Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 22, No. 2, 2026

Research on the Impact of Climate Policy Uncertainty on Corporate Carbon Performance

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Abstract: In response to the increasingly severe issue of global climate change, countries around the world have formulated climate policies to drive climate governance initiatives. However, frequent policy changes can exacerbate the policy uncertainty faced by enterprises, thereby affecting their carbon performance. Based on this, this paper takes Shanghai and Shenzhen A-share listed companies from 2007 to 2023 as the research sample to examine the impact of climate policy uncertainty on corporate carbon performance. The research results indicate that climate policy uncertainty has a significant negative impact on corporate carbon performance. This result remains robust after a series of tests, including replacing core explanatory variables, excluding sample data from special years, and altering the clustering level of standard errors. Further analysis reveals that an increase in climate policy uncertainty inhibits corporate carbon performance by weakening the quality of the external financial environment, suppressing corporate green innovation, and hindering corporate digital transformation. Moreover, the inhibitory effect of climate policy uncertainty on corporate carbon performance is more pronounced for enterprises with weaker green awareness among executives, lower levels of policy environmental regulation, lower market competition intensity, and those that are capital- and technology-intensive. This study not only enriches the theoretical discussion on the relationship between climate policy uncertainty and corporate carbon performance but also provides important theoretical foundations and practical guidance for relevant departments in formulating climate policies and for enterprises in improving their carbon performance.

Keywords: Climate Policy Uncertainty; Corporate Carbon Performance; Green Innovation; Digital Transformation; Green Finance Environment.

1. Introduction

In recent years, extreme weather events have become frequent, and abnormal climate changes pose an unprecedented threat to the Earth's ecosystem stability and integrity, as well as a severe challenge to the sustainability of the human living environment. Climate change has risen to the top of the global agenda (Sun et al., 2024) [1].

Given the significant externality of climate issues, relying solely on the spontaneous actions of economic entities is insufficient (Wang and Zhou, 2023) [2]. Governments thus need to engage in climate governance and introduce relevant policies to guide rational market resource allocation. As a major global economy and the largest carbon emitter, China proposed the "dual carbon" goals (carbon peaking and carbon neutrality) at the UN General Assembly in September 2020, aiming to build a low-carbon and zero-carbon society domestically. However, climate policies are characterized by significant uncertainty due to the difficulty for micro-entities to fully anticipate policy implementation timing, intensity, and details (Wang et al., 2024) [3]. The escalation of international conflicts and protectionism further complicate the policy-making environment, exacerbating this uncertainty (He and Xiang, 2025) [4]. Investors and financial institutions view climate policy uncertainty as a risk, raising corporate capital costs and affecting cost structures and expected returns (Zhang et al., 2024) [5]. This can inhibit corporate green innovation (Wang and Hu, 2024) [6], reduce investment efficiency (Sun et al., 2024) [1], and induce upgrading dilemmas (Wang et al., 2024) [3].

Climate risks are essentially carbon risks, so the core objective of climate policies is to reduce carbon emissions. As key economic units and major carbon emitters, corporate carbon reduction responsibilities are increasingly important (Dong and Zhao, 2025) [7]. Carbon performance measures a company's comprehensive performance in climate governance, reflecting both its effectiveness in reducing carbon emission intensity and optimizing resource utilization, as well as its economic outcomes. Although extensive research has been conducted on climate policy uncertainty and corporate carbon performance, insufficient attention has been paid to the impact of the former on the latter. This paper uses listed companies on the Shanghai and Shenzhen A-share markets from 2007 to 2023 as a sample and employs a two-way fixed-effects model to study this impact and its mechanisms.

The marginal contributions of this paper are threefold: First, it supplements the factors influencing corporate carbon performance from the perspective of climate policy uncertainty, enriching climate finance research. Second, it explores potential mechanisms through which climate policy uncertainty affects corporate carbon performance by examining external green finance environment, green innovation, and digital transformation from the perspectives of external resources, internal core technologies, and operations and management, deepening our understanding of the relationship between the two. Third, in practical terms, with the continuous improvement of climate governance policies and stricter regulatory standards, companies face a more complex external environment. This study provides practical decision-making bases and coping strategies for companies to effectively respond to climate policy uncertainties and enhance their competitiveness and sustainable development capabilities.

2. Theoretical Analysis and Research Hypotheses

2.1. Climate Policy Uncertainty and Corporate Carbon Performance

Carbon performance reflects the coordinated relationship between a firm's control of carbon dioxide emissions and the enhancement of its operational efficiency. Climate policy uncertainty simultaneously impacts both corporate operations and carbon emissions, thereby constraining carbon performance.

In terms of corporate operations, firstly, climate policy uncertainty makes it difficult for firms to form stable expectations (Zhao et al., 2025) [8], leading them to adjust their investment decisions—for example, by reducing fixed asset investments and increasing financial investments (Liu et al., 2025) [9]. However, such adjustments may suppress total factor productivity (Wang et al., 2024) [3]. Secondly, uncertainty raises capital costs and exacerbates financing constraints (Yu and Yu, 2025) [10], weakening corporate profitability and investment willingness. Lastly, supply chains may also be disrupted, adversely affecting business operations (Li et al., 2025) [11]. Regarding carbon emissions, studies show that climate policy uncertainty can increase carbon emissions (Li et al., 2025; Persakis, 2024) [12-13]. From the supply side, high-carbon energy and industrial structures persist due to sluggish transitions (Li et al., 2025) [12]. Adjustments in energy and industrial structures may be delayed (Ren et al., 2023) [14], and capital tends to flow more into traditional high-carbon industries (Ren et al., 2022) [15]. From the demand side, consumers may shift toward high-carbon options as the expected utility of low-carbon products declines (Li et al., 2025) [12].

In summary, climate policy uncertainty may simultaneously reduce corporate operational performance and increase carbon emissions, thereby inhibiting corporate carbon performance. Based on this analysis, the following hypothesis is proposed:

Hypothesis 1: Climate policy uncertainty inhibits corporate carbon performance.

2.2. Climate Policy Uncertainty, External Green Financial Environment, and Corporate Carbon Performance

The development of green finance provides funding support for corporate low-carbon transition through instruments such as green credit and green bonds (Zuo and Zhao, 2025) [16] and contributes to emission reduction and ecological protection (Kwilinski et al., 2025) [17]. However, climate policy uncertainty disrupts risk pricing and expectations in the green financial market.

First, climate policy uncertainty exacerbates information asymmetry between financial institutions and firms, making it difficult for lenders to accurately assess the returns on corporate carbon reduction projects (Zhang et al., 2024) [18]. Concurrently, heightened uncertainty can trigger negative investor sentiment, leading to sell-offs and increasing liquidity pressure on financial institutions (Wu and Liu, 2023) [19]. To mitigate risks, financial institutions respond by tightening the scale of green credit and raising financing thresholds (Chen et al., 2024) [20]. Second, for carbon-intensive firms, climate policy uncertainty elevates the stranding risk of their high-carbon assets (Xiao et al., 2025) [21], which depreciates the value of collateral and consequently reduces their access to loanable funds (Dang and Zhong, 2025) [22], further tightening financing constraints. Finally, frequent changes in climate regulations increase corporate compliance costs and regulatory pressure on financial institutions, further deteriorating the quality of the external green financial environment (Chen et al., 2024) [20]. The deterioration of the external green financial environment creates difficulties for firms in securing green financing. As carbon reduction activities rely on long-term capital and technological investment (Cheng et al., 2025) [23], constrained financing may lead firms to postpone emission-reduction projects or reallocate funds to shorter-term, lower-risk general investments (Sun et al., 2024) [24], thereby impairing their carbon reduction capacity and overall carbon performance. Therefore, the following hypothesis is proposed:

Hypothesis 2: Climate policy uncertainty inhibits corporate carbon performance by undermining the quality of the external green financial environment.

2.3. Climate Policy Uncertainty, Green Innovation, and Corporate Carbon Performance

Green technology innovation is characterized by substantial investment, long cycles, and high risks, often relying on government policy incentives (Wang and Hu, 2024) [6]. However, climate policy uncertainty may also suppress corporate green innovation (Zhang et al., 2024; Hu et al., 2023) [5, 25]. According to real options theory, policy uncertainty increases the difficulty for firms to evaluate the value of innovation, heightens risk aversion among management, and leads to the delay or reduction of green investment, resulting in a "crowding-out effect" (Zhang et al., 2024) [5]. Green innovation directly reduces carbon emissions through technological advancements, process optimization, and the adoption of clean energy (Qiu et al., 2025) [26]. At the same time, by developing low-carbon products and establishing efficient production systems, it enhances corporate operational capabilities, thereby comprehensively improving corporate carbon performance. Thus, the following hypothesis is proposed:

Hypothesis 3: Climate policy uncertainty reduces corporate carbon performance by inhibiting corporate green innovation.

2.4. Climate Policy Uncertainty, Digital Transformation, and Corporate Carbon Performance

Corporate digital transformation is a high-risk, long-cycle strategic investment that is susceptible to market and policy environments. Climate policy uncertainty impedes this process from both financing and resource perspectives: on one hand, policy uncertainty exacerbates corporate operational and default risks, prompting banks to tighten credit (Yu and Yu, 2025) [10]. This leads to constrained financing and strained cash flow for enterprises, causing them to postpone or reduce digital investments. On the other hand, companies incur additional costs to adapt to policy changes (such as carbon footprint monitoring), which diverts budgets and human resources originally allocated for digital transformation (Zhang et al., 2024) [5]. Simultaneously, digital transformation directly enhances corporate carbon performance by optimizing production processes and organizational management. At the production level, digital technologies facilitate precise production planning and the adoption of intelligent systems (Sun et al., 2025; Zhang et al., 2024) [27-28], enabling emission reduction at the source while improving operational efficiency. At the management level, data sharing supports the establishment of a comprehensive corporate carbon emission management system, allowing for refined emission reduction strategies (Yang et al., 2025) [29]. Thus, digital transformation synergistically advances both emission reduction and efficiency gains. In summary, the following hypothesis is proposed:

Hypothesis 4: Climate policy uncertainty reduces corporate carbon performance by inhibiting corporate digital transformation.

3. Research Design

3.1. Sample Selection and Data Sources

This study selects A-share listed companies in Shanghai and Shenzhen from 2007 to 2023 as the initial sample. The sample is refined through the following steps: (1) excluding companies labeled as ST, *ST, or delisted; (2) removing observations with severe missing data in key variables; (3) excluding companies in the financial industry; and (4) applying a 1% bilateral winsorization to all continuous variables. After processing, a final sample of 35,167 valid observations is obtained. The Climate Policy Uncertainty Index is sourced from the Energy Finance Committee of the International Energy Transition Society (IEFN). Annual report data related to corporate carbon performance are collected from the Ju chao Information Network, while financial data and control variables are obtained from the CSMAR database.

3.2. Variable Definitions

(1) Explained Variable: Corporate Carbon Performance (CP). Drawing on the methods of Wang et al. (2022)[30] and He et al. (2017) [31], this study measures corporate carbon performance as the ratio of operating revenue to corporate carbon emissions (i.e., revenue per unit of carbon emission). Corporate carbon emission data are sourced from the social responsibility reports, sustainability reports, and environmental reports disclosed annually by listed companies. Following the Greenhouse Gas Protocol, these data are calculated and then transformed using the natural logarithm.

(2) Core Explanatory Variable: Climate Policy Uncertainty (CPU). This study employs the China Climate Policy Uncertainty Index developed by Ma et al. (2023) [32]. The construction of this index involves the following steps: First, based on credibility, influence, and international reach, Ma et al. selected six major newspapers—People's Daily, Guang ming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service—as primary data sources. Second, a deep learning algorithm, the Mac BERT model, was used to automatically analyze the text content and extract keywords related to climate policy and uncertainty. Third, the number of news articles containing climate policy uncertainty-related keywords within a specific period was counted and divided by the total number of articles during that period to derive raw data. Finally, the raw data were standardized to produce the Climate Policy Uncertainty Index, which includes annual, monthly, and weekly data at the national, provincial, and city levels. This study utilizes the annual data at the provincial level to measure climate policy uncertainty.

(3) Control Variables: Drawing on relevant literature, this study selects the following control variables: firm size (Size), asset-liability ratio (Lev), return on assets (ROA), institutional investor ownership ratio (INST), listing age (List Age), whether audited by a Big Four accounting firm (Big4), and whether the firm incurred a loss in the current year (Loss). Detailed variable definitions are provided in Table 1.

Table 1. Description of Main Variables

Variable Type	Variable Name	Variable Name	Variable Description
Explained Variable	CP	Carbon Performance of Enterprises	Operating Revenue / Carbon Emissions
Explanatory Variable	CPU	Climate Policy Uncertainty Index	Provincial-level index constructed by Ma et al. (2023)
Control Variables	Size	Enterprise Size	ln (Total Assets)
	Lev	Asset-Liability Ratio	Total Liabilities at Year-End / Total Assets
	ROA	Return on Assets	Net Profit / Total Assets at Year-End
	INST	Institutional Investor Shareholding Ratio	Number of Shares Held by Institutional Investors / Total Outstanding Shares
	List Age	Years Since Listing	ln(Current Year - Listing Year + 1)
	Big4	Audited by Big Four	1 if audited by the Big Four (PwC, Deloitte, KPMG, EY), 0 otherwise
	Loss	Net Loss in the Current Year	1 if net profit for the current year is negative, 0 otherwise

3.3. Descriptive Statistics

Table 2 presents the descriptive statistical analysis results of the main variables designed in the empirical section of this paper, as follows:

Table 2. Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
CP	35,167	0.653	0.804	0.242	4.061
CPU	35,167	0.210	0.813	-1.932	3.512
Size	35,167	22.23	1.329	19.41	26.45
Lev	35,167	0.423	0.205	0.0274	0.927
ROA	35,167	0.0443	0.0636	-0.375	0.255
Loss	35,167	0.131	0.338	0	1
List Age	35,167	2.048	0.922	0	3.434
INST	35,167	0.451	0.250	0.00102	0.940
Big4	35,167	0.0659	0.248	0	1

3.4. Model Design

Based on the theoretical analysis above, to examine the impact of climate policy uncertainty in China on corporate carbon performance, this paper adopts a two-way fixed effects model constructed as follows:

$$CP_{i,n,t} = \alpha + \alpha_1 CPU_{n,t} + \beta_k \sum Controls_{i,t}^{k} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{1}$$

Among them, i denotes different firm entities, n denotes the province where firm i is located, and t denotes the year, $CP_{i,n,t}$ represents the carbon performance of firm i in t year, while $CPU_{n,t}$ denotes the climate policy uncertainty index of province n in year t, $\sum Controls_{i,t}^{k}$ refers to a set of control variables. δ_i and γ_t represent firm fixed effects and year fixed effects, respectively, $\varepsilon_{i,t}$ represent firm fixed effects and year fixed effects, respectively, and α is the constant term. Standard errors in this paper are clustered at the firm level.

4. Analysis of Empirical Results

4.1. Baseline Regression

Table 3. Baseline Regression Results

Variable	(1)	(2)	(3)	(4)
	CP	CP	CP	CP
CPU	-	-	-	-
	(-3.14)	(-3.21)	(-3.30)	(-3.82)
Size		0.028***	0.014**	-0.003
		(4.47)	(2.09)	(-1.03)
ROA		0.146***	0.284***	0.097**
		(3.33)	(5.85)	(2.41)
Lev			0.123***	0.113***
			(4.45)	(7.02)
INST			0.043*	-0.005
			(1.69)	(-0.46)
List Age			0.015*	-
			(1.88)	(-4.63)
Big4			-0.024	-0.011
			(-1.06)	(-1.16)
Loss			0.011	-0.001
			(1.37)	(-0.13)
Constant	0.655***	0.034	0.223	0.694***
	(663.24)	(0.24)	(1.54)	(13.05)
Observations	35,136	35,136	35,136	35,167
R^2	0.881	0.881	0.881	0.840
Year FE	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	No

Note: The parentheses in the table report t-values based on clustered robust standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The same applies hereafter.

Table 3 presents the results of the baseline regression. Column (1) introduces only the core explanatory variable, CPU, while controlling for firm and year fixed effects. The regression coefficient is -0.015 and is statistically significant at the 1% level. Columns (2) and (3) further incorporate multiple control variables, and the regression coefficients remain significantly negative. Column (4), while including control variables, controls only for year fixed effects, and the coefficient remains significantly negative, further supporting the reliability of the baseline results. Therefore, the baseline regression results preliminarily demonstrate that climate policy uncertainty inhibits corporate carbon performance, which supports Hypothesis 1 of this study.

4.2. Endogeneity Tests

4.2.1. Instrumental Variable Method

This paper selects the Climate Physical Risk Index (CPRI) as the instrumental variable (Dong and Zhao, 2025; data sourced from Guo et al., 2024) [7, 33]. The index is constructed based on meteorological station observation data and covers four types of extreme climate events: extreme low temperature, extreme high temperature, extreme rainfall, and extreme drought, which effectively measures regional climate physical risks. As an instrumental variable, CPRI satisfies the requirements of relevance and exogeneity. On the one hand, frequent extreme climate events typically elevate societal attention to climate issues, thereby promoting discussions and the introduction of climate policies. On the other hand, the index is primarily determined by natural factors and is not directly influenced by corporate behavior, thus indirectly affecting corporate carbon performance by influencing policy formulation.

The results in Table 4 show that in the first-stage regression, CPRI has a significantly positive impact on climate policy uncertainty (at the 1% level). Moreover, the Cragg-Donald Wald F statistic is 24.431 (greater than 16.38), and the Kleibergen-Paap rk LM statistic is 25.514 (significant at the 1% level), indicating that the instrumental variable is robust and effective, with no weak instrument problem. In the second-stage regression, corporate carbon performance is significantly negatively correlated with the instrumental variable at the 1% level, demonstrating that the baseline conclusion remains robust after addressing endogeneity.

Table 4. Results of Instrumental Variable Method and PSM

Variable	(1) First Stage	(2) Second Stage	(3) PSM
	CPU	CP	CP
CPRI	0.002***		
	(5.21)		
CPU _ hat		-0.716***	
		(-5.32)	
CPU			-0.0197***
			(-2.7074)
Size	0.010**	0.022***	0.0111
	(2.13)	(3.55)	(1.3416)
Lev	-0.057***	0.061**	0.1331***
	(-2.86)	(2.49)	(3.7217)
ROA	0.028	0.221***	0.2915***
	(0.59)	(5.40)	(4.1563)
INST	-0.039**	-0.013	0.0461
	(-2.06)	(-0.60)	(1.4854)
List Age	0.042***	0.046***	0.0231**
	(6.99)	(5.52)	(2.3086)
Big4	0.012	-0.004	-0.0334
	(0.71)	(-0.20)	(-1.1249)
Loss	-0.004	0.006	0.0204*
	(-0.48)	(0.88)	(1.8031)
Constant	-0.134	0.111	0.3168*
	(-1.32)	(0.89)	(1.8086)
Year FE	Yes	Yes	Yes
Id FE	Yes	Yes	Yes
Observations	30,725	30,725	18,705
R^2	0.774	0.886	0.898
Cragg-Donald Wald F Statistic	24.431	—	—
Kleibergen-Paap rk LM Statistic	25.514***	—	—

4.2.2. PSM

To further examine whether sample selection bias leads to estimation errors, this paper employs the Propensity Score Matching (PSM) method for endogeneity testing. Specifically, samples with climate policy uncertainty above the industry average are defined as the treatment group. Using the previously mentioned control variables as matching covariates, 1:1 nearest neighbor matching is performed. The balance test results, shown in Column (3) of Table 4, indicate that after matching, the regression coefficient for the explanatory variable is -0.0197 and remains statistically significant at the 1% level. This suggests that, after controlling for differences in firm characteristics, the inhibitory effect of policy uncertainty on carbon performance remains robust.

Table 5 presents the balance test results. After matching, the standardized bias for all covariates is below 10%, and no significant differences exist between the control and treatment groups in any of the covariates. This confirms that all covariates pass the balance test.

Table 5. Balance Test Results

Variable	Sample	Mean		Standardized Bias (%)	Absolute Reduction in Bias (%)	T-test	
		Treatment Group	Control Group			T-statistic	P-value
Size	Unmatched	22.297	22.194	7.7	99.8	7.10	0.000
	Matched	22.297	22.297	0.0		0.02	0.988
Lev	Unmatched	0.42649	0.42017	3.1	83.4	2.83	0.005
	Matched	0.42649	0.42754	-0.5		-0.43	0.669
ROA	Unmatched	0.04422	0.04431	-0.1	-197.0	-0.12	0.905
	Matched	0.04422	0.04447	-0.4		-0.32	0.749
INST	Unmatched	0.45576	0.44814	3.1	96.8	2.80	0.005
	Matched	0.45576	0.45551	0.1		0.08	0.934
List Age	Unmatched	2.0789	2.0271	5.6	91.1	5.15	0.000
	Matched	2.0789	2.0835	-0.5		-0.42	0.675
Big4	Unmatched	0.06911	0.06384	2.1	60.7	1.95	0.051
	Matched	0.06911	0.07118	-0.8		-0.68	0.498
Loss	Unmatched	0.1373	0.12745	2.9	92.0	2.68	0.007
	Matched	0.1373	0.13651	0.2		0.19	0.848

4.3. Robustness Check

4.3.1. Replacing the Core Explanatory Variable

Currently, there are multiple measurement methods for the Climate Policy Uncertainty (CPU) index. If benchmark regression results depend on the choice of a specific measurement approach, their theoretical value and policy significance would be greatly diminished. Therefore, this paper examines the sensitivity of baseline results to variable definition and mitigates potential measurement errors by constructing an alternative CPU indicator. Specifically, following the method of Gu et al. (2018)[34], the annual geometric mean of the monthly CPU index (G_CPU) is calculated for robustness testing. As shown in column (1) of Table 6, the regression coefficient for CPU is -0.019 and statistically significant at the 5% level, indicating a significant negative impact of climate policy uncertainty on corporate carbon performance. This confirms that the findings are not driven by the specific variable measurement method, thereby supporting the robustness of the baseline regression.

4.3.2. Excluding Data from Extraordinary Years

As rare global extreme external shocks, the 2008 financial crisis and the COVID-19 pandemic that emerged in 2020 may, on the one hand, affect the government's formulation of climate policies—for instance, the government may adopt unconventional policy interventions. On the other hand, these shocks may lead enterprises to prioritize survival-oriented emergency strategies in the face of extreme adversities, temporarily postponing long-term carbon performance improvement plans. Consequently, such extraordinary periods may generate anomalous data that could interfere with the findings of this study. Therefore, drawing on the approach of Li et al. (2025) [11], this paper conducts robustness tests by excluding data samples from the exceptional years of 2008 and 2020. As shown in column (2) of Table 6, the coefficient of the core explanatory variable remains negative and statistically significant at the 1% level. This demonstrates that the baseline regression results are not driven by a few exceptional events but rather reflect a stable economic relationship between the variables.

4.3.3. Adding a Time Trend Term

Although individual and year fixed effects have been controlled for in the baseline regression model, differentiated linear trends across provinces—such as those in green technology innovation and environmental awareness enhancement—may simultaneously affect climate policy uncertainty and corporate carbon performance, potentially leading to confounding bias. Therefore, drawing on the method of Wang and Hu (2024) [6], this study further refines the baseline model by introducing a province-year time trend term (prov_year_trend) to obtain more purified regression estimates. As shown in column (3) of Table 6, the regression coefficient of the core explanatory variable is -0.015 and statistically significant at the 5% level. This indicates that even under this stricter specification, climate policy uncertainty continues to exert a significant negative impact on corporate carbon performance, thereby robustly confirming the reliability of the baseline regression results.

Table 6. Robustness Check I

Variable	(1)	(2)	(3)
	CP	CP	CP
G_CPU	-0.019**		
	(-2.55)		
CPU		-0.018***	-0.015**
		(-3.42)	(-2.30)
prov _year _trend			0.143***
			(50.22)
Size	0.014**	0.015**	0.014**
	(2.09)	(1.98)	(2.29)
Lev	0.124***	0.134***	0.123***
	(4.46)	(4.32)	(3.72)
ROA	0.284***	0.317***	0.284***
	(5.85)	(5.72)	(4.12)
INST	0.043*	0.048*	0.043
	(1.69)	(1.65)	(1.15)
List Age	0.015*	0.015*	0.015
	(1.88)	(1.77)	(1.20)
Big4	-0.024	-0.025	-0.024
	(-1.06)	(-0.98)	(-1.13)
Loss	0.011	0.010	0.011
	(1.37)	(1.18)	(1.09)
Constant	0.222	-0.107	1.356***
	(1.53)	(-0.68)	(9.89)
Observations	35,136	31,206	35,167
R2	0.881	0.885	0.865
Year FE	Yes	Yes	Yes
Id FE	Yes	Yes	Yes
Clustering	Id	Id	Id

4.3.4. Changing the Clustering Level of Standard Errors

In Model (1), standard errors are clustered at the firm level. However, firms within the same industry or province may be subject to common shocks, leading to correlated error terms at higher levels. If such correlation exists but is not properly accounted for, standard errors may be underestimated, resulting in an increased risk of over-rejecting the null hypothesis. Therefore, following the approach of Mao et al. (2024) [35], this paper conducts robustness analyses by clustering standard errors at the industry level and the province level, respectively. Industry-level clustering accounts for within-group correlation driven by common factors such as industry-wide regulations, while province-level clustering captures shared shocks at the regional level, such as local policies and resource endowments. As shown in columns (1) and (2) of Table 7, climate policy uncertainty continues to exert a significant negative impact on corporate carbon performance under different clustering levels. This confirms that the baseline regression results are highly robust to alternative assumptions regarding the error correlation structure.

4.3.5. Controlling for High-Dimensional Fixed Effects

Table 7. Robustness Check II

Variable	(1)	(2)	(3)	(4)
	CP	CP	CP	CP
CPU	-0.015***	-0.015**	-0.015***	-0.017***
	(-3.44)	(-2.30)	(-3.29)	(-3.52)
Size	0.014*	0.014**	0.014**	0.014**
	(1.83)	(2.29)	(2.09)	(2.05)
Lev	0.123***	0.123***	0.123***	0.105***
	(3.79)	(3.72)	(4.45)	(3.79)
ROA	0.284***	0.284***	0.284***	0.289***
	(5.72)	(4.12)	(5.85)	(5.85)
INST	0.043	0.043	0.043*	0.045*
	(1.42)	(1.15)	(1.69)	(1.77)
List Age	0.015	0.015	0.015*	0.018**
	(0.97)	(1.20)	(1.88)	(2.38)
Big4	-0.024	-0.024	-0.024	-0.016
	(-1.02)	(-1.13)	(-1.06)	(-0.69)
Loss	0.011	0.011	0.011	0.006
	(1.35)	(1.09)	(1.37)	(0.75)
Constant	0.223	0.223	0.223	0.227
	(1.33)	(1.65)	(1.54)	(1.55)
Observations	35,136	35,136	35,136	35,105
R^2	0.881	0.881	0.881	0.892
Year FE	Yes	Yes	Yes	No
Id FE	Yes	Yes	Yes	Yes
Ind FE	No	No	Yes	No
Ind×Year FE	No	No	No	Yes
Clustering	Ind	Prov	Id	Id

Although individual and year fixed effects are already controlled for in the baseline regression, potential endogeneity issues due to omitted variables may still exist. For example, unobserved factors such as industry-specific policy shocks or technological changes may vary simultaneously across industries and over time. If these factors are correlated with the core explanatory variable, estimation bias could arise. Chen (2020) argues that for environmental factors with distinct regional and industry characteristics, such omitted variation can be addressed by including high-dimensional fixed effects such as industry-year interactions [36]. Following this approach, this paper further refines the baseline specification by sequentially incorporating industry fixed effects and industry×year fixed effects. The results are presented in columns (3) and (4) of Table 7. Column (3) adds industry fixed effects, yielding a coefficient of −0.015 that remains statistically significant at the 1% level. Column (4) introduces industry×year high-dimensional fixed effects, with a coefficient of −0.017, also significant at the 1% level. These results confirm the robustness of the baseline regression findings.

5. Further Analysis

5.1. Mechanism Analysis

The previous section examined the impact of climate policy uncertainty on corporate carbon performance. To further investigate the mechanisms through which climate policy uncertainty affects corporate carbon performance, this paper empirically tests hypotheses 2 to 4 from the theoretical section using the two-step mediation effect approach. The first step involves estimating Model (1). In the second step, based on Model (1), the following model is constructed:

$$GFI_{i,n,t} = \alpha + \alpha_1 CPU_{n,t} + \beta_k \sum Controls_{i,t}^{k} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{2}$$

$$GI_{i,n,t} = \alpha + \alpha_1 CPU_{n,t} + \beta_k \sum Controls_{i,t}^{k} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

$$DCP_{i,n,t} = \alpha + \alpha_1 CPU_{n,t} + \beta_k \sum Controls_{i,t}^{k} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

Among them, GFI, GI, and DCP represent the mechanism variables—Green Finance Environment, Green Innovation, and Digital Transformation, respectively. The definitions of all other variables remain consistent with those in Model (1).

5.1.1. External Green Finance Environment (GFI)

An increase in climate policy uncertainty raises potential bad debt risks and stranded asset risks for high-carbon assets within financial institutions. Under such circumstances, financial institutions tend to prudently control the scale of green credit and raise the threshold for enterprises to access green financing, leading to a deterioration of the external green finance environment faced by firms. This directly results in a shortage of green capital for enterprises, causing delays or cancellations of related green project investments, ultimately negatively affecting corporate carbon performance. Therefore, drawing on the measurement approach of Chen et al. (2024) [20], this paper employs the entropy method to evaluate the external green finance environment for firms across seven dimensions: green credit, green insurance, green bonds, green investment, green funds, green equity, and green support. A higher value indicates a more favorable external green finance environment for the firm. The regression results, presented in column (1) of Table 8, show that the coefficient for climate policy uncertainty is -0.048 and is statistically significant at the 1% level. This indicates that climate policy uncertainty significantly deteriorates the external green finance environment faced by firms, thereby exerting a negative impact on corporate carbon performance.

5.1.2. Green Innovation (GI)

Zhang et al. (2024) point out that as climate policy uncertainty rises, enterprises face more frequent external shocks, heightened market risks, and intensified external competition [5]. Under such circumstances, firms encounter greater investment uncertainty, leading them to reduce long-term investments and narrow their innovation space, thereby inhibiting green innovation. According to Ding (2025) [37], green technological innovation can lower energy consumption and environmental pollution in production processes through the research, development, and adoption of advanced clean technologies, thereby improving corporate carbon performance. Therefore, increased climate policy uncertainty suppresses green innovation, which in turn reduces corporate carbon performance.

Drawing on the methods of Wang and Wang (2021)[38] and Li et al. (2023) [39], this paper adopts the natural logarithm of the number of green patent applications filed by a firm plus one as the measure of corporate green technological innovation. The regression results, presented in column (2) of Table 8, show that the coefficient for green innovation is -0.019 and is statistically significant at the 1% level. This indicates that climate policy uncertainty significantly suppresses corporate green innovation, thereby reducing corporate carbon performance.

5.1.3. Digital Transformation (DCP)

This study follows the approach of Zhao et al. (2021)[40] and employs text analysis to identify high-frequency terms related to digital transformation from listed companies' annual reports, forming a specialized dictionary. The disclosure frequency of keywords is counted across four dimensions: digital technology application, internet-based business models, intelligent manufacturing, and modern information systems. The term-frequency data are then standardized, and the entropy method is applied to determine the weight of each indicator, ultimately constructing a digital transformation index.

As shown in column (3) of Table 8, the coefficient of the climate policy uncertainty index is negative and statistically significant at the 1% level, indicating that rising climate policy uncertainty suppresses the level of corporate digital transformation. Increased climate policy uncertainty exposes firms to greater unpredictability, leading to a decline in risk-taking capacity and a reduction in investments related to digital transformation. Consequently, the progress of green technology R&D and adoption slows down, thereby inhibiting the improvement of corporate carbon performance.

Table 8. Mechanism Analysis Results

Variable	(1)	(2)	(3)
	GFI	GI	DCG
CPU	-0.048***	-0.019***	-0.011***
	(-3.31)	(-3.32)	(-3.05)
Size	0.024*	0.059***	0.130***
	(1.85)	(4.30)	(7.47)
Lev	-0.088*	-0.029	0.013
	(-1.66)	(-0.70)	(0.25)
ROA	-0.103	-0.036	-0.168**
	(-0.71)	(-0.46)	(-2.21)
INST	-0.026	-0.133***	-0.052
	(-0.47)	(-2.99)	(-0.78)
List Age	-0.042*	-0.002	0.067***
	(-1.82)	(-0.13)	(5.76)
Big4	-0.038	0.062	0.043
	(-0.82)	(1.31)	(0.84)
Loss	0.025	-0.015	-0.009
	(1.14)	(-1.34)	(-0.92)
Constant	-0.381	-0.869***	-3.105***
	(-1.39)	(-3.02)	(-8.10)
Observations	31,095	34,969	35,135
R^2	0.108	0.672	0.778
Year FE	Yes	Yes	Yes
Id FE	Yes	Yes	Yes

5.2. Heterogeneity Analysis

5.2.1. Executives' Green Cognition

According to the Upper Echelons Theory, differences in executives' green cognition influence how firms respond to climate policy uncertainty. Following the method of Li et al. (2023) [41], this study uses the proportion of green-cognition-related keywords in annual reports as a proxy variable and divides the full sample into two groups—strong executive green cognition (HEGP) and weak executive green cognition (LEGP)—based on the industry-year median.

The regression results (columns (1) and (2) of Table 9) show that the coefficient for the weak-cognition group is -0.028 and significant at the 1% level, while the coefficient for the strong-cognition group is -0.005 and statistically insignificant. This indicates that the negative impact of climate policy uncertainty on corporate carbon performance is more pronounced among firms with weaker executive green cognition. The reason may be that executives with weaker green cognition tend to perceive policy uncertainty as a compliance risk, leading them to adopt conservative strategies that avoid long-term green investments, thereby restraining green innovation and carbon performance improvement. In contrast, executives with stronger green cognition are more capable of identifying strategic opportunities within policy fluctuations and proactively deploying green initiatives, which effectively mitigates the negative impact of uncertainty, rendering it statistically insignificant.

5.2.2. Government Environmental Regulation

The impact of climate policy uncertainty on corporate carbon performance varies across firms, a difference that is closely related to the external regulatory environment in which they operate. Therefore, this study selects the intensity of government environmental regulation for heterogeneity analysis, using the frequency of environment-related keywords in provincial government work reports as a proxy variable for environmental regulation intensity (Yin and Wu, 2021) [42]. The sample is divided into a high-intensity environmental regulation group (HERS) and a low-intensity environmental regulation group (LERS) based on the industry-year median. The regression results, as shown in Table 9, indicate that the coefficient for the low-regulation group is -0.017 and is significant at the 5% level, while the coefficient for the high-regulation group is -0.006 and is not statistically significant.

This suggests that the negative impact of climate policy uncertainty on corporate carbon performance is concentrated mainly in regions with relatively lenient environmental regulations. A possible explanation is that, in low-regulation environments, firms face less pressure and regulatory risk to transition, and the emergence of policy uncertainty heightens their concerns about future policy directions, leading them to adopt a "wait-and-see" approach. To avoid potential sunk costs from future policy changes, firms tend to postpone or avoid climate-related investments, resulting in a significant decline in their carbon performance. In contrast, in high-regulation environments, firms are already subject to stringent regulatory standards, with relatively higher baseline carbon performance. They have likely invested substantial resources in green technology research and development, having largely completed stable long-term green strategy deployment. As a result, short-term policy shocks are unlikely to substantially disrupt their established green strategies, and the negative impact is buffered by the existing strict regulatory framework.

Table 9. Executives' Green Cognition and Government Environmental Regulation

Variable	(1)	(2)	(3)	(4)
	HEGP	LEGP	HERS	LERS
CPU	-0.005	-0.028***	-0.006	-0.017**
	(-0.94)	(-3.18)	(-0.78)	(-2.44)
Size	0.010	0.019	0.018**	0.010
	(1.20)	(1.53)	(2.00)	(1.09)
Lev	0.094***	0.170***	0.127***	0.126***
	(3.01)	(3.35)	(3.63)	(3.12)
ROA	0.217***	0.384***	0.321***	0.218***
	(3.58)	(4.93)	(5.05)	(3.14)
INST	0.009	0.114**	0.044	0.021
	(0.32)	(2.42)	(1.39)	(0.57)
List Age	0.010	0.021	0.010	0.016
	(1.06)	(1.55)	(0.96)	(1.51)
Big4	-0.027	-0.016	-0.023	-0.047*
	(-1.05)	(-0.45)	(-0.71)	(-1.89)
Loss	0.008	0.010	0.018*	-0.003
	(0.79)	(0.79)	(1.73)	(-0.32)
Constant	0.329*	0.104	0.141	0.312
	(1.89)	(0.40)	(0.75)	(1.62)
Observations	21,735	12,667	19,913	14,506
R^2	0.891	0.898	0.891	0.896
Year FE	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	Yes

5.2.3. Degree of Market Competition

The degree of market competition may moderate the impact of climate policy uncertainty on corporate carbon performance. Therefore, we divided the sample into a low competition group (LMS) and a high competition group (HMS) based on the median market concentration. The regression results in Table 10 show that the coefficient for the low competition group is -0.006 (significant at the 1% level), while the coefficient for the high competition group is -0.02 (not significant).

This difference may stem from variations in corporate decision-making behaviors under different competitive environments. High-competition firms face greater survival pressures and have lower strategic flexibility. They are more inclined to prioritize their core business and short-term profits, making them more likely to delay or reduce carbon reduction investments when policy uncertainty arises, leading to a significant decline in carbon performance. In contrast, low-competition firms face less competitive pressure, often possess more stable cash flows and longer-term decision-making horizons, and are better equipped to cope with policy uncertainty, thereby mitigating its negative impact on carbon performance.

5.2.4. Industry Type

Different industry types exhibit varying responses to climate policies. To this end, this paper conducts a grouped analysis based on capital-intensive (CI), technology-intensive (TI), and labor-intensive (LI) classifications. The results in columns (3) to (5) of Table 10 show that the regression coefficients for the capital-intensive and technology-intensive groups are -0.026 and -0.014, respectively, both indicating a statistically significant negative impact on carbon performance at the 1% and 10% levels. In contrast, the coefficient for the labor-intensive group (-0.01) is not statistically significant.

Table 10. Industry Competition Intensity and Industry Types

Variables	(1)	(2)	(3)	(4)	(5)
	LMS	HMS	CI	TI	LI
CPU	-0.006	-0.020***	-0.026***	-0.014**	-0.010
	(-0.94)	(-2.88)	(-3.22)	(-1.97)	(-1.12)
Size	0.027***	0.011	0.023*	0.009	0.013
	(3.00)	(0.92)	(1.90)	(0.87)	(0.97)
Lev	0.095***	0.129***	0.071	0.168***	0.112**
	(2.73)	(3.09)	(1.43)	(3.97)	(2.11)
ROA	0.125**	0.386***	0.169*	0.395***	0.159
	(2.01)	(5.45)	(1.80)	(5.58)	(1.65)
INST	0.001	0.094**	-0.012	0.064*	0.077
	(0.02)	(2.46)	(-0.27)	(1.72)	(1.47)
List Age	0.016	0.004	-0.024	0.023**	0.017
	(1.41)	(0.36)	(-1.52)	(2.19)	(1.06)
Big4	-0.010	-0.025	0.055	-0.080**	-0.029
	(-0.45)	(-0.49)	(1.17)	(-2.47)	(-0.82)
Loss	0.009	0.014	0.023	0.010	-0.005
	(0.85)	(1.20)	(1.54)	(0.84)	(-0.40)
Constant	-0.148	0.390	0.124	0.349	0.156
	(-0.75)	(1.62)	(0.49)	(1.58)	(0.53)
Observations	15,938	18,955	10,018	16,950	8,168
R^2	0.892	0.881	0.872	0.889	0.877
Year FE	Yes	Yes	Yes	Yes	Yes
Id FE	Yes	Yes	Yes	Yes	Yes

This suggests that capital- and technology-intensive enterprises, characterized by high "rigid costs," strong path dependence, and greater sensitivity to policies, face higher transformation costs when confronted with climate policy uncertainty, making their carbon performance more susceptible to shocks. Meanwhile, labor-intensive enterprises, with their low fixed costs, low technological dependence, and flexible production adjustments, are better able to buffer the negative effects of policy uncertainty, resulting in no significant impact on their carbon performance.

6. Conclusions and Recommendations

6.1. Conclusions

Based on panel data from Chinese Shanghai and Shenzhen A-share listed companies spanning 2007 to 2023, this paper examines the impact of climate policy uncertainty on corporate carbon performance and analyzes the underlying mechanisms linking the two. The study yields the following key findings: First, climate policy uncertainty significantly inhibits corporate carbon performance—that is, higher climate policy uncertainty correlates with worse corporate carbon performance. This baseline regression result remains robust after a series of tests, including replacing explanatory variables, excluding data from specific years, and controlling for high-dimensional fixed effects. Second, mechanism analysis reveals that rising climate policy uncertainty undermines corporate carbon performance by weakening the quality of the external green finance environment, suppressing corporate green innovation, and hindering corporate digital transformation. Third, heterogeneity analysis indicates that the inhibitory effect of climate policy uncertainty on corporate carbon performance is more pronounced among capital-intensive and technology-intensive firms with weaker executive green awareness, lower intensity of government environmental regulations, and less market competition.

6.2. Recommendations

Based on the research findings above, this paper proposes the following recommendations:

First, given the significant negative impact of climate policy uncertainty on corporate carbon performance, the government should strive to enhance the stability and predictability of climate policies. On one hand, when formulating climate policies, relevant departments should conduct thorough research and scientific evaluation, solicit opinions extensively from enterprises, industry associations, and experts to ensure that policies are based on comprehensive and accurate information, thereby reducing arbitrariness and blindness in policymaking. On the other hand, a climate policy adjustment mechanism should be established. In the face of major climate change events or significant deviations between policy outcomes and expectations, the government should make appropriate adjustments through standardized procedures and publicly disclose the reasons, basis, and expected effects of such adjustments in a timely manner, enabling enterprises to prepare response measures in advance. Additionally, relevant departments should strengthen policy promotion and interpretation efforts, utilizing multiple channels to help enterprises accurately understand policy intentions and changes, thereby reducing the perceived uncertainty caused by information asymmetry.

Second, in light of the mechanism analysis results, governments and enterprises should collaborate to break the chain through which climate policy uncertainty inhibits corporate carbon performance. On the government side, efforts should be made to advance the development of a green innovation support system by establishing special guiding funds to provide early-stage financial support, implementing tax incentive policies to encourage investment, and creating platforms for transforming research outcomes into practical applications to foster collaboration. The development and guidance of digital transformation infrastructure should be strengthened by increasing investment in digital infrastructure, issuing guidance policies to clarify the direction of transformation, and launching pilot demonstration projects to share experiences. Policy information communication and feedback mechanisms should be improved by disseminating policy information promptly through multiple channels, setting up hotlines and feedback platforms to address questions and collect suggestions. On the enterprise side, there is a need to strengthen the strategic planning and investment in green innovation by incorporating it into long-term strategies, increasing financial input, forming specialized teams, engaging in industry-academia-research collaboration, and protecting and applying innovative achievements. Enterprises should actively advance their digital transformation processes by formulating detailed plans, introducing and applying digital technologies, and cultivating or recruiting digital talent. Efforts should also be made to enhance policy research and response capabilities by establishing dedicated departments to monitor policy developments, formulating response strategies, strengthening communication with the government, and actively participating in policy formulation. Furthermore, optimizing internal management to improve risk resilience can help mitigate the negative impact of climate policy uncertainty on corporate carbon performance.

Third, based on the heterogeneity analysis results, the government can implement differentiated policy guidance and support strategies. First, efforts should be made to enhance the green awareness of corporate executives. This can be achieved by establishing a corporate executive environmental training system, incorporating carbon performance into management evaluation indicators, and strengthening long-term strategic vision through "green leadership" training programs to drive a shift from "passive compliance" to "active transformation." Second, environmental regulations should be dynamically optimized. In regions with weaker regulatory intensity, a "step-by-step" approach to environmental enforcement should be adopted, starting with warnings and technical guidance and gradually increasing penalties for non-compliance. Simultaneously, a coordination mechanism for regulatory standards across regions should be established to avoid "pollution transfer." Additionally, market competition incentive mechanisms can be introduced. In industries with low competition levels, "green competition" policies such as setting awards for industry-leading enterprises in emission reduction and prioritizing low-carbon products in government procurement can stimulate corporate innovation. Finally, differentiated industry support and enhanced policy transparency should be promoted. For capital-intensive and technology-intensive enterprises, targeted research and development subsidies and tax incentives should be provided to reduce the risks associated with green technology investments. A climate policy uncertainty buffer fund should also be established to offer short-term financial support for corporate transitions. By regularly publishing climate policy roadmaps and creating channels for enterprise participation in policymaking, policy uncertainty can be reduced, and long-term investment confidence can be strengthened, particularly for capital- and technology-intensive industries.

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