Assessing the Effect of Climate Policy Uncertainty on Corporate Carbon Cost Leadership Strategy: Evidence from China

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Abstract

Frequent extreme climate events have heightened climate policy uncertainty (CPU) and incorporating the social cost of carbon has become a key element for countries seeking to improve their institutions in response to climate risks. Focusing on corporate efforts, this study innovatively constructs a carbon cost leadership strategy (CCLS) index for Chinese listed companies from 2010 to 2024 using a text-based machine learning approach. Drawing on institutional theory, we examine the relationship between CPU and firms' adoption of CCLS. Our findings indicate that CPU significantly inhibits the implementation of CCLS, primarily because CPU increases firms' operational risks and undermines firms' capacity to respond to climate regulations. Heterogeneity analysis reveals that this negative effect is more pronounced for state-owned enterprises, firms with low climate risk perception, those in low carbon-exposure and non-technology-intensive industries, and firms located in regions with weak public–government climate engagement. This study enriches the understanding of the social impacts of climate policy from the perspective of corporate carbon cost management and provides new insights for emerging economies to improve their social cost of carbon assessment systems and enhance firms' climate response capabilities.

Keywords: Carbon cost leadership; Climate policy uncertainty; Institutional theory; Legitimacy; Social cost of carbon; Textual analysis; China

1 Introduction

Amid global efforts to address climate change, the rising social cost of carbon (SCC) has become a key input in climate policy and economic analysis, increasing pressure on governments and firms to strengthen emissions reduction strategies (Aldy et al., 2021; Zhao et al., 2023; Tol, 2023). As major contributors to global carbon emissions, enterprises play a pivotal role in meeting national climate targets through their operations and in driving the broader low-carbon transition (Chu, Zhang, et al., 2024). With increasingly stringent climate

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policies such as carbon pricing and emission standards, carbon emissions have shifted from an external environmental issue to an internal, tangible cost that firms must effectively manage. Systematic carbon cost management has therefore become a core component of corporate sustainability rather than a discretionary choice. In this context, a forward-looking competitive strategy – Carbon Cost Leadership Strategy (CCLS) – has emerged. CCLS treats carbon as a critical cost element, on par with labour and capital, and requires firms to manage and reduce emissions-related costs across the value chain in a systematic way. Its ultimate aim is to achieve a lower carbon cost per unit of output than competitors, thereby forging a new form of competitive advantage that combines *low carbon* with *low cost* (Jain et al., 2023; Porter, 1997).

Global evidence suggests that implementing a CCLS has enabled some leading enterprises to simultaneously achieve dual improvements in both economic performance and environmental outcomes.[2] [3] However, unlike traditional strategies based mainly on internal operations and market forces, CCLS is closely and structurally tied to institutional environment (Rose, 2012): its success largely depends on firms' ability to balance policy-defined carbon costs (e.g., carbon taxes, allowance prices) with market-driven green demand and to continuously adjust to changes in both. Among external institutional factors, climate policy is both the institutional foundation for firms implementing a CCLS and a major source of uncertainty. It increases carbon cost pressures through 'hard constraints' such as carbon pricing and emissions caps, while also creating strategic opportunities through 'soft incentives' such as green subsidies and low-carbon standards (Mengesha & Roy, 2025). The effectiveness of these policies, however, depends on their stability and predictability. Ambiguous goals, inconsistent implementation, and frequent changes in policy instruments generate climate policy uncertainty (Ding et al., 2025; Sinha et al., 2025), which can distort firms' short-term investment decisions and weaken their long-term carbon cost management.

Based on the foregoing, this study aims to address two key research questions: first, does CPU affect firms' CCLS; and second, if such an effect exists, through which specific mechanisms does CPU influence firms' CCLS? To this end, we construct a novel firm-level indicator of carbon cost leadership strategy using textual analysis of corporate disclosures by Chinese listed firms over the period 2010–2024. We then conduct empirical analyses, drawing on institutional theory and legitimacy perspectives, to examine how CPU shapes firms' strategic behaviour in

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[2] For instance, Baosteel, a flagship enterprise in China's steel industry, leveraged cloud computing, big data, and artificial intelligence in 2022 to develop a comprehensive smart carbon data platform; see: https://www.baowugroup.com/glcmia/detail/277483. This system integrates core modules such as carbon accounting, carbon footprint tracking, and carbon asset management, and is projected to cut annual carbon-related costs by approximately RMB 180 million, according a 2024 report by the China Academy of Information and Communications Technology that is available at https://www.caict.ac.cn/kxyj/qwfb/ztbg/202402/P020240208433543113470.pdf.

[3] Similarly, since 2012, Microsoft has implemented an internal carbon fee across its business units, including data centres, offices, labs, manufacturing, and employee travel. The collected fees fund investments in renewable energy, energy efficiency, and carbon offset projects. These initiatives have delivered USD 10 million in annual cost savings and a 30% reduction in Scope 1 and 2 carbon emissions from the 2020 baseline in 2024. For further details, see: https://unfccc.int/climate-action/momentum-for-change/financing-for-climate-friendly/microsoft-global-carbon-fee and https://www.microsoft.com/en-us/corporate-responsibility/sustainability/report/.

managing carbon costs. This research deepens understanding of how the institutional environment shapes firms' carbon cost leadership behaviours, providing theoretical foundations and empirical insights for governments seeking to optimise climate policy design and for firms formulating robust climate strategies in uncertain environments.

This study contributes to the literature in three aspects. First, from a theoretical perspective, it expands the application boundaries of institutional theory in explaining firms' competitive strategy choices by introducing carbon cost as a core variable. Existing work on how firms respond to external pressures for legitimacy has largely focused on outcomes such as corporate social responsibility (Chu, Zhang, et al., 2024), while relatively neglecting the central role of cost management. In response, this study systematically conceptualises CCLS, embeds it within the institutional and legitimacy framework, and, for the first time, incorporates CPU into the analysis. Our findings show that institutional pressures not only shape firms' compliance behaviours but also significantly influence their willingness and ability to develop carbon cost advantages, offering a more integrated theoretical explanation of CCLS implementation under uncertainty.

Second, this study enriches the understanding of the socio-economic impacts of CPU from the perspective of CCLS. Prior work has mainly examined CPU's effects on specific corporate behaviours (e.g., green innovation) or aggregate performance indicators (e.g., ESG performance) (J. Huang et al., 2023; Pan et al., 2024). While informative about the 'green effects' of CPU, they do not reveal how CPU shapes firms' systematic CCLS aimed at building long-term advantages. This study addresses this gap by examining the internal mechanisms and conditions through which CPU affects CCLS. Specifically, it analyses the roles of factors such as financial stability, operational risk, climate-related innovation, and negative climate news from a dual perspective of managerial willingness and capability. It also investigates the heterogeneous effects of ownership structure, managers' climate risk perception, industry carbon exposure and technological intensity, and regional public–government climate interactions on the CPU–CCLS relationship. Together, these analyses provide a novel mechanistic account of how firms adjust their strategies under uncertainty and offer a new lens for evaluating the long-term economic and social effects of CPU.

Finally, in terms of variable measurement, this study proposes a feasible quantitative approach to capture the emerging and complex strategic concept of CCLS. Previous studies have often relied on proxy variables such as green patents, environmental investments, or third-party ESG ratings to measure corporate low-carbon strategies (Ge & Zhang, 2025; Huo et al., 2024). However, these proxies struggle to comprehensively and directly capture the systematic and integrated nature of CCLS within managerial cognition. Drawing on cutting-edge approaches, this study employs machine learning and natural language processing techniques to construct a nuanced text-based indicator derived from corporate annual reports, which captures firms' simultaneous focus on carbon transition and cost leadership. This methodological innovation offers a robust basis for our empirical analysis and a feasible, replicable, and scalable tool for measuring CCLS in future research.

2 Literature review and hypothesis development

2.1 Literature review

2.1.1 Green transformation and cost leadership strategy

Cost leadership strategy centres on achieving the lowest industry-wide cost structure to gain an advantage over rivals (Lynch, 2021). Traditionally, firms have relied on economies of scale (Mauler et al., 2021), technological innovation (Liu et al., 2021), and supply chain optimisation (Ni et al., 2021) to secure cost advantages. This paradigm, however, is increasingly challenged in the context of the global low-carbon transition. Conventional cost-reduction approaches, when applied under carbon constraints, may incur punitive carbon costs (Xia et al., 2024), while emerging decarbonisation investments often conflict with short-term cost minimisation. To navigate this dilemma, firms need to integrate carbon costs into strategic planning. Mechanisms such as internal carbon pricing can make carbon costs explicit, enabling firms to systematically assess climate-related risks and opportunities when making long-term decisions (Bento et al., 2021).

Although a comprehensive theoretical framework for carbon cost leadership is still lacking, carbon costs are increasingly integrated into the analytical framework of cost leadership strategy in recent literature. For example, Tsai et al. (2023) propose that effective carbon cost management is becoming crucial for building a cost leadership advantage. Companies can use tools such as carbon accounting to measure and manage emissions, and by investing in and applying green innovation technologies, reduce emissions at the source, thereby lowering both compliance and production costs and ultimately enhancing operational efficiency (Di Vaio et al., 2024). However, most current studies treat specific types of carbon cost management behaviour as outcome variables and focus on their policy or organisational drivers, such as the role of digital government development in improving energy efficiency (Tang et al., 2025), or the positive impact of executives' R&D backgrounds on low-carbon innovation (Wu, 2024). While these studies deepen understanding of the drivers of corporate decarbonisation, they overlook the integration of these practices into a cohesive carbon cost leadership strategy from both theoretical and empirical perspectives.

2.1.2 Impact of climate policy uncertainty

CPU exerts broad and significant effects on various aspects of corporate operations (Ren et al., 2022; C. Tan et al., 2025; Zhang et al., 2025; Zhang & Sun, 2025; Zhao, Ma, et al., 2025). Real options theory posits that when uncertainty is high, the value of waiting and observing increases, leading firms to postpone or reduce irreversible investments (Fuss et al., 2008; Lin & Wang, 2025). Empirical research finds that CPU significantly suppresses firms' investment levels and, more importantly, reduces investment efficiency (Zhang et al., 2025; Zhao, Ma, et al., 2025) and free cash flow (Ren et al., 2022). CPU may also prompt corporate management teams to engage in strategic information disclosure, undermining information quality in capital markets (Zhang and Sun, 2025)

In the context of corporate green transformation, the literature presents conflicting views on the impact of CPU. One strand argues that CPU exerts a suppression effect. J. Huang et al.

(2023) show that CPU significantly reduces firms' high-quality, long-term green innovation performance. Ge and Zhang (2025) find that CPU weakens firms' overall ESG performance by increasing operational risks and complicating resource allocation. Conversely, another strand identifies a stimulating effect. Consistent with the Porter Hypothesis, this view suggests that CPU signals the likelihood of stricter future environmental regulation, thereby pressuring firms to engage in forward-looking green innovation to secure technological leadership and first-mover advantages (for instance, see Huo et al. (2024)). Of particular relevance is carbon performance management, a critical component of corporate green transformation that has received only limited attention in the CPU literature, and the few existing studies report similarly divergent findings. On the one hand, CPU can act as a catalyst, prompting firms to proactively invest in sustainable capital to hedge anticipated regulatory risks and thereby reduce carbon emissions (Borozan & Pirgaip, 2024). On the other hand, CPU may discourage such initiatives by inducing firms to postpone green investments and technological innovation, creating a 'carbon lock-in' effect that hinders improvements in carbon performance and increases future carbon abatement costs (Zhao, Liu, et al., 2025).

2.1.3 Research gap

A review of the existing literature reveals several gaps. First, carbon constraints are reshaping traditional competitive strategies (Bento et al., 2021). However, work on the emerging CCLS, which aims to combine low emissions with low cost, remains in its infancy. Existing studies mainly examine the effects of individual carbon cost management policies (C. Huang et al., 2023; Lin & Wesseh, 2020), treating carbon costs as a constraint when discussing their impacts on firms. In addition, there is still no systematic framework explaining how CCLS – as a forward-looking strategy highly dependent on the external institutional environment – is shaped. Moreover, there is a lack of clear and rigorous measurement of CCLS. Second, although the literature on CPU has documented its broad influence on corporate behaviour, its effects in the context of green transformation remain contested (J. Huang et al., 2023; Huo et al., 2024). Existing work has examined CPU's impact on carbon management performance from an outcome-oriented perspective (Ge & Zhang, 2025), but cost-based carbon management strategies still lack solid theoretical and empirical support, and no study has yet analysed CPU and CCLS within a unified framework.

2.2 Hypothesis development

2.2.1 Climate policy uncertainty and corporate carbon cost leadership strategy

The theoretical framework of this study is grounded in institutional theory. This perspective posits that organisations are not isolated economic entities but are embedded in a complex institutional environment shaped by rules, norms, and beliefs (Meyer & Rowan, 1977). A core objective of organisational strategic decision-making is to achieve and maintain legitimacy, which can be defined as 'a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions' (Suchman, 1995). To achieve this, organisations must continually respond to regulatory, normative, and mimetic pressures from their institutional field, while interpreting external institutional signals related to sustainable development, compliance, and societal welfare to form strategic expectations and guide internal actions (Bitektine & Song, 2023). Therefore, the clarity and stability of institutional signals (e.g., policies) largely determine whether firms are willing to make high-risk, long-term strategic commitments.

As instruments such as carbon taxes, emissions trading systems, and carbon footprint disclosure requirements have been strengthened, external carbon-related externalities are increasingly internalised into firms' cost structures, giving rise to the 'carbon cost' borne by firms (Zhang et al., 2024), profoundly influencing day-to-day management decisions. CPU can be understood as a specific type of institutional environment characterised by institutional signals transmitted through regulative and normative pressures that that exhibit high levels of ambiguity, conflict, and instability (Zhang et al., 2025). In such an environment, firms struggle to clearly identify behaviours that can consistently and reliably garner regulatory support, societal approval, and market recognition, thereby impeding their ability to form stable expectations of legitimacy. The adoption of a CCLS, which requires substantial, long-term, and largely irreversible resource commitments, therefore becomes a high-stakes strategic choice under heightened CPU.

Faced with legitimacy risks induced by institutional uncertainty, firms generally adopt risk-avoidance strategies, manifested primarily as strategic delay, retrenchment, and mimetic isomorphism. First, to mitigate potential losses in profits and reputation, firms may proactively reduce their commitment to and the intensity of CCLS implementation. J. Huang et al. (2023) for example, find that cities with greater environmental policy uncertainty have significantly fewer green technology patents from local firms, indicating that firms intentionally curtail long-term, irreversible green innovation when institutional signals are ambiguous. Similarly, Pan et al. (2024) show that CPU significantly suppresses eco-investment by polluting firms, which respond passively by retaining cash and adjusting financial asset portfolios rather than undertaking organisational restructuring or capability enhancement. This suggests that, in uncertain institutional environments, many firms maintain only the minimum level of compliance investment needed to avoid non-compliance risks, rather than actively pursuing a proactive, forward-looking CCLS.

Second, driven by a fear of strategic failure, corporate management exposed to negative signals from an unstable institutional environment may seek the security through mimetic pressures (Majid et al., 2020). As highlighted by DiMaggio and Powell (1983) and Niu et al. (2023), in contexts with unclear rules and uncertain prospects, organisations are reluctant to undertake unique, high-risk, long-term green investments. Instead, they tend to adopt short-term, wait-and-see, imitative, and generally risk-averse strategies. Both strategic delay and retrenchment, as well as mimetic isomorphism, run counter to the intrinsic attributes of CCLS, which demand proactiveness, distinctiveness, foresight, and long-term commitment.

Taken together, these arguments suggest that CPU undermines firms' willingness and capacity to commit to and implement a CCLS. Accordingly, we propose the following hypothesis:

H1: CPU inhibits firms' CCLS implementation.

2.2.2 Mechanism 1: Operational risk

Instability in the institutional environment can provoke distrust among stakeholders towards firms, thereby translating into operational costs and risks that firms must confront (Greenwood et al., 2011). The escalation of operational risks significantly dampens firms' willingness to pursue a CCLS (Zeng et al., 2023).

In the context of CPU, the substantial costs firms incur to manage their legitimacy increase operational risks through two primary channels. First, CPU worsens firms' external financing and transaction environment, directly raising financial risk and thereby constraining the CCLS implementation. In capital markets, investors perceive CPU as a risk that hinders accurate assessment of firms' carbon risk exposure and therefore demand higher risk premia, forcing firms seeking legitimacy to accept more expensive financing (Barnett, 2023). This directly undermines firms' financial stability. Second, CPU-induced legitimacy concerns distort internal resource allocation. Firms divert resources to non-productive activities such as carbon accounting and climate scenario analysis; these managerial costs compress cost–profit margins (Ren et al., 2024). Concurrently, managers may favour symbolic low-carbon projects over technological transformations that genuinely reduce carbon costs in core production processes, leading to resource misallocation (Niu et al., 2023).

Based on the above, we propose the following mechanism hypothesis:

H2: CPU inhibits firms' CCLS implementation by increasing operational risk.

2.2.3 Mechanism 2: Climate institutional responsiveness

Climate institutional responsiveness refers to a firm's overall capability to maintain its legitimate identity and institutional standing through climate innovation, institutional alignment, and other adaptive actions in a volatile climate regulatory environment. Under uncertainty, firms often adopt evasive strategies towards societal legitimacy demands, weakening this responsiveness. A decline in such capability directly impairs a firm's ability to implement a CCLS. For example, reduced climate innovation leads to a lack of effective carbon-reduction technologies, making it difficult to develop actionable plans to enhance carbon efficiency and control emissions, thereby hindering carbon cost reduction (Chen & Wang, 2023).

CPU weakens climate institutional responsiveness in several ways. First, it erodes firms' capacity for climate innovation. Higher business risk and shrinking cost–profit margins squeeze resources for climate technology R&D, and firms worry that costly climate investments may not confer legitimacy under future policy regimes (Sun et al., 2024), prompting cuts in innovation output. Second, CPU impairs institutional alignment – that is, firms' ability to secure official certification for their low-carbon strategies. Firms may fear that approved projects, such as carbon capture and storage facilities, could later be halted due to policy changes (Niu et al., 2023), leading firms to pause or abandon related applications. Prolonged suspension weakens communication and interaction with government, reducing responsiveness, processing efficiency, and related institutional capabilities (L. Wang et al., 2022). Finally, rising CPU inherently increases the complexity of institutional responsiveness.

Greater negative climate-related news coverage can both reflect and reinforce weak responsiveness, while information opacity and regulatory ambiguity may encourage short-term, opportunistic environmental behaviour – such as greenwashing or perfunctory compliance—especially in firms with already limited responsiveness (Wang & Yang, 2025), further fuelling negative publicity.

Based on the above, we propose the following mechanism hypothesis:

H3: CPU inhibits firms' CCLS implementation by weakening climate institutional responsiveness.

Finally, we construct a conceptual framework (Figure 1) to highlight the core research questions and hypotheses of this study.

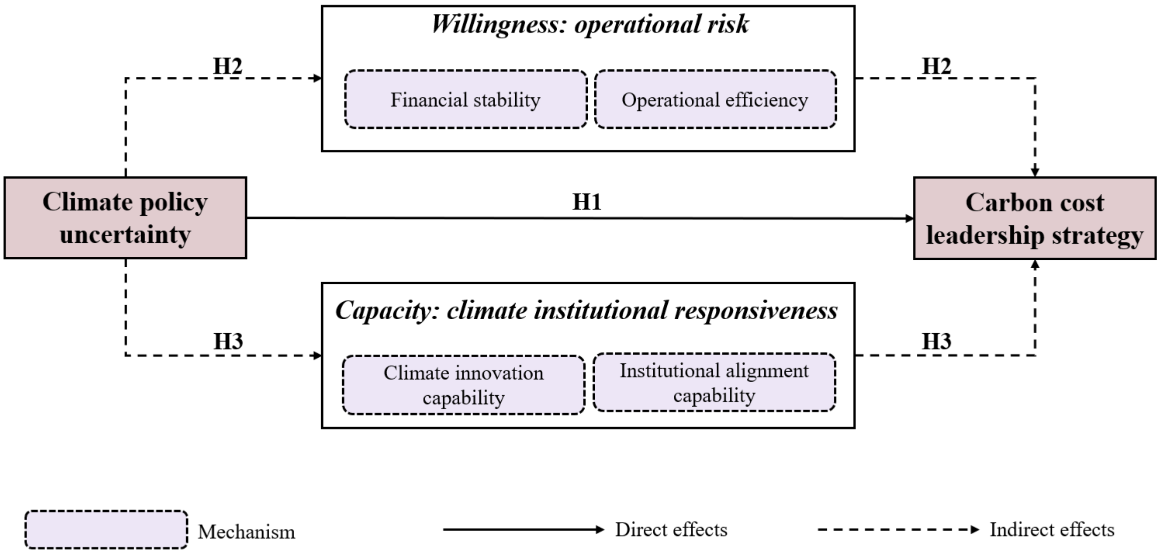

Figure 1: Conceptual framework

3 Research design

3.1 Model

This study employs the following econometric model to empirically examine the relationship between CPU and corporate carbon cost leadership strategy:

$$CCLS_{i,t} = \alpha + \beta CPU_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + Firm\ FE + Year\ FE + City\ FE + \varepsilon_{i,t} \qquad (1)$$

where i and t denote individual firm and year, respectively. The dependent variable *CCLS* is the firm's carbon cost leadership strategy, and the independent variable *CPU* is climate policy uncertainty. The specific calculation methods for *CCLS* and *CPU* are detailed in Sections 3.2. $\boldsymbol{X}_{i,t}$ represents a series of control variables. *Firm FE*, *Year FE*, and *City FE* denote firm, year, and city fixed effects, respectively. ε denotes the random error term.

To examine whether the proposed mechanisms hold, we follow Alesina and Zhuravskaya (2011) and Hayes (2017) and employ a two-step method to test the significance of the mechanism variables. Specifically, the first step estimates model (1) to validate the relationship between the core independent variable and the dependent variable. The second step estimates model (2) to examine the effect of the core independent variable on the mechanism variable. Finally, drawing on prior literature and theoretical arguments, we assess whether the mechanism variable affects the dependent variable. Model (2) is specified as follows:

$$M_{i,t} = \delta + \rho CPU_{i,t-1} + \tau \boldsymbol{X}_{i,t-1} + Firm\ FE + Year\ FE + City\ FE + \varepsilon_{i,t} \qquad (2)$$

where M denotes the mediating (mechanism) variable under examination, and all other variables remain the same as in model (1). In addition, we conduct subgroup regressions (heterogeneity analyses; see Section 4.4 for further substantiation and discussion of the proposed mechanisms.

3.2 Variables

3.2.1 Dependent variable

Our dependent variable is *CCLS*, a firm-level text-based index that measures a firm's focus on carbon cost leadership strategy. Textual big data from corporate disclosure contain profound summaries of management's current business strategies and forward-looking predictions about future development trends. These have become a critical source for external parties to understand a firm's strategic planning (Abedin et al., 2024; Sautner et al., 2023; W. Tan et al., 2025). Building on this premise, we analyse the Management Discussion and Analysis (MD&A) section of annual reports from Chinese A-share listed firms to construct a measure that quantify Chinese firms' focus on carbon cost leadership strategy.

The detailed measurement method for the *CCLS* and its steps are as follows. First, we develop two thematic dictionaries: one for *carbon transition* and one for *cost leadership strategy*. These keywords are sourced from: (1) relevant textbooks on carbon transition and cost leadership; (2) government policy documents and related news releases, from which we manually extract high-frequency terms related to the two themes; and (3) validation and refinement using a powerful large language model (i.e., DeepSeek), which randomly reviews 100 MD&A sections to assess the adequacy of the keywords and suggest additions or deletions. The final *carbon transition* dictionary contains 105 terms (e.g., 'carbon emission reduction', 'dual control of energy consumption', 'carbon footprint', 'carbon pricing'). The *cost leadership strategy* dictionary builds on prior studies (Dess & Davis, 1984; Porter, 1980) and is adapted to the carbon transition context, comprising 106 terms (e.g., 'cost control', 'operating costs', 'optimal allocation'). Table Appendix A.1 presents the example of keywords for each theme, including both the original Chinese terms and their corresponding English translations. Second, any sentence that simultaneously contains at least one *carbon transition*-related keyword and one *cost leadership strategy*-related keyword is classified as describing the firm's CCLS.

In summary, the CCLS score for a firm-year is calculated as the proportion of sentences in each report that simultaneously mention both *carbon transition*-related terms and *cost leadership strategy*-related terms in the MD&A section. A higher value of this indicator suggests a more comprehensive carbon cost strategy for the firm. We validate the reliability of the CCLS measure in Appendix C.

3.2.2 Independent variable

Our independent variable is the city-level climate policy uncertainty (CPU) index constructed by Ma et al. (2023), which measures the degree of climate policy uncertainty across Chinese cities. This index is derived through a combination of manual auditing and deep learning algorithms. Specifically, six leading and authoritative Chinese national newspapers – *People's Daily*, *Guangming Daily*, *Economic Daily*, *Global Times*, *Science and Technology Daily*, and *China News Service* – were selected based on criteria of credibility, influence, and international reach as primary data sources. Using the MacBERT deep learning model, relevant textual content was automatically identified to extract keywords related to climate policy and uncertainty. Subsequently, the number of news articles containing these keywords during a given period was counted and divided by the total number of articles published in the same period to obtain raw frequency data. Finally, this data was standardised to generate the climate policy uncertainty index for each city. A higher value of this index indicates a greater degree of climate policy uncertainty. This methodology has been widely recognised and validated in the literature (Zhao, Liu, et al., 2025; Zhong et al., 2025).

3.2.3 Control variables

To reduce estimation bias, we follow Teng et al. (2024) and Zhong et al. (2025) and include a set of control variables, including firm age (*Age*), size (*Size*), profitability (*ROA*), board size (*Board*), leadership structure (*Dual*), operating revenue (*ATO*), cash ratio (*Cash*), capital intensity (*Fix*), debt-to-equity ratio (*Lev*), growth (*TQ*), equity concentration (*Top5*), and board structure (*Indep*). The calculation methods for all variables used in the baseline regression are detailed in Appendix B.

3.3 Data sources and summary statistics

We select Chinese A-share listed companies from 2010 to 2024 as the research sample. China presents an ideal context for examining this intricate relationship due to its unique position as the world's largest developing economy and carbon emitter, where policy practices and corporate responses carry global significance. With China transitioning from an exploratory to a deepening phase in its climate policy framework, the frequent introduction and adjustment of policy tools create a dynamic environment of policy uncertainty (Wang et al., 2024). Coupled with the steady advancement of its carbon market and increasingly stringent disclosure requirements, Chinese firms face growing and diverse carbon cost pressures (S. Yang et al., 2024). As such, the Chinese context provides a unique and valuable lens for analysing how CPU influences CCLS, offering insights with global relevance.

The CPU index for China was sourced from Ma et al. (2023). Annual reports of listed companies and data for control variables were collected from the CSMAR and Wind databases. Furthermore, we follow the literature to exclude financial firms, firms classified as 'ST' (special treatment) or *ST, firms with an abnormal listing status, and firms with missing key variable(s). To mitigate the influence of outliers, key variables are winsorised at the 1% level. Descriptive statistics for all variables in the baseline regression model are presented in Table 1.

In Table 1, the mean value of the *CCLS* is 0.4548 (i.e., the frequency of sentences related to the carbon cost leadership strategy accounts for 0.4548% of the total sentence frequency), suggesting that most firms still show a relatively weak tendency to implement this strategy. The standard deviation of this variable is 0.1489, representing approximately 32.7% of the mean, indicating substantial variation in firms' emphasis on this strategy. The mean of CPU is 1.8108 with a standard deviation of 0.6105, and there is a large gap between its maximum and minimum values, indicating substantial fluctuations in China's climate policy uncertainty over the study period. The distributions of the control variables are consistent with those reported in the existing literature, supporting the reliability and representativeness of the data.

Table 1 Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
CCLS	25,822	0.4548	0.1480	0.0000	1.3743
CPU	25,822	1.8108	0.6105	0.0000	4.0568
Size	25,822	22.3084	1.2943	19.9634	26.3553
Age	25,822	2.9058	0.3354	1.0986	4.1589
Lev	25,822	0.4330	0.1976	0.0616	0.8782
Roa	25,822	0.0406	0.0622	-0.2181	0.2231
ATO	25,822	0.6786	0.4550	0.0880	2.7313
Cash	25,822	0.0517	0.0657	-1.1312	0.2424
Fix	25,822	0.2275	0.1610	0.0050	0.7079
TQ	25,822	2.1147	1.3702	0.8496	8.7325
Board	25,822	2.1379	0.2010	1.0986	2.8904
Indep	25,822	0.3741	0.0552	0.0000	0.8000
Dual	25,822	0.2501	0.4331	0.0000	1.0000
Top5	25,822	0.5223	0.1537	0.0081	0.9923

4 Empirical analyses

4.1 Baseline results

Table 2 reports the baseline regression results. We employ a rigorous stepwise regression approach to examine the impact of CPU on firms' CCLS. Compared to the models in Columns (1) and (2), the models in Columns (3) and (4) additionally control for year, city, and firm fixed effects. The results in columns (1) through (4) consistently show that the coefficients on *CPU* are significantly negative at the 1% significance level. This indicates that CPU significantly suppresses the implementation of the CCLS, supporting our hypothesis ***H1***. Moreover, the finding aligns with those of Zhao et al. (2025) from a different perspective, that institutional uncertainty hinders firms from engaging in long-term green investment.

Table 2 Baseline regression results – impact of CPU on CCLS

	(1)	(2)	(3)	(4)
Variables	*CCLS*	*CCLS*	*CCLS*	*CCLS*
CPU	–0.0397***	–0.0306***	–0.0046***	–0.0036***
	(0.0015)	(0.0015)	(0.0014)	(0.0014)
Size		–0.0081***		–0.0082***
		(0.0009)		(0.0019)
Age		–0.0118***		–0.1009***
		(0.0027)		(0.0109)
Lev		–0.0565***		–0.0353***
		(0.0058)		(0.0072)
ROA		0.1769***		0.0609***
		(0.0175)		(0.0142)
ATO		0.0280***		0.0018

		(0.0020)		(0.0034)
Cash		–0.0879***		0.0136
		(0.0153)		(0.0113)
Fix		0.2270***		0.0790***
		(0.0062)		(0.0094)
TQ		–0.0054***		–0.0026***
		(0.0007)		(0.0007)
Board		–0.0431***		–0.0121*
		(0.0057)		(0.0067)
Indep		–0.1180***		–0.0058
		(0.0184)		(0.0186)
Dual		0.0149***		0.0079***
		(0.0021)		(0.0021)
Top5		0.0616***		0.0782***
		(0.0060)		(0.0096)
Constant	0.5267***	0.7882***	0.4632***	0.9199***
	(0.0029)	(0.0225)	(0.0026)	(0.0535)
Observations	25,822	25,822	25,822	25,822
Adjusted R^2	0.0268	0.1080	0.6721	0.6803
Firm FE	NO	NO	YES	YES
Year FE	NO	NO	YES	YES
City FE	NO	NO	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses.

4.2 Robustness checks

4.2.1 Instrumental variables approach

The baseline regression results may be subject to endogeneity issues arising from reverse causality that firms unwilling to implement a CCLS might actively obstruct the introduction of clear and strict climate policies through political lobbying and other means, thereby increasing CPU. To address this issue, we employ the instrumental variable (IV) approach using two-stage least squares (2SLS) regressions.

We construct a time-varying instrumental variable, defined as the interaction between the cumulative number of drought and flood disasters experienced by each city over the past 500 years (1470–1979, cross-sectional data) and the annual number of newspaper types in each province. The logic behind the design of this instrumental variable is as follows.

From the perspective of relevance, historical extreme climate events such as droughts and floods profoundly shape the long-term attention and sensitivity of local governments and the public to climate change (Chu, Zhang, et al., 2024), which is reflected in a greater number of CPU-related reports in local media outlets. The number of newspaper types at the provincial level reflects the region's capacity and breadth of information dissemination (Chu, Yang, et al., 2024); a greater variety of newspapers amplifies the coverage of climate-related issues, thereby intensifying the effect of climate policy uncertainty in the information dissemination process.

From the perspective of exogeneity, historical climate data are strictly exogenous and unaffected by contemporary corporate strategic decisions. Similarly, the number of newspaper types, as a macro-level indicator of the information environment, is unlikely to directly influence firm-level decisions regarding the implementation of a CCLS. Therefore, their interaction term satisfies the exogeneity requirement for an instrumental variable.

As shown in Column (1) of Table 3, the coefficient on *IV* is 0.0266 and is statistically significant at the 1% level; the under-identification and weak instrument tests both confirm the appropriateness of the selected instrument. Column (2) shows that, after controlling for endogeneity using the IV approach, the coefficient on *CPU* remains significantly negative at the 1% level, demonstrating the robustness of the findings from the baseline regressions.

4.2.2 PSM-DID

Beyond concerns regarding reverse causality, it is also necessary to address potential bias arising from omitted variables. Following the approach in Chu, Zhang, et al. (2024), we classify firms into high- and low-CPU groups based on the median value of CPU. We then employ the control variables used in previous model as matching covariates and construct counterfactual samples using nearest-neighbour matching under calliper constraints, with both 1:1 and 1:2 matching schemes. The post-matching balance diagnostics indicate that the standardised differences for most covariates fall below 5%, and the t-tests show no statistically significant differences between treated and control groups at the 10% significance level – suggesting satisfactory matching quality. The regression results based on the matched samples are presented in Columns (3)–(4) of Table 3, and the baseline findings remain robust.

4.2.3 Placebo test

Following Cantoni et al. (2017), we conduct a placebo test by randomly assigning the *CPU* values to each firm to generate a new set of independent variable. This process is repeated 500 times. The estimation results of this placebo test are shown in Figure 2.

Figure 2 shows that the regression coefficients from the new samples approximately follow a normal distribution with a mean of zero, and that most of the associated p-values exceed 0.1, clearly differing from the actual estimated coefficient (–0.0036) in the baseline regression. This indicates that the baseline results are unlikely to be influenced by other unobserved factors, further confirming the robustness of the baseline regression results.

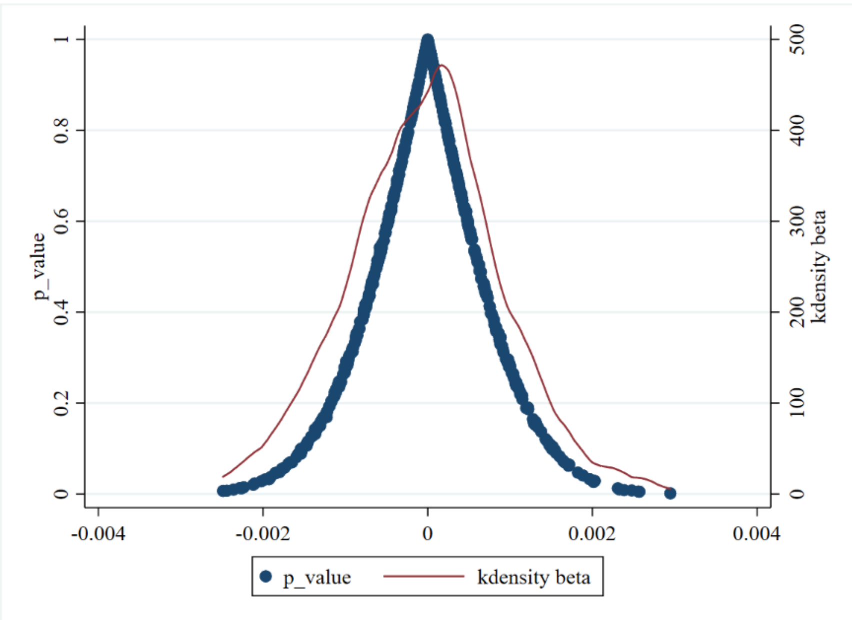

Figure 2. Placebo test results

4.2.4 Heckman two-step method

To mitigate potential endogeneity arising from sample selection bias and omitted variable concerns, we re-estimate our model following the Heckman two-stage regression framework. Specifically, we first construct a probit selection model (Eq. (3)) as the first-stage estimation.

$$CCLS_{dummy_{i,t}} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t-1} + \beta_2 IV_{i,t} + Year\ FE + City\ FE + Firm\ FE + \varepsilon_{i,t} \qquad (3)$$

The dependent variable, $CCLS_{dummy}$, equals one if a firm adopts a CCLS in year t, and zero otherwise. The $\boldsymbol{X}_{it}$ includes all control variables used in the baseline regressions. In addition, we introduce the instrument discussed in Section 4.2.1 as an exclusion restriction, whose relevance and exogeneity have been previously validated. Using this model, we compute the Inverse Mills Ratio (*IMR*), which is then included in Model (1) for the second-stage estimation. The results are reported in Column (5) of Table 3. After controlling for the IMR, the negative coefficient of CPU on CCLS remains significantly negative at the 1% level, consistent with our baseline findings.

Table 3 Robustness tests: IV approach, PSM-DID, and Heckman two-step approaches

	(1) 2SLS	(2) 2SLS	(3) PSM 1:1	(4) PSM 1:2	(5) Heckman
Variables	*CPU*	*CCLS*	*CCLS*	*CCLS*	*CCLS*
CPU		–0.0278**	–0.0061***	–0.0044***	–0.0036***
					(0.0014)
		(0.0132)	(0.0021)	(0.0016)	
IV	0.0266***				
	(0.0017)				
IMR					–0.0013
					(0.0034)
Constant			0.9542***	0.9175***	
			(0.0784)	(0.0625)	
K-P rk LM statistic	244.63***				
C-D Wald F statistic	253.18				
K-P Wald rk F statistic	232.89				
Observations	25,400	25,400	13,886	20,041	25,067
Adjusted R^2			0.6745	0.6784	0.6830
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses.

4.2.5 Excluding samples from direct-administered municipalities

In China, direct-administered municipalities, though termed cities, are under the direct authority of the central government rather than provincial governments. These municipalities possess the same political, economic, and jurisdictional rights as a province. There are four such municipalities in China: Beijing, Chongqing, Shanghai, and Tianjin. Given that they hold unique political status, higher levels of economic development, and stronger policy enforcement capacity, firms located in these cities may inherently exhibits a stronger willingness and capacity to implement a CCLS than those in non-municipal cities.

To address this, we re-estimate the regression after excluding the samples of firms located in the aforementioned municipalities. The results in Column (1) of Table 4 show that, even after excluding these distinctive samples, the coefficient of *CPU* on the CCLS remains significantly negative, indicating that the core findings of this study are not driven by firms in a few municipalities and are broadly applicable to firms in general cities.

4.2.6 Adjusting for clustering

We further cluster the standard errors at the firm level. This approach accounts for unobserved firm-level factors (e.g., managerial ability, organisational culture) that may be correlated across years, potentially causing autocorrelation in the error term within firms. Clustering standard errors at the firm level effectively controls for such within-firm correlations over time, yielding more robust estimates. The regression results in Column (2) of Table 4 show that the coefficient on *CPU* remains negative and statistically significant under this specification.

4.2.7 Accounting for industry and macroeconomic factors

The baseline regression results may also be affected by unobserved, time-varying factors at the industry or regional level. To mitigate this concern as much as possible, we further incorporate high-dimensional fixed effects (HDFE) into the estimation. Specifically, to control for industry-specific cyclical fluctuations that do not vary across firms, Column (3) of Table 4 reports the regression results in which the year fixed effects are replaced with industry–year interaction fixed effects. To further account for time-varying macroeconomic policies or systemic risks at the provincial level, the model in Column (4) of Table 4 additionally controls for province–year interaction fixed effects. In addition to the above methods, we follow Li and Huang (2024) and re-estimate the model by incorporating a set of city-level control variables, including per capita GDP, industrial structure (share of secondary industry), financial development (the ratio of total outstanding loans of financial institutions to regional GDP), internet development (number of Internet users), and air pollution (industrial SO_2 emissions). The results are reported in Column (5) of Table 4. The results of these regressions consistently show that, even after accounting for the aforementioned potential confounding factors, the inhibitory effect of CPU on CCLS remains significant.

4.2.8 Alternative measures for the dependent variable

To ensure that the baseline results are not contingent on a specific measurement of the dependent variable, we re-construct *CCLS* using two alternative methods. For the first one, we take the natural logarithm of one plus the total word frequency of carbon transition and cost leadership strategy theme words (*CCLS_2*). For the second one, we take the natural logarithm of one plus the number of sentences containing both theme words (*CCLS_3*).

Columns (6) and (7) of Table 4 report the regression results using these two alternative dependent variables. The results show that, regardless of the proxy used, the regression coefficient on *CPU* remains statistically significantly negative. This demonstrates that the core finding of this study are robust and insensitive to the measurement of the dependent variable.

Table 4 Robustness tests: excluding samples from direct-administered municipalities, adjusting clustering, controlling for multidimensional fixed effects, adding city-level control variables, and using alternative dependent variables

	(1) Removing municipalities	(2) Cluster adjustment	(3) HDFE	(4) HDFE	(5) Additional city-level control variables	(6) Alternative dependent variable	(7) Alternative dependent variable
Variables	*CCLS*	*CCLS*	*CCLS*	*CCLS*	*CCLS*	*CCLS_2*	*CCLS_3*
CPU	–0.0042***	–0.0036**	–0.0031**	–0.0037**	–0.0037***	–0.0130***	–0.0146**
	(0.0015)	(0.0017)	(0.0014)	(0.0019)	(0.0014)	(0.0038)	(0.0059)
Constant	0.9632***	0.9199***	0.9256***	0.9111***	1.1330***	4.3020***	3.6719***
	(0.0617)	(0.0862)	(0.0542)	(0.0545)	(0.0802)	(0.1438)	(0.2236)
Observations	20,508	25,822	25,822	25,822	24,956	25,822	25,822
Adjusted R^2	0.6647	0.6768	0.6952	0.7003	0.6828	0.6981	0.7575
Controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	NO	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Ind-Year FE	NO	NO	YES	YES	NO	NO	NO
Prov-Year FE	NO	NO	NO	YES	NO	NO	NO

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1; robust standard errors are in the parentheses.

4.2.9 Ruling out effects of other policies

During the sample period, the government and industry associations in China also implemented other related policies that could potentially interfere with firms' implementation of a CCLS. To ensure that the inhibitory effect of CPU is not confounded by these contemporaneous policies, we include dummy variables representing these policies in the regression models.

First, in 2015, SynTao Green Finance published ESG ratings for listed companies for the first time, aiming to encourage firms to actively fulfil social responsibilities and pursue green, low-carbon transformation strategies, supporting China's national 'dual-carbon' goals. Next, in 2017, to advance green financial reform and innovation, the State Council designated specific regions in Zhejiang, Guangdong, Jiangxi, Guizhou, and Xinjiang as pilot zones. These pilot zones were intended to reduce corporate emissions and facilitate the transition towards green, low-carbon development through financial innovation. Finally, in 2018, the Supply Chain Innovation and Application Pilot was officially launched, requiring pilot cities and firms to establish mechanisms for environmentally friendly procurement, carbon footprint tracking, and green technology innovation to develop a full-process green supply chain system. This requirement to directly intervene in firms' carbon management strategies and cost structures could potentially impact the implementation of a CCLS.

To control for the potential interference of the aforementioned policy shocks, we construct dummy variables representing the implementation of each policy and include them in the baseline regression as robustness checks. Columns (1)–(3) of Table 5 report the regression results controlling for the SynTao ESG ratings (ESG), green finance reform (GFR), and supply chain innovation and application pilot (SCIA) policy shocks, respectively. The results show that, after including these policy control variables, the coefficients on *CPU* remain significantly negative, while the coefficients of the corresponding policy dummy variables on *CCLS* are not statistically significant. These regression results indicate that the core conclusions of this study remain robust even after accounting for the potential confounding effects of other major concurrent policies.

Table 5 Robustness tests: results of ruling out confounding effects of related policies

	(1) SynTao ESG	(2) Green finance reform	(3) Supply chain innovation pilot
Variables	*CCLS*	*CCLS*	*CCLS*
CPU	–0.0037***	–0.0036***	–0.0037**
	(0.0014)	(0.0014)	(0.0014)
ESG	0.0019		
	(0.0023)		
GFR		-0.0007	
		(0.0027)	
SCIA			0.0005
			(0.0024)
Constant	0.9241***	0.9194***	0.9198***
	(0.0538)	(0.0536)	(0.0535)
Observations	25,822	25,822	25,822
Adjusted R^2	0.6803	0.6803	0.6803
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses.

4.3 Mechanism analysis

4.3.1 Operational risk

As argued earlier in Section 2.2.2, CPU raises operational risks, further undermines their legitimacy and reduces their willingness to implement a CCLS. This section tests the mediating role of operational risk in the effect of CPU on CCLS, focusing on financial stability and operational efficiency.

First, following Wu et al. (2022), we employ the Z-score index to measure a firm's financial stability, which reflects its external financing environment. The regression results in Column (1) of Table 6 show that CPU significantly reduces firms' financial stability, making them more likely to postpone or scale back the implementation of a CCLS.

Second, we use two indicators – cost-to-profit ratio (*Cost_profit*) and inefficient investment (*Ineff*) – to measure firms' operational efficiency. The cost-to-profit ratio is defined as total profit divided by total costs, whereas the inefficient investment measure is calculated based on the Richardson investment expectation model to capture firms' non-optimal investment behaviour (Chen et al., 2011). The corresponding regression results in Columns (2) and (3) of Table 6 show that CPU reduces firms' cost-to-profit ratio and increases inefficient investment, respectively. Existing literature suggests that a decline in the cost-to-profit ratio may lead management to prioritise cost control and short-term profitability (Camanho et al., 2024), thereby discouraging early-stage projects related to carbon cost leadership strategies that do not yield immediate returns. Similarly, increased inefficient investment consumes financial resources that could otherwise be allocated to carbon reduction initiatives (Liu & Pan, 2024), thus undermining firms' motivation to pursue a CCLS.

Finally, following Bruno et al. (2025), we assess firms' overall operational risk by measuring the volatility of their return on assets over the past three years (*Operate_risk*). The corresponding results in Column (4) of Table 6 show that CPU significantly increases firms' operational risk.

Taken together, these findings indicate that CPU not only reduces financial stability but also diminishes operational efficiency, ultimately leading to an increase in firms' operational risk. In line with relevant literature, the exacerbation of operational risk significantly weakens firms' willingness to implement a CCLS (C. Yang et al., 2024). Thus, our hypothesis ***H2*** is supported.

Table 6 Mechanism analysis – operational risk

	(1) Financial stability	(2) Operational efficiency	(3) Operational efficiency	(4) Operational risk
Variables	*Z-score*	*Cost_profit*	*Ineff*	*Operate_risk*
CPU	–0.0028**	–0.0014***	0.0044**	0.0011**
	(0.0011)	(0.0005)	(0.0018)	(0.0005)
Constant	0.5293***	0.2671***	–0.3210**	0.1413***
	(0.0552)	(0.0267)	(0.1329)	(0.0188)
Observations	23,349	23,349	21,096	25,290
Adjusted R^2	0.2665	0.2675	0.0888	0.3673
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1; robust standard errors are in the parentheses.

4.3.2 Climate institutional responsiveness

As discussed in Section 2.2.3, the second key channel through which CPU hinders CCLS implementation is by weakening firms' capacity to respond to climate-related institutions. We examine these mechanisms from two aspects: climate innovation capability, institutional alignment capability.

First, to gauge climate innovation capability, we follow the approach in Chu, Zhang, et al. (2024). We collected data on the number of firms' climate-related innovation patent applications (*Cpatent_apply*) and grants (*Cpatent_grant*) from the Chinese Research Data Services Platform (CNRDS) database. Next, we use the natural logarithm of one plus these counts as proxies for firms' climate innovation capability. Corresponding results in Columns (1) and (2) of Table 7 show that both patent applications and grants are significantly suppressed by CPU, indicating that greater CPU reduces firms' climate innovation capability. Prior literature suggests that a decline in climate innovation capability significantly undermines the foundation for a firm to convert technological advantages into strategic advantages (Garrido-Moreno et al., 2024), leaving firms lacking necessary technological support to implement and advance CCLS.

Second, we measure firms' institutional alignment capability using the natural logarithm of one plus the number of environmental permit applications (*Env_Cert*), with data sourced from the MioTech[4] database. Column (3) of Table 7 shows that CPU significantly reduces the number

[4] https://www.miotech.com/en-US/solution/data/esg

of such applications, which implies that firms' institutional alignment capability declines as CPU increases. This will make it more difficult for firms to proactively lower their operational carbon costs through policy endorsement or government subsidies in the future (Lyu et al., 2024), thereby deterring the implementation of a CCLS.

Finally, considering that involvement in negative climate-related news indirectly reflects a firm's capability to cope with climate regulations, we follow W. Tan et al. (2025) and adopt a machine learning approach to identify negative climate risk news concerning listed companies. In this process, we exclude news articles that merely report weather conditions without reflecting a firm's climate risk. We then take the natural logarithm of one plus this count to construct the corresponding indicator *Neg_Cnews*. Column (4) of Table 7 show that CPU significantly increases the volume of negative climate-related news coverage. This suggests that, under heightened CPU, firms are more likely to face environmental non-compliance issues, insufficient climate-related disclosures, and other shortcomings in climate risk management, leading to more frequent negative media exposure. Such negative coverage not only damages firms' reputations but also creates short-term obstacles in securing government support and gaining market recognition (Gokce et al., 2024), weakening their ability to leverage external endorsement to support and implement a CCLS. Taken together, these results support our hypothesis ***H3***.

Table 7 Mechanism analysis – climate institutional responsiveness

	(1) Climate innovation capability	(2) Climate innovation capability	(3) Institutional alignment capability	(4) Capability deficiency
Variables	*Cpatent_apply*	*Cpatent_grant*	*Env_Cert*	*Neg_Cnews*
CPU	–0.1284***	–0.1379**	–0.0366***	0.0474***
	(0.0489)	(0.0601)	(0.0122)	(0.0109)
Constant	–4.6393*	–2.9343	2.2314***	–7.1345***
	(2.4641)	(1.9890)	(0.7955)	(0.4172)
Observations	12,237	11,384	15,646	25,822
Adjusted R^2	0.8445	0.6948	0.6241	0.6724
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses.

4.4 Heterogeneity analysis

Institutional theory suggests that organisations do not respond homogeneously to external environmental pressures. Firms' strategic responses to institutional uncertainty are contingent on their own institutional embeddedness and organisational cognitive frameworks (Garrido-Moreno et al., 2024). To further unpack the mechanism through which CPU influences CCLS and to strengthen the robustness of our mechanism analysis, this section follows Chu, Zhang, et al. (2024), and examines the heterogeneous effects of CPU on CCLS along three dimensions: (1) internal firm characteristics, which shape the distinct institutional logics firms face (Sun & Ko, 2023); (2) managers' risk perception, which reflects how decision-makers interpret ambiguous policy signals within an uncertain institutional field (Zhao, Liu, et al., 2025); and (3) external environment characteristics, which represent external constraints (Liu et al., 2025).

4.4.1 Firm-level heterogeneity

First, we focus on differences arising from firm ownership. On the one hand, state-owned enterprises (SOEs) bear multiple objectives, including policy compliance and social responsibility (Chu, Zhang, et al., 2024). When policy directions are uncertain, SOEs may be more hesitant to invest in strengthening climate regulation-related capabilities, such as applying for environmental permits or engaging in climate innovation. On the other hand, SOEs typically have longer internal decision-making chains and greater financial prudence, which makes them more risk-averse (X. Wang et al., 2022) Cost fluctuations caused by CPU can substantially increase their future operational risk, leading them to adopt a more cautious approach when implementing high-investment, long-term carbon strategy projects. We divide the sample into SOEs and non-SOEs and perform separate estimations. Columns (1) and (2) of Table 8 show that the negative effect of CPU on CCLS is primarily concentrated among SOEs.

Moreover, management team's perception of climate risk plays a critical role. Compared with firms whose managers have high climate risk perception, those with low perception typically show weaker climate institutional responsiveness, reflected in the absence of systematic climate-innovation investment plans and delays in applying for environmental permits (Li & Tian, 2024). When CPU intensifies, these firms struggle to proactively respond to external changes through climate innovation and regulatory alignment. Additionally, because they lack these coping mechanisms, low-risk-perception firms are more likely to interpret policy uncertainty as uncontrollable operational risk (Niu et al., 2023), in turn choosing to shelve the implementation of a CCLS. Following Chu, Zhang, et al. (2024), we construct a firm-level climate risk perception indicator and divide the sample at the median. Columns (3) and (4) of Table 8 report the subsample regression results, indicating that the inhibitory effect of CPU is mainly present among firms with low-risk-perception.

Table 8 Firm-level heterogeneity analyses

	(1) SOEs	(2) non-SOEs	(3) Low climate risk perception	(4) High climate risk perception
Variables	*CCLS*	*CCLS*	*CCLS*	*CCLS*
CPU	–0.0055***	–0.0018	–0.0054**	–0.0021
	(0.0020)	(0.0019)	(0.0021)	(0.0021)
Constant	0.8305***	0.9561***	0.9529***	0.8723***
	(0.0772)	(0.0732)	(0.0849)	(0.0855)
Observations	11,208	14,614	12911	12911
Adjusted R^2	0.6804	0.6777	0.6920	0.6841
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1; robust standard errors are in the parentheses.

4.4.2 Industry- and regional level heterogeneity

Industry carbon exposure. On the one hand, industries with low carbon exposure have historically faced less stringent regulation and therefore show weaker institutional sensitivity and a thinner cognitive basis regarding carbon issues. When confronted with CPU, firms in these industries often lack well-developed carbon strategies and formal response mechanisms, making them more likely to interpret potential policy tightening as heightened perceived operational risk (Zeng et al., 2022). On the other hand, since these firms do not rely on carbon-reduction capabilities as a key source of competitive advantage, they are less inclined to proactively build climate-related institutional responsiveness under policy uncertainty (Kucuksayacigil et al., 2025). We classify heavily polluting industries as high-carbon-exposure industries and all other industries as low-carbon-exposure. The results in Columns (1) and (2) of Table 9 show that the negative effect of CPU on CCLS is significant only for the low-carbon-exposure industry group.

Industry technological intensity. The fundamental pathway to achieving carbon cost leadership lies in technological innovation, which is central to improving climate institutional responsiveness. Compared with firms in technology-intensive industries, those in non-technology-intensive industries have weaker climate innovation capabilities. When climate policy signals become more ambiguous, the pathways through which they can improve climate institutional responsiveness are more likely to be obstructed. Owing to their limited capacity to cope with uncertainty, these firms face higher operational risks (Ofori et al., 2023), making their CCLS more susceptible to fluctuations in climate policy. Using the classification standards by the National Bureau of Statistics of China, we divide firms into technology-intensive and non-technology-intensive industries. The results in Columns (3) and (4) of Table 9 show that CPU's inhibitory effect on CCLS is significant only for firms in non-technology-intensive industries.

Regional public-government interaction. Compared with regions that exhibit high levels of public-government interaction on climate issues, regions with low interaction often lack transparency and continuity in policy formulation and execution. This makes it difficult for firms to obtain clear climate policy signals through diverse interactions with policymakers and the public, resulting in more directionless designs for enhancing climate institutional responsiveness (Rukanova et al., 2023). Furthermore, information asymmetry and the absence of effective feedback mechanisms amplify firms' perceived operational risks (Qiao & Zhao, 2023), reducing their willingness to implement a CCLS. Based on above, following Sun et al. (2025), we construct an indicator of government responsiveness to climate risks based on co-occurrence data from Chinese government's online *Message Board for Leaders* and divide the sample using the median value. The results in Columns (5) and (6) of Table 9 indicate that the negative effect of CPU on CCLS is more pronounced for firms located in regions with low levels of public–government interaction on climate issues.

Table 9 Industry- and regional level heterogeneity analyses

	(1) High carbon-exposure	(2) Low carbon-exposure	(3) Technology-intensive	(4) Non-technology-intensive	(5) Low public–government interaction	(6) High public–government interaction
Variables	*CCLS*	*CCLS*	*CCLS*	*CCLS*	*CCLS*	*CCLS*
CPU	–0.0013	–0.0032**	–0.0016	–0.0052***	–0.0048**	–0.0032
	(0.0025)	(0.0016)	(0.0019)	(0.0019)	(0.0020)	(0.0022)
Constant	0.9455***	0.8614***	0.9422***	0.7127***	0.9883***	0.7374***
	(0.1024)	(0.0613)	(0.0766)	(0.0752)	(0.0952)	(0.0813)
Observations	8,790	17,032	15,412	10,410	12,913	12,909
Adjusted R^2	0.5946	0.6950	0.6568	0.7128	0.7061	0.6986
Controls	YES	YES	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses.

5 Conclusion and recommendations

5.1 Conclusions

Systematic research on the relationship between CPU and firms' CCLS remains limited, particularly with respect to the underlying mechanisms. Drawing on data from Chinese listed companies between 2010 and 2024, on one hand, we apply machine learning and natural language processing techniques to extract carbon cost management–related expressions from annual reports, constructing a novel firm-level measure of the CCLS. On the other hand, grounded in institutional theory, we examine how legitimacy pressure influences firms' responses to CPU through the dual dimensions of strategic capability and strategic willingness, providing an in-depth analysis of the influence mechanisms.

This study yields the following main conclusions. First, CPU significantly inhibits the implementation of the CCLS. Second, CPU increases firms' operational risks by reducing financial stability, compressing cost–profit margins, and increasing inefficient investments, thereby weakening their willingness to implement the CCLS. At the same time, CPU undermines firms' capability to cope with climate regulations by inhibiting climate innovation, reducing the number of environmental permit applications, and increasing negative media coverage. Overall, CPU systematically restrains the CCLS by simultaneously weakening firms' strategic willingness and strategic capability. Finally, heterogeneity analysis reveals that this inhibitory effect is more pronounced among state-owned enterprises, firms with low climate risk perception, firms in low carbon-exposure and non-technology-intensive industries, and firms located in regions with low levels of public–government interaction on climate issues.

The findings of this study possess profound social impacts. The core objective of CCLS is to achieve emission reductions at the lowest possible cost, representing an optimal allocation of societal resources. When policy uncertainty leads firms to adopt a 'wait-and-see' strategy and postpone the implementation of CCLS, it not only undermines corporate competitiveness but also severely reduces the overall efficiency of the low-carbon transition at the societal level. This implicitly raises the social cost of carbon and shifts a heavier climate governance burden onto future generations. Therefore, reducing policy uncertainty is not only a way to protect enterprises but also a necessary condition for safeguarding long-term social welfare. In terms of research significance, this study offers robust empirical evidence to guide policymakers aiming to enhance the predictability of climate policies and bolster firms' confidence and capacity for low-carbon transformation. Furthermore, from the perspective of institutional legitimacy, this study enriches the theoretical understanding of the formation pathways of CCLS, contributing to a deeper academic insight into the logic of firms' strategic behaviour under policy uncertainty. It is worth emphasising that, although the conclusions are drawn from the Chinese context, the core theoretical mechanism identified in this study that climate policy uncertainty inhibits firms' long-term low-carbon strategic investment by increasing operational risks and weakening institutional responsiveness has important generalisability to other national contexts. This logic applies not only to other emerging economies that are in the process of building carbon pricing mechanisms (such as India and Southeast Asian countries) but may also extend to developed economies with mature markets that nonetheless experience climate policy volatility arising from partisan political cycles (such as the United States and Australia).

5.2 Management implications

The results of this study have significant implications for both policymakers and corporate managers.

For public authorities, we propose the following implications for management and policy design. First, they should commit to enhancing the stability and predictability of climate policies. Specific measures include publishing legally binding medium- and long-term emission reduction roadmaps, setting clear guidance ranges for carbon taxes or carbon market prices, and establishing mechanisms for pre-announcing and buffering policy adjustments. Second, governments should create dedicated financial instruments to help hedge corporate financial risks. For example, sovereign credit guarantees or specialised low-carbon transition funds can provide credit enhancement for green investments during periods of policy volatility. At the same time, long-horizon investment tax credit policies should be implemented to ensure that tax incentives are not withdrawn because of short-term policy changes, thereby offsetting the risk premiums demanded by capital markets. Third, governments should adopt policy grandfathering and regulatory sandbox mechanisms. To address firms' reluctance to invest in R&D or apply for permits due to fear of future policy tightening, regulators should explicitly commit that approved major low-carbon technological transformation projects will be exempt from more restrictive policy changes within a specified time window. Fourth, regulation and support should be differentiated by industry and ownership type. To address innovation challenges in non-technology-intensive industries, governments can establish public low-carbon technology service platforms to lower barriers to technology access. For state-owned enterprises, authorities should issue more detailed compliance guidelines and exemption lists, providing them with greater room for trial and error in ambiguous policy environments.

For corporate managers, the following strategies are recommended. First, transform external ambiguous uncertainty into internal, quantifiable operating costs. Managers should not passively wait for policies to become clearer but should establish systematic carbon price sensitivity analysis and climate scenario stress-testing mechanisms. Second, shift from symbolic to substantive disclosure in order to restore market trust and strengthen legitimacy. Firms should reduce the use of vague long-term narratives and instead frequently disclose concrete, completed decarbonisation actions and interim quantitative results. Third, firms that are more vulnerable to climate policy risk should adopt differentiated risk management strategies. For example, state-owned enterprises can take the lead in establishing internal carbon pricing mechanisms to convert external uncertainty into an internal cost signal. Non-technology-intensive firms should actively pursue strategic partnerships or technology acquisitions with technologically leading companies to rapidly narrow gaps in climate innovation capabilities.

5.3 Limitation and future directions

This study certainly has limitations, which also point to directions for future research.

First, regarding the research sample and context, this study focuses on Chinese listed companies. The applicability of the findings to small- and medium-sized enterprises, which may have more limited resources and face institutional pressures more directly, remains to be examined. Future studies could use survey data to explore differences in strategic responses to CPU across firms of varying sizes. Moreover, as mentioned earlier, the core theoretical logic of this study has broad generalisability. However, it remains to be seen whether cases and data from other institutional backgrounds (such as the European Union with a more mature carbon market, or the United States with a more pluralistic policy-making process) can provide further validation or boundary expansion for the theoretical logic of this paper. Therefore, future research could distil a more universally applicable framework of the mechanism by which CPU affects CCLS through cross-country comparative analysis.

Second, regarding the exploration of micro-level decision-making mechanisms, this study primarily investigates the impact mechanism of CPU on corporate carbon cost leadership strategy from the organisational level, with less focus on managerial cognition and micro-psychological mechanisms. In reality, how corporate managers perceive and construct external uncertainty can significantly influence strategic choices. Future research could focus on the managerial level, using surveys or in-depth interviews to examine how managerial characteristics and cognitive frames regarding CPU moderate its suppressive effect on CCLS.

Third, in terms of methodological development, this study constructs a novel text-based CCLS measure, providing an essential foundational tool for quantitative research in the field of carbon management. This measure can be used to explore broader economic consequences, such as the effects of CCLS on corporate cost stickiness, financial resilience, and long-term market valuation. Moreover, future research could draw on more advanced Large Language Models to further refine this measure, enabling it to capture semantic nuances more accurately than simple keyword co-occurrence methods.

Finally, according to the Porter Hypothesis, CPU may also encourage firms to engage in forward-looking strategic planning. The large-sample regression analysis in this study captures an average inhibitory effect but does not reveal potential facilitating effects under specific conditions. Future research could explore the boundary conditions of this suppressive effect, for example, employing quantile regression to test whether CPU has nonlinear impacts on firms with different strategic levels, or using case studies to investigate firms that have successfully implemented a CCLS despite high uncertainty.

Appendix A Carbon cost leadership strategy dictionary

Table Appendix A.1 Keywords example for constructing the carbon cost leadership strategy index

Carbon transition-related keywords	Cost leadership strategy-related keywords
碳减排 (Carbon emission reduction)	采购成本 (Procurement cost)
碳排放核算 (Carbon emission accounting)	成本费用 (Cost and expenses)
低碳采购标准 (Low-carbon procurement standards)	开源节流 (Increase revenue and reduce expenditure)

低碳工艺 (Low-carbon process)	存货采购 (Inventory procurement)
低碳供应链 (Low-carbon supply chain)	高效 (Efficient)
低碳技术 (Low-carbon technology)	高性价比 (High cost–performance ratio)
低碳原材料采购 (Low-carbon raw material procurement)	全面预算管理 (Comprehensive budget management)
低碳运输 (Low-carbon transportation)	过程控制 (Process control)
低碳运营 (Low-carbon operation)	降本增效 (Cost reduction and efficiency improvement)
能耗双控 (Dual control of energy consumption)	精细化管理 (Refined management)
清洁能源 (Clean energy)	成本管控 (Cost control)
清洁生产 (Clean production)	目标成本 (Target cost)
碳捕集 (Carbon capture)	管理效率 (Management efficiency)
碳储存 (Carbon storage)	生产标准 (Production standards)
碳定价 (Carbon pricing)	运行效率 (Operational efficiency)
碳交易 (Carbon trading)	质量标准 (Quality standards)
碳配额 (Carbon quota)	最小化 (Minimisation)
碳信用 (Carbon credit)	最优配置 (Optimal allocation)
碳资产管理 (Carbon asset management)	内控标准 (Internal control standards)
碳足迹 (Carbon footprint)	经营成本 (Operating costs)

Appendix B Variable definitions

Type	Variable	Definition
Independent variable	*CCLS*	See Section 3.2.1 (Unit: %)
Dependent variable	*CPU*	See Section 3.2.2
Control variables	*Size*	Ln (Total assets)
	Age	Ln (Age of the firm)
	Lev	Total liabilities/Total assets
	ROA	Net profit / Average assets
	ATO	Operating revenue / Average total assets
	Cash	Total cash and cash equivalents / Current liabilities
	Fix	Net fixed assets / Total assets
	TQ	Market value/ (Total assets - net intangible asset - net goodwill)
	Board	Ln (one plus the number of board members)
	Indep	The proportion of independent directors
	Dual	Indicator that equals one if the Chairman and CEO are the same person, and zero otherwise
	Top5	Percentage of shares held by the largest five shareholders

Appendix C Validity tests of CCLS indicator

This section validates the reliability of the CCLS measure using two approaches. First, we examine whether CCLS differs significantly across industries and firms with distinct characteristics. We group firms according to their levels of carbon exposure and climate risk perception and then test for differences in CCLS across these groups. As shown in Table Appendix C.1, firms operating in high carbon-exposure industries and those with higher climate risk perception exhibit significantly higher CCLS values. This finding is consistent with Cao et al. (2024) and Baratta et al. (2023), who argue that such firms generally exhibit stronger incentives to reduce carbon emissions. Notably, these results align with our heterogeneity analysis presented in Section 4.4.

Table Appendix C.1 Cross-industry and cross-firm comparison of CCLS

Panel A:	High carbon-exposure industry	Low carbon-exposure industry	Difference between groups
CCLS	0.5200	0.4212	0.0988***
Panel B:	High climate risk perception firm	Low climate risk perception firm	Difference between groups
CCLS	0.4584	0.4512	0.0072***

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Second, we further validate the effectiveness of the CCLS measure by examining its relationship with potential corporate environmental-performance indicators and by assessing how other climate-related policies influence CCLS. On one hand, because CCLS reflects a substantive green strategy, it should plausibly translate into stronger environmental performance and compliance outcomes. To test this, we regress CCLS on three indicators: the environmental dimension score of the *Huazheng* ESG index (*HZ_Escore*) and the *CNRDS* ESG index (*CNRDS_Escore*), and the ratio of a firm's annual environmental penalties to its total assets (*Penalties*). Columns (1)–(3) of Table Appendix C.2 show that CCLS is significantly and positively associated with both mainstream ESG environmental scores, and significantly negatively associated with environmental penalties. This indicates that the strategic measure extracted from firms' annual reports aligns well with their externally observed environmental performance. On the other hand, given that CCLS should also respond positively to the stringency of external climate policies, we follow Ma et al. (2023) and regress CCLS on two policy variables: carbon reduction policy intensity (*PI_CR*) and low-carbon technology policy intensity (*PI_Tech*). Columns (4) and (5) of Table Appendix C.2 show that both indicators are significantly positively correlated with CCLS, suggesting that changes in CCLS move in a logically consistent direction with the evolution of the broader climate-policy environment.

Taken together, these findings demonstrate that the CCLS indicator exhibits strong reliability, conceptual soundness, and empirical validity.

Table Appendix C.2 Relationship with potential corporate environmental performance indicators

	(1)	(2)	(3)	(4)	(5)
Variables	*Penalties*	*HZ_Escore*	*CNRDS_Escore*	*CCLS*	*CCLS*
CCLS	–0.0332***	0.0903***	0.0860***		
	(0.0048)	(0.0077)	(0.0072)		
PI_CR				0.0156***	
				(0.0056)	
PI_Tech					0.0228**
					(0.0099)
Constant	–0.2995***	–0.0997**	0.1807***	0.9084***	0.9122***
	(0.0376)	(0.0492)	(0.0518)	(0.0536)	(0.0536)
Observations	25,822	25,108	25,108	25,808	25,808
Adjusted R2	0.7415	0.5984	0.5082	0.6803	0.6802
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; robust standard errors are in the parentheses. Both *PI_CR* and *PI_Tech* are included with a one-year lag.

Acknowledgements

This research is supported by the National Social Science Fund of China (Grant Number: 24CGL118) and the Fundamental Research Funds for the Central Universities (CXJJ-2024-334).

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this research.

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