the status quo as certain loss, i.e., future policy penalties, and view green technology innovation as uncertain gains, they are more willing to take on innovation risks. The innovative behavior of forward-looking firms will alter the reference points for other industry managers. Climate policy uncertainty stimulates managers risk perception, making them more sensitive to the future and prompting them to proactively choose green technology innovation. Following Xu Shuai (Xu et al., 2023), we define the forward-looking indicator (Forward) . Using the mechanism test method, in this paper, we examine the significant positive correlation between climate policy uncertainty and managerial foresight, as shown in Table 5. We also test the significant positive correlation between climate policy uncertainty and corporate green technology innovation, as shown in Table 3. In summary, the influence path "climate policy uncertainty—promoting managerial foresight—promoting corporate green technology innovation" holds true.

2. Analyst Coverage Channel

Analyst coverage reflects the extent to which a firm attracts market attention and professional scrutiny. In response to climate policy uncertainty, investors demand more timely and detailed information to evaluate firms' climate-related risks, prompting a larger number of analysts to follow the firm and increasing the volume of research reports issued. Such heightened attention imposes reputational pressure on management and intensifies external oversight, thereby encouraging firms to pursue visible strategic actions—including green technological innovation—to signal their long-term viability. We measure analyst coverage (Coverage) using data from the CSMAR database. Employing the mediation testing approach, we first examine the positive relationship between climate policy uncertainty and analyst coverage, as shown in Table 5. We also confirm the positive relationship between climate policy uncertainty and green innovation, as reported in Table 3. After including both CPU_Score and Coverage, the coefficient of Coverage remains significantly positive, while that of CPU_Score decreases in magnitude but remains significant, indicating partial mediation. In summary, climate policy uncertainty promotes green technological innovation by enhancing analyst coverage.

*Table 5: Further analysis*

| | **Forward** | | | **Coverage** | | | **East** | **Non East** |
|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **(13) Forward** | **(14) Forward** | **(15) Envrpat 1** | **(16) Coverage** | **(17) Coverage** | **(18) Envrpat 1** | **(19) Envrpat 1** | **(20) Envrpat 1** |
| CPU_Score | 3.871*** | | 0.017*** | 0.290** | | 0.011* | 0.017*** | 0.029*** |
| | (0.37) | | (0.00) | (0.14) | | (0.01) | (2.96) | (3.90) |
| L.CPU_Score | | 2.451*** | | | 0.226* | | | |
| | | (0.37) | | | (0.11) | | | |
| Forward | | | 0.0002* | | | | | |
| | | | (0.00) | | | | | |
| Coverage | | | | | | 0.001** | | |

| | Forward | | | Coverage | | | East | Non East |
|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **(13) Forward** | **(14) Forward** | **(15) Envrpat 1** | **(16) Coverag e** | **(17) Coverag e** | **(18) Envrpat 1** | **(19) Envrpat 1** | **(20) Envrpat 1** |
| | | | | | | (0.00) | | |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| CompanyFE | YES | YES | YES | YES | YES | YES | YES | YES |
| YearFE | YES | YES | YES | YES | YES | YES | YES | YES |
| R2_a | 0.401 | 0.405 | 0.174 | 0.100 | 0.100 | 0.167 | 0.157 | 0.166 |
| Fisher Bootstrap | | | | | | | p=0.054 | |

### 5.2 Heterogeneity Analysis

Region Nature (Zone). The "Eleventh Five-Year Plan" proposed a four-sector plan of "East, Central, West, and Northeast." Listed companies were categorized by their provincial location, with the sample sizes for Eastern region and non-Eastern region enterprises being 16,371 and 8,811, respectively. The test results are shown in Table 5. For both Eastern region and non-Eastern region enterprises, climate policy uncertainty has a significant impact on green technology innovation, consistent with the overall sample. Fisher's bootstrap test method was used to examine the differences in coefficients between groups, using the Bootstrap method and setting the number of sampling repetitions to 1,000. The p-value for the component coefficient difference test was significant. Moreover, the impact coefficient of Eastern region enterprises (0.017** <0.029***) is weaker than that of non-Eastern region enterprises. The reasons for this result may be: According to the "China Enterprise Green Development Report," Eastern region enterprises have stronger environmental awareness and social responsibility, leading to more green technology innovation driven by long-term strategic considerations. In contrast, non-Eastern region enterprises rely more on policy incentives, resulting in lower initiative in green technology innovation. The internal motivation for green technology innovation is stronger in Eastern region enterprises, making policy uncertainty less impactful. Non-Eastern region enterprises, however, depend more on external policy incentives, where policy uncertainty significantly influences their green technology innovation decisions.

## 6. Results and Discussion

This paper uses 3,603 Chinese A-share listed companies as research samples from 2013 to 2023, employing text analysis to empirically examine the impact of climate policy uncertainty on corporate green technology innovation. The study finds that climate policy uncertainty can significantly promote corporate green technology innovation, with robust results; compared to substantive green technology innovation, climate policy uncertainty has a greater promoting effect on strategic green technology innovation; climate policy uncertainty influences corporate green technology innovation by affecting managers' foresight and by mitigating information asymmetry; climate policy uncertainty has a stronger positive impact on corporate green technology innovation in non-Eastern regions.

Based on the empirical findings, this paper proposes targeted implications for firm managers and policymakers.For enterprises: Firms shall fully acknowledge the long-run shocks of climate regulatory policies, embed substantive green technological innovation into core operational strategies, expand high-quality invention patent output, respond proactively to policy adjustments, and mitigate associated operational risks. By advancing green innovation, enterprises can strengthen long-term competitiveness and capture emerging dividends from the low-carbon transition. Firms should also refrain from short-termist decision-making and adopt forward-looking planning, anticipating prospective policy shifts and market evolution to adjust resource allocation in a timely manner.In addition, firms should recognize the role of external information intermediaries—such as analyst coverage—in shaping market perceptions and reducing information asymmetries with investors.In terms of policy uncertainty: While moderate policy uncertainty may incentivize firms to stay flexible and sustain green innovation to cut pollution and production costs for competitive advantages, frequent policy shifts would disrupt firms' long-term operational expectations and interfere with their stable green innovation plans. Therefore, policymakers should balance the incentive effect of moderate policy unpredictability against its adverse costs when designing climate and environmental regulations. This study does not further explore how to identify the optimal equilibrium between the benefits and downsides of policy uncertainty, which leaves room for future research.

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