

Article

Constraining or Enabling? The Impact of Climate Transition Risk on Green Innovation in China

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Abstract

The literature on the climate transition risk–green innovation nexus remains divided: some studies find negative effects, while others report positive effects. Using data on Chinese A-share listed firms from 2011 to 2023, we analyze firm-level directional sensitivity to public climate attention and document that, at the aggregate level, climate transition risk is not significantly related to green innovation. However, decomposition reveals polarization: positive sensitivity is associated with higher green innovation, whereas negative sensitivity is linked to lower green innovation. Two channels operate in opposite directions: financing constraints ease with positive sensitivity and tighten with negative sensitivity, and R&D investment rises with positive sensitivity and falls with negative sensitivity. The patterns are more pronounced among manufacturing firms, non-state-owned enterprises, firms without financial backgrounds, and firms in central-western or low-marketization regions. A policy-shock analysis around the Paris Agreement indicates that regulatory uncertainty amplifies the adverse effect associated with negative sensitivity. These findings suggest that climate policy and support instruments should account for firm-level heterogeneity and target financing and R&D frictions that condition the innovation response.

Keywords: climate transition risk; green innovation; heterogeneity; R&D investment; financing constraints



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1. Introduction

Climate change is a critical global challenge that poses substantial threats to economic and social development worldwide. According to the World Economic Forum's Global Risks Report 2025 [1], environmental risks dominate the long-term global risk landscape. The American Meteorological Society's 35th State of the Climate Report (2025) indicates that 2024 set records for key climate indicators, including greenhouse gas concentrations, land and ocean surface temperatures, and sea-level rise [2]. Similarly, the World Meteorological Organization (WMO) reports that the global average temperature in 2024 was 1.55 °C (± 0.13 °C) above pre-industrial levels, the highest since records began [3]. These findings underscore that climate change poses an immediate, rather than distant, threat.

According to the TCFD framework, climate risk encompasses the uncertainties associated with physical climate impacts and the transition to a low-carbon economy [4]. As fundamental units of socioeconomic activity, firms are exposed to both physical and transition risks [5]. Physical risk stems from acute climate events and long-term shifts in climate patterns that can damage production facilities, disrupt supply chains, and cause casualties [6,7], thereby impairing productivity and economic performance [8]. Transition risk arises from climate-related policy shifts, regulatory changes, technological advances, and

market transformations, such as tighter environmental regulations and higher emission-reduction targets, which compel firms to adjust their operational and technological strategies [9]. Compared to the direct and observable nature of physical risks, transition risk, driven by policy and systemic factors, exerts more complex and far-reaching influences on strategic corporate decisions: particularly green innovation. Accordingly, we focus on transition risk.

Green innovation is widely regarded as being central to corporate green transformation and is a key driver of sustainable development in a low-carbon economy [10]. It plays a significant role in enhancing energy efficiency and firm performance [6]. However, green innovation is typically characterized by long development cycles, substantial capital requirements, high uncertainty in returns, and dual externalities from environmental protection and knowledge spillovers. These features often result in market failures. Growing environmental pressures and corporate climate actions have heightened scholarly interest in how climate change influences innovation behavior: particularly firms' engagement in green innovation.

This study examines the impact of climate transition risk on corporate green innovation and seeks to reconcile divergent findings regarding the inhibiting versus facilitating effects in the existing literature. Our study is informed by two contrasting perspectives. On the one hand, a cost-based view posits that climate risk can inhibit green innovation by increasing debt costs [11], forcing deleveraging, eroding operating profits, and heightening cash-flow volatility [12], which undermines the risk-bearing capacity [13] and ultimately depresses the R&D investment [14,15], thereby dampening green innovation. On the other hand, a competing view, consistent with the Porter Hypothesis [16,17], argues that climate risk can incentivize innovation by raising managerial attention and uncovering new opportunities [18], prompting firms to increase R&D expenditure [19] and accelerate green technological breakthroughs [20–22].

We argue that the mixed evidence may reflect insufficient consideration of firm-level heterogeneity in responsiveness to climate transition risk. The apparent contradiction, along with statistically insignificant aggregate relationships, may arise when the sample includes firms with opposing behavioral responses. Drawing on options theoretical perspectives (real and growth options) [23,24], we posit that corporate green innovation reflects a complex trade-off between short-term costs and long-term benefits, and between conservative and proactive strategies. To capture this heterogeneity, we introduce a directional sensitivity distinction: “positive sensitivity” (*Sens_Pos*), where firms perceive climate risk signals as opportunities, and “negative sensitivity” (*Sens_Neg*), where such signals are perceived as threats. Our primary objective is to test whether the coexistence of these opposing sensitivities explains the mixed evidence in prior research and the potential masking of significant underlying relationships.

To systematically test this proposition, we construct firm-level measures of sensitivity to public climate attention, using data on Chinese A-share listed companies from 2011 to 2023. Following Gong et al., Lin et al., Chen et al., and Huynh and Xia [25–28], we use Baidu Search Index data on climate transition risk-related keywords as a proxy for shifts in public attention to climate risk, given Baidu's dominance in China's search market. We then estimate firm-level return sensitivities to these attention shocks, to construct three variables: the composite sensitivity measure (*Sens*), positive sensitivity (*Sens_Pos*), and negative sensitivity (*Sens_Neg*). We subsequently examine how these sensitivities relate to corporate green innovation, with particular emphasis on the financing constraints and R&D investment channels, and we conduct heterogeneity analyses by considering industry attributes, ownership type, board and executive financial backgrounds, and regional characteristics.

China provides a compelling empirical setting for our analysis for two reasons that are directly related to transition dynamics. First, as the world's largest carbon emitter, accounting for roughly 35 percent of global CO₂ emissions in 2023 [29], China's pursuit of its "dual carbon" goals has prompted the development of a comprehensive and evolving regulatory framework. Policies such as the Implementation Plan for Improving the Market-Oriented Green Technology Innovation System exemplify this transition pressure [30] and explicitly position green innovation as a strategic national priority. Second, this period of heightened policy activity coincides with a measurable surge in green technology development, including an average annual growth rate of about 10 percent in green low-carbon patents between 2016 and 2023 [31]. This combination of significant regulatory pressure and vibrant innovative activity provides a favorable context for identifying how firms navigate climate transition risk.

Our analysis yields findings that help to reconcile conflicting evidence. At the aggregate level, we observe a statistically insignificant relationship between climate transition risk and corporate green innovation. However, this null result masks substantial underlying heterogeneity. Disaggregating by sensitivity type reveals a clear polarization: positive sensitivity (*Sens_Pos*) is associated with higher green innovation, whereas negative sensitivity (*Sens_Neg*) is associated with lower green innovation. This pattern suggests that the coexistence of opposing firm-level responses can obscure the underlying relationship. Further analyses confirm that financing constraints and R&D investment are channels operating in opposite directions. Moreover, this polarization pattern is more pronounced among manufacturing firms, non-state-owned enterprises, firms without financial backgrounds, and firms in central-western or low-marketization regions.

This study makes three contributions to the literature on climate risk and corporate innovation. First, it identifies an overlooked empirical pattern: a statistically insignificant aggregate relationship between climate transition risk and corporate innovation. In contrast to prior studies that report either significant negative effects [11,12] or significant positive effects [18,20], our baseline analysis reveals a null aggregate relationship. We demonstrate that this does not imply the absence of underlying effects; rather, it reflects the aggregation of strong but opposing firm-level responses. Second, we develop and validate a firm-level heterogeneity framework that reconciles conflicting perspectives by introducing the distinction between positive and negative sensitivity to public climate attention. We demonstrate that the "inhibition" and "promotion" narratives apply to distinct types of sensitivity, and that neglecting such heterogeneity may bias inference about how climate risk influences innovation. Third, we provide granular evidence for the mechanisms driving these divergent outcomes. We establish that financing constraints and R&D investment are key channels operating in opposite directions, depending on a firm's sensitivity type. These mechanisms offer micro-level insights into how the same macro-level risk can lead to fundamentally different innovation strategies, providing empirical support for our core argument that a statistically insignificant aggregate effect masks heterogeneous responses.

The remainder of the paper is organized as follows. Section 2 develops the theoretical analysis and hypotheses. Section 3 describes the research design. Section 4 presents the main empirical results, including robustness tests. Section 5 examines the underlying mechanisms. Section 6 conducts heterogeneity analyses across industry, ownership, board and executive financial backgrounds, and regional dimensions. Section 7 provides additional analyses, including the policy shock around the Paris Agreement. Section 8 concludes with key findings and policy implications.

2. Theoretical Analysis and Research Hypothesis

This section explores how the relationship between climate transition risk and corporate green innovation reflects a set of strategic trade-offs, and how these trade-offs can lead to opposing firm-level responses. We first set out the competing effects that render the aggregate impact theoretically indeterminate and motivate our competing hypotheses. We then describe the mechanisms through which these effects operate, focusing on financing constraints and R&D investment as two testable channels.

The relationship between uncertainty and innovation presents a theoretical puzzle that is best understood through two competing yet complementary perspectives: real options theory and growth options theory [23,24]. The traditional real options perspective emphasizes what we term the “inhibiting effect” of uncertainty. Under this framework, when environmental uncertainty increases, risk-averse firms tend to delay irreversible investments to preserve flexibility and gather additional information. Applied to the green innovation context, this translates to a cautious approach where unclear technology paths, volatile policy directions, and ambiguous market demand collectively encourage firms to adopt a “wait-and-see” strategy until uncertainty diminishes to more manageable levels.

However, building on a different theoretical foundation, the growth options perspective challenges this conservative view by highlighting the “facilitating effect” of uncertainty on investment decisions [24]. Under this theoretical lens, uncertainty paradoxically increases the option value when future growth opportunities carry substantial potential, as option holders can capture upside gains while limiting downside exposure. In the climate transition context, this translates to a more aggressive investment stance, driven by strengthening policy support, evolving consumer preferences toward sustainability, and the potential for technological breakthroughs that create significant upside potential for green innovation. Under these conditions, moderate levels of uncertainty function as investment catalysts rather than deterrents.

The fundamental distinction between these theoretical perspectives lies in their underlying assumptions about market competitiveness and timing advantages. Real options theory typically assumes firms possess exclusive or quasi-exclusive investment opportunities, allowing them the luxury of patient capital allocation. In contrast, growth options theory operates within a competitive framework where first-mover advantages and preemption effects create urgency that can override uncertainty concerns [32].

Climate transition risk adds complexity by simultaneously altering both the intrinsic value and optimal timing of these strategic options. This dual influence creates competing mechanisms that pull firm behavior in opposite directions. The first mechanism, which we label the “information value effect”, suggests that the rising transition risk increases the value of waiting. When confronted with multi-faceted uncertainties, ranging from regulatory changes to technological disruptions, postponing investment decisions allows firms to observe and incorporate more valuable information, ultimately enabling more optimal resource allocation decisions. This effect naturally aligns with the real options framework, where policy uncertainty embedded in transition risk, combined with the high sunk costs of green innovation, increases the option value of waiting. The incentive to delay is stronger when agency frictions are pronounced, leading managers to prioritize short-term financial security and metric-based performance targets [33], and this is more evident in capital-intensive, high-carbon industries where regulatory timing can shift the profitability of abatement paths [34].

Simultaneously, climate transition risk can intensify competitive dynamics through what we term the “competitive pressure effect”. As regulatory frameworks tighten and market opportunities for green technologies become more apparent, the opportunity cost of delay escalates rapidly. Firms operating under these conditions face compressed de-

cision windows where maintaining a wait-and-see approach risks sacrificing the market position and first-mover advantages to more aggressive competitors. This competitive urgency pushes firms toward immediate action despite uncertainty, as proactive innovation in increasingly competitive low-carbon technology markets enables firms to secure first-mover advantages and lock in future market positions through preemption, standard-setting, and the appropriation of intellectual property [24]. The dynamic capabilities perspective extends this logic, arguing that transition risk can act as a catalyst for organizational and technological change that converts external pressure into opportunities for building sustainable advantages [35].

The relative dominance of these competing mechanisms determines the aggregate impact of transition risk on green innovation decisions. This complexity deepens when we consider that firms facing identical climate transition risk signals may respond very differently, based on their managerial cognition and agency considerations.

Managerial interpretation of uncertainty plays a pivotal role in determining which theoretical framework dominates the decision-making processes. Managers with risk-averse cognitive biases tend to emphasize the costs and potential losses associated with premature investment, naturally gravitating toward real options strategies that prioritize flexibility and patience [36]. These managers frame uncertainty primarily as a threat to be managed through careful timing and risk mitigation. Conversely, managers with entrepreneurial orientations or opportunity-focused mindsets interpret the same uncertainty as a source of competitive advantage, leading them to pursue growth options strategies characterized by proactive investment, despite incomplete information [37]. This cognitive framing fundamentally shapes how environmental signals are translated into strategic action.

Agency theory provides an additional layer of explanation for these divergent responses [33]. The separation of ownership and control that is inherent in modern corporations introduces agency costs that systematically influence option exercise decisions. Managers, acting as agents for shareholders, may rationally prioritize their own short-term interests over long-term firm value maximization. Engaging in risky, long-term green R&D investments, while potentially beneficial for shareholders, might jeopardize a manager's current position or compensation structure [38]. This agency-driven short-termism naturally aligns with the "option to wait" strategy, even when immediate investment would serve the firm's long-term interests. Consequently, agency problems can systematically amplify tendencies toward real options strategies at the expense of value-creating growth options [39].

These theoretical considerations collectively suggest that opposing firm-level responses to climate transition risk can and should coexist within any given sample of firms, rendering the aggregate effect theoretically uncertain. Some firms will increase their green innovation efforts, because growth option potential, competitive pressure, and opportunity-focused managerial cognition create powerful incentives for immediate action. Simultaneously, other firms will reduce or delay such investments, because the value of waiting, resource constraints, and agency-driven short-termism create equally compelling incentives for patience. Since both strategic orientations are theoretically justified and empirically observable in market contexts, the ultimate direction and magnitude of climate transition risk's effect on green innovation depends critically on firm-specific factors that influence its sensitivity to climate risk signals.

Given this theoretical ambiguity and the competing mechanisms that we have identified, we propose the following competing hypotheses to guide our empirical investigation.

H1a. *Climate transition risk positively influences corporate green innovation.*

H1b. *Climate transition risk negatively influences corporate green innovation.*

Having established why the aggregate effect can be ambiguous, we next examine the specific mechanisms through which transition risk affects green innovation. We identify two key behavioral mechanisms that drive differential firm responses.

First, managerial cognitive framing determines the strategic orientation. Risk-averse managers interpret transition risks as threats requiring cautious approaches and tend to show negative sensitivity. In contrast, opportunity-focused managers view risks as competitive advantages and demonstrate positive sensitivity [36]. Second, agency considerations influence decision-making horizons. Severe agency problems promote short-term thinking and negative responses, while aligned interests encourage long-term strategies and positive sensitivity [33]. These behavioral mechanisms operate through two empirically testable channels: financing constraints and R&D investment decisions. We examine these as complementary pathways for understanding heterogeneous firm responses.

On the financing side, these behavioral mechanisms manifest in differential constraint patterns. For firms with positive sensitivity, opportunity-focused managerial framing and aligned agency interests create eased constraints. From a growth options perspective, positive sensitivity signals that climate transition enhances the value of firms' growth options and strategic flexibility. This increased option value improves debt capacity by reducing default risk, as the upside potential from green innovation creates valuable contingent claims that function as embedded call options for future market opportunities. The asymmetric payoff structure of these options—with limited downside risk but substantial upside potential—translates into lower required risk premiums and enhanced lending terms [40]. Financial institutions increasingly incorporate environmental, social, and governance (ESG) criteria into lending decisions, offering preferential rates to firms demonstrating credible green transformation capabilities [41,42].

By contrast, risk-averse framing and agency misalignment in negative sensitivity firms lead to tighter financing constraints. From a real options perspective, negative sensitivity signals that climate transition diminishes the value of firms' existing assets and growth options. This erosion of option value restricts debt capacity by increasing the default risk, as potential stranded assets create contingent liabilities that function as embedded options on declining market segments [40]. Banks recognize this diminished option value through deteriorated credit assessments, viewing firms with negative sensitivity as holding portfolios of potentially impaired assets in contracting markets [43]. The asymmetric risk structure—with substantial downside exposure but limited upside protection—translates to higher required risk premiums and restrictive lending terms [44]. These observations lead to the following mechanism hypothesis on financing.

H2. *Climate transition risk affects corporate green innovation through the financing constraints channel. Constraints ease with positive sensitivity and tighten with negative sensitivity.*

On the innovation input side, the underlying behavioral mechanisms drive differential R&D investment patterns. For firms with positive sensitivity, long-term oriented managers with aligned incentives pursue higher R&D intensity. From a growth options perspective, these firms view green R&D investments as opportunities to acquire valuable growth options in emerging markets, while the strategic logic centers on option creation rather than immediate returns. Firms with positive sensitivity view green R&D as essential for building a durable competitive advantage, strategically increasing R&D intensity to develop low-carbon technologies that align with the anticipated policy trajectories [35]. Facing Knightian uncertainty, these firms leverage external uncertainty as a differentiation opportunity, with R&D serving as a commitment device to capture nascent market opportunities and shape industry standards through patents and alliances [45]. Each R&D project functions like acquiring call options on future technological trajectories, where early in-

vestment secures positions that enable learning-by-doing and scale economies as markets mature [24,32].

By contrast, short-term-focused managers facing agency pressures in negative sensitivity firms exhibit reduced and deferred R&D investment. This pattern reflects the real options logic of waiting under uncertainty, amplified by the behavioral and organizational frictions described above. When transition risk threatens existing assets, the option value of delaying irreversible R&D investments increases significantly [23,46]. Risk-averse managers exhibiting loss aversion may overestimate the sunk costs and downside risks of green innovation while underestimating long-term returns, leading to systematic deferral and project cancellation [47,48]. Agency frictions from misaligned evaluation horizons intensify this short-term bias, as managers facing short-term evaluation horizons favor incremental improvements or compliance fixes over uncertain green R&D with extended pay-back periods [33,39]. Simultaneously, immediate compliance pressures divert both managerial attention and financial resources toward operational adjustments, crowding out green R&D in resource-allocation decisions [49,50]. This results in a strategic preference for preserving flexibility through inaction, rather than committing to potentially obsolete R&D investments.

H3. *Climate transition risk affects corporate green innovation through the R&D investment channel. R&D increases with positive sensitivity and decreases with negative sensitivity.*

3. Research Design

3.1. Model Specification

Following Bai et al. [9], we estimate the following fixed-effects model to analyze the relationship between climate transition risk and corporate green innovation:

$$GI_{i,t} = \alpha + \beta Sens_{i,t-1} + \gamma Controls_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (1)$$

where $GI_{i,t}$ measures the green innovation level of firm i in year t . The key independent variable, $Sens_{i,t-1}$, captures firm-level sensitivity to public climate attention. We lag this variable by one year to mitigate concerns about reverse causality. The vector $Controls_{i,t}$ includes firm-level characteristics. We include firm fixed effects, u_i and year fixed effects, v_t , and $\varepsilon_{i,t}$ denotes the idiosyncratic error term.

3.2. Variable Definitions and Measurement

3.2.1. Independent Variable

We construct firm-level measures of sensitivity to public climate attention, specific to transition risk, by using a two-stage approach following Chen et al. and Huynh and Xia [26,27]. This measure captures both the magnitude and the sign of firms' stock-return responses to shifts in public climate attention.

In the first stage, we construct a daily climate risk attention index, $Atten_t$, using the Baidu Search Index as a proxy for shifts in attention to climate transition risk. Following prior studies [26,51–53], we compile a list of 40 keywords pertaining to climate transition risk, remove duplicates and incomplete entries (full list in Appendix A), and manually collect daily search volumes from desktop and mobile platforms in China for 2011–2023.

In the second stage, we estimate each firm's excess-return sensitivity to public climate attention using the following regression:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} Atten_t + \gamma_{i,t} X_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $R_{i,t}$ is the excess stock return of firm i on day t , $Atten_t$ represents the daily public climate attention index, and $X_{i,t}$ includes the three Fama–French factors: market (MKT), size (SMB), and value (HML).

We then construct three binary variables, based on the statistical significance and sign of the estimated coefficient $\beta_{i,t}$. Climate risk attention sensitivity (*Sens*) equals 1 if $\beta_{i,t}$ is statistically significant at the 10 percent level (irrespective of sign) and 0 otherwise. Positive sensitivity (*Sens_Pos*) equals 1 if $\beta_{i,t}$ is positive and significant at the 10 percent level and 0 otherwise. Negative sensitivity (*Sens_Neg*) equals 1 if $\beta_{i,t}$ is negative and significant at the 10 percent level and 0 otherwise. These measures thus capture positive and negative sensitivity to public climate attention, enabling the examination of their heterogeneous effects on green innovation within a unified empirical model.

3.2.2. Dependent Variable

Following an established empirical practice that is widely adopted in the literature, we measure corporate green innovation (*GI*) based on the number of green patent applications [9,15,22]. This output-based approach directly captures innovation outcomes and reflects competitive performance, in contrast to input-based metrics such as R&D expenditures that may not fully reflect actual innovation achievements.

We use the natural logarithm of one plus the annual number of green invention patent applications as our primary measure of *GI*. Patent applications are particularly well-suited for measuring innovation performance, as they are less affected by time limitations and external environmental factors compared to patent grants, thus better reflecting corporate green innovation activities in a given year [9].

To ensure the robustness of our findings, we also construct alternative measures based on both green invention patents and green utility model patents, applying the same logarithmic transformation. This comprehensive approach allows us to capture the full spectrum of corporate green innovation outputs while maintaining consistency with established measurement practices in the innovation literature.

3.2.3. Mechanism Variables

To measure financing constraints (*FC*), we use the Whited–Wu (WW) index [54], which summarizes the internal and external financing conditions at the firm level. Higher values indicate tighter financing constraints. For R&D investment (*RD*), following Bai et al. [9], we define it as the natural logarithm of one plus the firm’s annual R&D expenditure.

3.2.4. Control Variables

Consistent with previous studies [12,18], we include a set of firm-level characteristics to mitigate omitted-variable bias and improve estimation accuracy. Specifically, we control for *Size*, measured as the natural logarithm of total assets; *Lev*, defined as the ratio of total liabilities to total assets; *Fixed*, calculated as the ratio of fixed assets to total assets; *Board*, represented by the natural logarithm of the number of directors; *Indep*, measured as the fraction of independent directors on the board; *Dual*, a dummy variable that equals 1 if the CEO also serves as the chairperson of the board and 0 otherwise; and *Balance*, measured as the ratio of shares held by the second-largest shareholder to those held by the largest shareholder. All data are obtained from the CSMAR database. Variable definitions are detailed in Appendix B Table A1.

3.3. Sample Selection and Data Sources

Our sample comprises A-share firms listed on the Shanghai and Shenzhen stock exchanges for the period 2011–2023. Consistent with the prior literature, we exclude finan-

cial firms and firms with special treatment status (ST or *ST), due to distinct regulatory and financial characteristics. The sensitivity measures are constructed using daily excess stock returns from 1 January 2011 to 31 December 2023. Data on green patent applications are sourced from the Chinese Research Data Services Platform (CNRDS), and financial and corporate governance variables are obtained from the CSMAR database. After removing observations with missing values and Winsorizing continuous variables at the 1st and 99th percentiles, we obtain an unbalanced panel of 35,023 firm–year observations across 4437 unique firms. All statistical analyses and model estimations were performed using Stata 18.0 (StataCorp LLC, College Station, TX, USA).

4. Empirical Results

4.1. Descriptive Statistics

Table 1 presents the summary statistics for the main variables used in our analysis. The mean of the green patent applications (*GI*) is 0.878, with the 75th percentile being at 1.609, indicating substantial cross-firm variation in green innovation. The mean of the composite sensitivity measure (*Sens*) is 0.079, indicating that roughly 7.9 percent of firm–year observations exhibit statistically significant sensitivity to climate risk. Within this group, the means for positive sensitivity (*Sens_Pos*) and negative sensitivity (*Sens_Neg*) are 0.037 and 0.042, respectively, implying that 3.7 and 4.2 percent of observations exhibit statistically significant positive and negative sensitivity. Summary statistics for other firm-level controls are broadly in line with prior studies [9,12] and the distributions appear well-behaved.

Table 1. Summary statistics.

Variable	N	Mean	SD	p_{25}	p_{50}	p_{75}
<i>GI</i>	35,023	0.878	1.202	0.000	0.000	1.609
<i>Sens</i>	35,023	0.079	0.270	0.000	0.000	0.000
<i>Sens_Pos</i>	35,023	0.037	0.190	0.000	0.000	0.000
<i>Sens_Neg</i>	35,023	0.042	0.200	0.000	0.000	0.000
<i>Size</i>	35,023	22.217	1.296	21.284	22.010	22.940
<i>Lev</i>	35,023	0.414	0.208	0.246	0.404	0.567
<i>Fixed</i>	35,023	0.202	0.155	0.081	0.169	0.288
<i>Board</i>	35,023	2.113	0.197	1.946	2.197	2.197
<i>Indep</i>	35,023	0.377	0.054	0.333	0.364	0.429
<i>Dual</i>	35,023	0.303	0.460	0.000	0.000	1.000
<i>Balance</i>	35,023	0.373	0.286	0.126	0.298	0.588

4.2. Validation of the Sensitivity Measures

To validate our interpretation that *Sens_Pos* captures market-perceived green opportunities while *Sens_Neg* reflects climate-related threats, we examine their association with independent ESG ratings. We match each firm in our sample to ESG scores from two widely used databases (Bloomberg and Huazheng) and compare average ESG scores between the two groups using one-tailed *t*-tests.

As shown in Table 2, the results are consistent and robust across both data sources: the mean ESG score for *Sens_Neg* firms is statistically lower than that for *Sens_Pos* firms (Bloomberg: 29.90 vs. 32.27, $p < 0.01$; Huazheng: 73.50 vs. 73.83, $p < 0.05$). These consistent results support our theoretical interpretation: positive sensitivity is associated with superior environmental credentials, suggesting that these firms are better positioned to capitalize on green opportunities. Conversely, negative sensitivity is associated with poorer environmental performance, indicating greater exposure to climate-related threats and transi-

tion risks. These validation tests strengthen our claim that *Sens_Pos* and *Sens_Neg* indeed capture perception-driven opportunity and threat sensitivities, respectively.

Table 2. *t*-test results, based on ESG scores.

Group	ESG Data Source	N	ESG (Mean)	Std.Dev	T-Stat	<i>p</i> -Value (One-Tailed)
<i>Sens_Neg</i>	Bloomberg	598	29.90	<i>Sens_Pos</i>	−3.76	0.001
<i>Sens_Pos</i>		433	32.27	9.61		
<i>Sens_Neg</i>	Huazheng	1227	73.50	5.08	−1.65	0.049
<i>Sens_Pos</i>		1225	73.83	4.79		

Note: The Bloomberg data provides more limited sample coverage compared to the Huazheng database.

4.3. Baseline Results and Discussion

Table 3 presents baseline estimates of the relationship between climate transition risk and corporate green innovation. In column (1), the coefficient for the composite sensitivity measure (*Sens*) is 0.001 and is not statistically significant, indicating no discernible aggregate effect of climate risk sensitivity on green innovation. In column (2), the coefficient for positive sensitivity (*Sens_Pos*) is 0.054 and is significant at the 1 percent level, implying that positive sensitivity is associated with higher green innovation. Specifically, a one-unit increase in *Sens_Pos* is associated with an approximately 5.4 percent increase in green innovation. By contrast, in column (3), the coefficient for *Sens_Neg* is −0.050 and is statistically significant at the 1 percent level, indicating that negative sensitivity is associated with lower green innovation. Specifically, a one-unit increase in *Sens_Neg* is associated with an approximately 5.0 percent reduction in green innovation.

Table 3. Baseline results.

	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>
<i>Sens</i>	0.001 (0.04)		
<i>Sens_Pos</i>		0.054 *** (2.77)	
<i>Sens_Neg</i>			−0.050 *** (−2.61)
<i>Size</i>	0.371 *** (18.29)	0.372 *** (18.32)	0.371 *** (18.34)
<i>Lev</i>	−0.159 *** (−2.75)	−0.157 *** (−2.71)	−0.158 *** (−2.73)
<i>Fixed</i>	0.026 (0.27)	0.031 (0.33)	0.028 (0.30)
<i>Board</i>	0.039 (0.58)	0.037 (0.56)	0.039 (0.59)
<i>Indep</i>	0.279 (1.33)	0.276 (1.32)	0.280 (1.34)
<i>Dual</i>	0.016 (0.93)	0.016 (0.92)	0.016 (0.93)
<i>Balance</i>	0.044 (1.05)	0.044 (1.03)	0.045 (1.07)

Table 3. *Cont.*

	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>
Constant	−7.485 *** (−15.07)	−7.510 *** (−15.10)	−7.490 *** (−15.09)
<i>Firm FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023
<i>Adj.R²</i>	0.73	0.73	0.73

Note: *t*-statistics are in parentheses and *** represents significance at the 1 percent level. Standard errors are clustered at the firm level.

These results are consistent with the competing hypotheses set forth in this study, revealing a fundamental divergence in outcomes based on the sign of firm-level sensitivity to public climate attention. Specifically, a positive correlation between stock excess returns and public climate attention is associated with higher green innovation, which is consistent with H1a; conversely, a negative correlation is associated with lower green innovation, which is consistent with H1b. The coexistence of these countervailing responses yields a statistically insignificant overall effect on the aggregate specification. This finding offers an empirical explanation and a unifying framework that help reconcile conflicting evidence in the existing literature.

4.4. Robustness Tests

4.4.1. Instrumental Variable (IV) Approach

Although our baseline specification incorporates firm and year fixed effects and uses one-period lagged explanatory variables to alleviate endogeneity concerns, residual endogeneity may persist. To strengthen identification, we employ an instrumental variable (IV) approach.

Following previous studies [55], we use the U.S. Climate Policy Uncertainty (CPU) index as an external shock for our instrument [56]. Our identification strategy rests on two key assumptions. First, climate change is a globally interconnected challenge, and initiatives such as the Leaders' Climate Summit demonstrate the synchronized nature of international climate policy efforts. This synchronization implies that U.S. climate policy uncertainty serves as a credible proxy for global climate policy sentiment, thereby affecting transition risk assessment worldwide. Second, while the U.S. CPU index directly influences American firms, it plausibly satisfies the exclusion restriction, because the U.S.'s domestic policy uncertainty has no direct channel through which to affect individual Chinese firms' innovation decisions, other than through the general climate risk awareness it generates. These two assumptions together justify using U.S. CPU as an instrument for Chinese firms' climate sensitivity variables.

To address the concern that the raw U.S. CPU index represents an aggregate, macro-level shock affecting all firms uniformly, we adopt a shift-share instrumental variable design [57]. Specifically, we interact the U.S. CPU index with each firm's predetermined exposure, measured by the average climate sensitivity of firms within the same industry–province combination. This design exploits the differential impact of global climate policy shocks on firms based on their inherent, time-invariant susceptibility to climate-related risks.

The IV estimates are presented in Table 4. The first-stage results, reported in columns (1), (3), and (5), show a strong positive association between the instrument and each endogenous variable (*Sens*, *Sens_Pos*, and *Sens_Neg*), with statistical significance at the

1 percent level. The Cragg–Donald Wald F statistics substantially exceed the conventional threshold of 10, with all values exceeding 100, alleviating concerns about weak instruments. The second-stage results, reported in columns (2), (4), and (6), show that the coefficient for *Sens* remains to be not statistically significant. By contrast, the coefficients on *Sens_Pos* and *Sens_Neg* remain significant at the 5 percent level, respectively, with signs that are consistent with the baseline estimates. These results reinforce our baseline conclusions and mitigate concerns about endogeneity.

Table 4. Instrumental variable estimates.

	(1) <i>Sens</i>	(2) <i>GI</i>	(3) <i>Sens_Pos</i>	(4) <i>GI</i>	(5) <i>Sens_Neg</i>	(6) <i>GI</i>
<i>IV1</i>	0.006 *** (74.46)					
<i>Sens</i>		−0.012 (−0.41)				
<i>IV2</i>			0.006 *** (59.90)			
<i>Sens_Pos</i>				0.082 ** (2.15)		
<i>IV3</i>					0.006 *** (52.48)	
<i>Sens_Neg</i>						−0.09 ** (−2.29)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023	35,023	35,023	35,023

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

4.4.2. PSM Test

To mitigate potential endogeneity issues arising from sample self-selection bias, we employ propensity-score matching (PSM) as a robustness check. We use the control variables as covariates and perform 1:1 nearest neighbor matching with replacement to construct a matched sample for comparison. To evaluate the effectiveness of this procedure, we conduct balance tests. Appendix B Figure A1 illustrates that, while noticeable differences existed between groups prior to matching, the distributions became well-aligned afterward. Appendix B Table A2 further presents the balance-test results: all covariates exhibit substantially reduced and insignificant t-statistics after matching, demonstrating that the PSM procedure effectively eliminates systematic differences between the treated and control groups.

We proceed to re-estimate the baseline regressions on the matched sample. The regression results are presented in Table 5 and largely align with the baseline results in Table 3. Specifically, the coefficient for *Sens* remains statistically insignificant in column (1), while the coefficients for *Sens_Pos* in column (2) and *Sens_Neg* in column (3) remain significantly positive and significantly negative, respectively. These results confirm that our main conclusions are robust, after addressing potential selection bias through PSM.

Table 5. PSM methods estimates.

	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>
<i>Sens</i>	−0.019 (−0.83)		
<i>Sens_Pos</i>		0.09 ** (2.47)	
<i>Sens_Neg</i>			−0.058 ** (−2.31)
<i>Constant</i>	−9.34 *** (−9.17)	−9.46 *** (−9.23)	−9.36 *** (−9.22)
<i>Controls</i>	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Observations</i>	6622	6622	6622
<i>Adj.R²</i>	0.87	0.87	0.65

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

4.4.3. Alternative Measures of Climate Transition Risk

We implement several alternative measures for climate transition risk sensitivity to address potential concerns regarding measurement error in our primary independent variables and to ensure the robustness of our conclusions. First, we re-estimate firm-level sensitivities using the Fama–French five-factor asset pricing model (rather than the baseline three-factor model) in the second stage of our construction methodology. Second, acknowledging that our baseline keyword set might capture broader economic trends, we construct an alternative climate risk attention index using a more refined set of keywords, following the methodology proposed by Gong et al. [25]. Third, we move beyond the binary classification of sensitivity. Instead of a simple 0/1 indicator, we replace the sensitivity variable with a quantile measure, classifying firms into ten decile groups based on the magnitude of the estimated $\beta_{i,t}$ coefficient and treating these ranks as ordinal categorical variables.

The regression results using these alternative specifications are presented in Table 6 (Fama–French five-factor model in Columns (1)–(3); alternative keywords in Columns (4)–(6)) and Table 7 (categorical variables in Columns (1)–(3)). In all reported models, the signs and statistical significance of the coefficients on *Sens*, *Sens_Pos*, and *Sens_Neg* remain consistent with our baseline findings. This comprehensive set of tests confirms that our results are robust across different asset pricing model specifications, alternative definitions of climate attention keywords, and various scaling approaches for the sensitivity measure.

Table 6. Robustness: alternative climate risk measures.

	Fama–French Five-Factor Model			Alternative Keywords		
	(1) <i>GI₁</i>	(2) <i>GI₁</i>	(3) <i>GI₁</i>	(4) <i>GI₁</i>	(5) <i>GI₁</i>	(6) <i>GI₁</i>
<i>Sens</i>	0.003 (0.19)			0.003 (0.21)		
<i>Sens_Pos</i>		0.046 ** (2.32)			0.049 ** (2.42)	
<i>Sens_Neg</i>			−0.037 * (−1.89)			−0.038 ** (−2.02)

Table 6. *Cont.*

	Fama–French Five-Factor Model			Alternative Keywords		
	(1) GI_1	(2) GI_1	(3) GI_1	(4) GI_1	(5) GI_1	(6) GI_1
<i>Constant</i>	−7.48 *** (−15.07)	−7.51 *** (−15.10)	−7.49 *** (−15.09)	−7.48 *** (−15.07)	−7.51 *** (−15.09)	−7.49 *** (−15.09)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023	35,023	35,023	35,023
<i>Adj.R²</i>	0.73	0.73	0.73	0.76	0.76	0.76

Note: *, ** and *** represent significance at the 10, 5 and 1 percent levels, respectively.

Table 7. Robustness: alternative climate risk measures using categorical variables.

	(1) GI	(2) GI	(3) GI
<i>Sens</i>	0.002 (1.15)		
<i>Sens_Pos</i>		0.008 *** (2.62)	
<i>Sens_Neg</i>			−0.008 *** (−2.67)
<i>Constant</i>	−7.48 *** (−15.06)	−7.51 *** (−15.09)	−7.49 *** (−15.09)
<i>Controls</i>	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023
<i>Adj.R²</i>	0.76	0.76	0.76

Note: *** represents significance at the 1 percent level.

4.4.4. Alternative Dependent Variables

We next assess the sensitivity to the measurement of the dependent variable, by employing two alternative proxies for green innovation. GI_1 is defined as the natural logarithm of one plus the number of green invention patent applications, and GI_2 as the natural logarithm of one plus the number of green utility model patent applications. Table 8 presents the estimates.

Table 8. Robustness: alternative green innovation measures.

	(1) GI_1	(2) GI_1	(3) GI_1	(4) GI_2	(5) GI_2	(6) GI_2
<i>Sens</i>	0.008 (0.71)			−0.004 (−0.38)		
<i>Sens_Pos</i>		0.053 *** (3.13)			0.045 *** (2.66)	

Table 8. Cont.

	(1) <i>GI</i> ₁	(2) <i>GI</i> ₁	(3) <i>GI</i> ₁	(4) <i>GI</i> ₂	(5) <i>GI</i> ₂	(6) <i>GI</i> ₂
<i>Sens_Neg</i>			−0.034 ** (−2.06)			−0.051 *** (−3.07)
<i>Constant</i>	−6.103 *** (−13.08)	−6.125 *** (−13.10)	−6.103 *** (−13.09)	−4.988 *** (−12.35)	−5.011 *** (−12.38)	−4.995 *** (−12.39)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023	35,023	35,023	35,023
<i>Adj.R</i> ²	0.71	0.71	0.71	0.68	0.68	0.68

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

Columns (1)–(3) of Table 8 report results for *GI*₁, and columns (4)–(6) for *GI*₂. Across both sets of estimates, the coefficients on *Sens_Pos* and *Sens_Neg* retain their expected signs and are statistically significant, whereas *Sens* is not statistically significant. These results indicate that our conclusions are not sensitive to the specific measure of green innovation.

4.4.5. Alternative Samples

To address potential biases arising from atypical market conditions and limited data availability, we perform two sample restriction tests with different exclusion criteria. First, we exclude observations from 2015 to 2016, to minimize the influence of the extraordinary market volatility in China’s stock market during this turbulent period. The results presented in columns (1)–(3) of Table 9 show no material change in the signs or statistical significance of the key coefficients, confirming that our baseline findings remain intact. Second, we exclude firms with fewer than three years of observations, to alleviate concerns about estimation bias arising from short panels and to ensure adequate time-series variation for reliable coefficient estimation.

Table 9. Robustness: alternative samples.

	Sample 1			Sample 2		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	0.000 (0.00)			0.001 (0.04)		
<i>Sens_Pos</i>		0.066 *** (3.08)			0.056 *** (2.82)	
<i>Sens_Neg</i>			−0.061 *** (−2.84)			−0.052 *** (−2.67)
<i>Constant</i>	−7.488 *** (−14.91)	−7.522 *** (−14.96)	−7.488 *** (−14.91)	−7.477 *** (−15.01)	−7.503 *** (−15.05)	−7.482 *** (−15.04)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023	35,023	35,023	35,023
<i>Adj.R</i> ²	0.73	0.73	0.73	0.73	0.73	0.73

Note: *** represents significance at the 1 percent level.

As shown in columns (4)–(6) of Table 9, the estimates from this balanced panel continue to indicate that *Sens_Pos* and *Sens_Neg* are statistically significant with the expected signs, whereas *Sens* remains not statistically significant. These results further corroborate the robustness of our main findings against alternative sample constructions.

5. Mechanism Analysis

Our baseline findings reveal heterogeneous firm responses to climate transition risk. We therefore examine the channels through which these heterogeneous responses affect corporate green innovation. Following Li et al. [58], we employ a mediation model to test the roles of financing constraints and R&D investment:

$$\text{Channel}_{i,t} = \alpha + \beta \text{Sens}_{i,t-1} + \gamma \text{Controls}_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (3)$$

where *Channel* denotes the mediating variables: financing constraints (*FC*) and R&D investment (*RD*). *Sens* refers to the firm-level sensitivity to public climate attention specific to transition risk, measured as the composite sensitivity (*Sens*) and its positive (*Sens_Pos*) and negative (*Sens_Neg*) components. All models include firm and year fixed effects, and explanatory variables are lagged by one year.

5.1. Financing Constraints Channel

We measure financing constraints using the Whited–Wu (WW) index [54]. Columns (1)–(3) of Table 10 present the results. In column (1), the coefficient for *Sens* is not statistically significant, suggesting that the composite measure of climate transition risk has no discernible association with financing constraints. In column (2), *Sens_Pos* is negatively associated with *FC* and is statistically significant at the 5 percent level, implying that positive sensitivity eases financing constraints. Specifically, a one-unit increase in *Sens_Pos* is associated with a 0.011 decrease in the WW index. By contrast, in column (3), *Sens_Neg* is positively associated with *FC* and is significant at the 1 percent level, indicating tighter financing constraints. Specifically, a one-unit increase in *Sens_Neg* is associated with an approximate 0.009 increase in the WW index.

Table 10. Mechanism analysis.

	Channel 1			Channel 2		
	(1) <i>FC</i>	(2) <i>FC</i>	(3) <i>FC</i>	(4) <i>RD</i>	(5) <i>RD</i>	(6) <i>RD</i>
<i>Sens</i>	0.000 (0.18)			−0.006 (−0.49)		
<i>Sens_Pos</i>		−0.011 ** (−2.43)			0.045 *** (2.94)	
<i>Sens_Neg</i>			0.009 *** (3.68)			−0.055 *** (−3.17)
<i>Constant</i>	0.711 ** (2.22)	0.714 ** (2.22)	0.712 ** (2.22)	0.711 ** (−15.01)	0.714 ** (−15.05)	0.712 ** (−15.04)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023	35,023	35,023	35,023
<i>Adj.R²</i>	0.18	0.18	0.18	0.73	0.73	0.73

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

These findings are consistent with Hypothesis H2 and indicate that climate transition risk sensitivity matters for green innovation, via the financing constraints channel. The evidence for *Sens_Pos* is consistent with improved access to green financing, reflecting perceived sustainability commitment [41], whereas the evidence for *Sens_Neg* is consistent with adverse treatment in credit markets and reduced subsidies [44], raising financing costs and leading to more conservative financial policies [59]. Collectively, these results demonstrate that the asymmetric effects of climate transition risk create distinct financing environments that either facilitate or impede firms' capacity to invest in green innovation projects.

5.2. R&D Investment Channel

We define R&D investment (*RD*) as the natural logarithm of one plus annual R&D expenditure. Columns (4)–(6) of Table 10 present the results. In column (4), *Sens* is not statistically significant. In column (5), *Sens_Pos* is positive and significant at the 1 percent level. Specifically, a one-unit increase in *Sens_Pos* is associated with a 4.5 percent increase in R&D investment. In column (6), *Sens_Neg* is negative and significant at the 1 percent level. Specifically, a one-unit increase in *Sens_Neg* is associated with a 5.5 percent decrease in R&D investment.

These findings are consistent with Hypothesis H3, suggesting that climate transition risk influences green innovation through its effect on R&D investment. Evidence for *Sens_Pos* indicates that external uncertainty is treated as a growth option and R&D is increased to build a sustainable competitive advantage [35], whereas evidence for *Sens_Neg*, which is consistent with agency frictions and loss aversion [33], indicates deferred R&D and a focus on short-term performance [48].

Overall, our mediation tests indicate that both financing constraints and R&D investment are important channels through which climate risk sensitivity affects green innovation. The direction of sensitivity systematically shifts firms' financing and investment behavior, providing a micro-level mechanism for the observed heterogeneity in green innovation. These results are consistent with the financing constraints and R&D investment channels that are derived from our integrated theoretical framework in Section 2.

6. Heterogeneity Analysis

6.1. Heterogeneity by Industry

Manufacturing firms typically operate in more carbon-intensive settings and face greater exposure to climate transition risk than their non-manufacturing counterparts [60], often incurring higher costs for adopting green technologies and upgrading equipment. Following the China Securities Regulatory Commission (CSRC) Industry Classification Guidelines (2012), we test for heterogeneous effects across manufacturing and non-manufacturing subsamples to assess whether industry characteristics modulate firms' responses to climate transition risk.

As shown in Table 11, the coefficient for the composite sensitivity measure (*Sens*) is not statistically significant in either subsample. However, decomposition reveals notable differences. In the manufacturing subsample, *Sens_Pos* is positive and statistically significant at the 1 percent level (coefficient = 0.061), whereas *Sens_Neg* is negative and statistically significant at the 10 percent level (coefficient = −0.047). In the non-manufacturing subsample, neither coefficient is statistically significant.

These findings are consistent with differential exposure to transition risk. Manufacturing firms, which face higher asset specificity and transition costs, respond more strongly to transition risk signals. Positive sensitivity is consistent with viewing green innovation as a strategic opportunity and leveraging improved financing and R&D, whereas negative sensitivity is consistent with more conservative strategies under tighter constraints. The

absence of significant effects among non-manufacturing firms points to lower exposure to transition risk and fewer immediate incentives for strategic or organizational adjustments.

Table 11. Heterogeneity by industry.

	Manufacturing			Non-Manufacturing		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	0.010 (0.58)			−0.013 (−0.53)		
<i>Sens_Pos</i>		0.061 *** (2.63)			0.034 (0.86)	
<i>Sens_Neg</i>			−0.047 * (−1.90)			−0.045 (−1.50)
<i>Constant</i>	7.778 *** (−10.70)	7.825 *** (−10.75)	7.761 *** (−10.70)	6.782 *** (−6.84)	6.833 *** (−6.86)	6.792 *** (−6.87)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	22,900	22,900	22,900	12,043	12,043	12,043
<i>Adj. R²</i>	0.74	0.74	0.74	0.74	0.74	0.74

Note: * and *** represent significance at the 10 and 1 percent levels, respectively.

6.2. Heterogeneity by Ownership

We further examine whether ownership type (state-owned [SOE] versus non-state-owned [non-SOE]) moderates the relationship between climate risk and innovation. SOEs' institutional context, including soft budget constraints and distinct governance structures [61], may shape their responsiveness to climate pressures.

Table 12 presents the results. The composite measure (*Sens*) is not statistically significant in either subsample. Upon decomposition, a clear contrast emerges. Among non-SOEs, *Sens_Pos* is positive and statistically significant at the 10 percent level (0.038), whereas *Sens_Neg* is negative and statistically significant at the 5 percent level (−0.049). By contrast, in the SOE subsample, neither coefficient is statistically significant.

Table 12. Heterogeneity by ownership.

	SOEs			Non-SOEs		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	−0.017 (−0.63)			−0.001 (−0.09)		
<i>Sens_Pos</i>		0.044 (0.98)			0.038 * (1.72)	
<i>Sens_Neg</i>			−0.050 (−1.61)			−0.049 ** (−1.97)
<i>Constant</i>	−7.778 *** (−10.70)	−7.825 *** (−10.75)	−7.761 *** (−10.70)	−6.782 *** (−6.84)	−6.833 *** (−6.86)	−6.792 *** (−6.87)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	11,705	11,705	11,705	22,420	22,420	22,420
<i>Adj. R²</i>	0.78	0.78	0.78	0.68	0.68	0.68

Note: *, **, *** represent significance at the 10, 5 and 1 percent levels, respectively.

This pattern suggests that non-SOEs, operating under harder budget constraints and stronger market discipline, exhibit more pronounced responses to transition risk signals. The muted response among SOEs may reflect distinct incentive structures and greater insulation from immediate market pressures. These patterns are consistent with the financing constraints and R&D investment channels developed in Section 2.

6.3. Heterogeneity by Region

Substantial regional disparities in economic development across China may lead to variation in corporate innovation responses [62]. We assess regional heterogeneity by classifying firms according to whether they are headquartered in eastern versus central-western provinces.

As shown in Table 13, the composite measure, *Sens*, is not statistically significant in either region. Differential effects emerge upon decomposition. Among central-western firms, *Sens_Pos* is positive and statistically significant at the 5 percent level (0.080), whereas *Sens_Neg* is negative and statistically significant at the 1 percent level (−0.103). For eastern firms, neither sensitivity measure is statistically significant.

Table 13. Heterogeneity by region.

	Eastern Region			Central-Western Regions		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	0.005 (0.30)			−0.019 (−0.72)		
<i>Sens_Pos</i>		0.040 * (1.74)			0.080 ** (2.18)	
<i>Sens_Neg</i>			−0.030 (−1.28)			−0.103 *** (−2.99)
<i>Constant</i>	−7.294 *** (−12.95)	−7.315 *** (−12.97)	−7.297 *** (−12.97)	−7.415 *** (−8.43)	−7.446 *** (−8.45)	−7.423 *** (−8.47)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	25,112	25,112	25,112	9896	9896	9896
<i>Adj.R²</i>	0.74	0.74	0.74	0.69	0.69	0.69

Note: *, ** and *** represent significance at the 10, 5 and 1 percent levels, respectively.

These patterns are consistent with the financing constraints and R&D investment channels developed in Section 2. In less-developed central-western regions, lower competitive pressure makes green innovation more likely to be treated as a strategic opportunity when exposed to transition risk, with firms seeking excess returns and policy support. At the same time, relatively less-developed market mechanisms and more severe financing constraints raise capital costs and limit external funding for transition investments. Consequently, negative sensitivity is associated with the curtailed innovation investment, in response to tighter constraints.

6.4. Heterogeneity by Board and Executive Financial Backgrounds

Prior research suggests that top decision-makers with financial backgrounds can leverage their networks and understanding of capital markets to improve firms' access to external financing [63]. In the Chinese institutional context, this background often facilitates connections to financial institutions, effectively easing financing constraints. To examine whether leadership-level financial backgrounds influence firms' responses

to transition risk in green innovation, we follow prior studies [64] and classify firms based on whether any of their directors, supervisors, or senior managers have a financial background (CSMAR).

Table 14 shows that the composite measure (*Sens*) is not statistically significant in either group, but differential effects emerge upon decomposition. Among firms with board and executive financial backgrounds, *Sens_Pos* is positive and marginally significant at the 10 percent level (0.050), whereas *Sens_Neg* is not statistically significant. By contrast, for firms without financial backgrounds, *Sens_Pos* is larger and statistically significant at the 5 percent level (0.088), while *Sens_Neg* is negative and statistically significant at the 1 percent level (−0.095).

Table 14. Heterogeneity by board and executive financial backgrounds.

	With Financial Background			Without Financial Background		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	0.004 (0.19)			−0.008 (−0.31)		
<i>Sens_Pos</i>		0.050 * (1.91)			0.088 ** (2.54)	
<i>Sens_Neg</i>			−0.042 (−1.59)			−0.095 *** (−2.84)
<i>Constant</i>	−7.766 *** (−12.00)	−7.782 *** (−12.00)	−7.770 *** (−12.01)	−7.881 *** (−9.77)	−7.919 *** (−9.81)	−7.892 *** (−9.80)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	20,555	20,555	20,555	11,366	11,366	11,366
<i>Adj. R²</i>	0.75	0.75	0.75	0.71	0.71	0.71

Note: *, ** and *** represent significance at the 10, 5 and 1 percent levels, respectively.

These differential responses are consistent with the financing constraints channel. Financial backgrounds improve capital access, thereby buffering firms against transition-risk-induced financing shocks. Firms without such backgrounds face tighter financing constraints and are therefore more vulnerable to market climate signals. Appendix B Table A3 validates this interpretation, using the FC index as a measure of financing constraints [65], showing that firms without financial backgrounds face significantly higher financing constraints (mean FC = 0.46 vs. 0.41, $p < 0.01$), confirming that financing constraints are the dominant mechanism driving the observed heterogeneity.

6.5. Heterogeneity by Marketization Level

We further examine whether regional disparities in market development influence the impact of climate transition risk on corporate green innovation. Regions with more advanced marketization typically feature stronger institutional environments, including better intellectual property protection and more efficient technology markets, which may influence how firms respond to climate risk. To test this, we classify firms into high- and low-marketization groups, using the annual province-level median of the regional marketization index in Wang et al. [66].

Table 15 reports the subgroup regression results. The composite measure (*Sens*) remains to be not statistically significant in both subsamples, which is consistent with the baseline results. However, decomposition reveals notable differences: in high-marketization regions, neither *Sens_Pos* nor *Sens_Neg* is statistically significant; in low-marketization

regions, *Sens_Pos* is 0.064 and is statistically significant at the 5 percent level, whereas *Sens_Neg* is −0.102 and is statistically significant at the 1 percent level.

Table 15. Heterogeneity by marketization level.

	High Marketization			Low Marketization		
	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>	(4) <i>GI</i>	(5) <i>GI</i>	(6) <i>GI</i>
<i>Sens</i>	0.026 (1.34)			−0.027 (−1.38)		
<i>Sens_Pos</i>		0.042 (1.59)			0.064 ** (2.21)	
<i>Sens_Neg</i>			0.008 (0.26)			−0.102 *** (−3.99)
<i>Constant</i>	−7.510 *** (−10.38)	−7.522 *** (−10.38)	−7.497 *** (−10.37)	−7.248 *** (−10.86)	−7.278 *** (−10.88)	−7.265 *** (−10.90)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	16,602	16,602	16,602	18,404	18,404	18,404
<i>Adj.R²</i>	0.72	0.72	0.72	0.74	0.74	0.74

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

These results are consistent with the financing constraints and R&D investment channels. In high-marketization regions, firms enjoy better access to capital and more developed technology markets, which may encourage them to acquire external technologies rather than pursue uncertain in-house R&D, thereby weakening the link between climate risk and green innovation. In low-marketization regions, firms face tighter financing conditions and fewer mature technology trading platforms, making their innovation decisions more responsive to climate risk signals.

7. Further Analysis

To examine whether a plausibly exogenous policy shock moderates the impact of climate transition risk on corporate green innovation, we focus on the announcement and ratification of the Paris Agreement. The Agreement, announced on 12 December 2015, set the goal of keeping the increase in global temperature well below 2 °C, while pursuing efforts to limit warming to 1.5 °C above pre-industrial levels. Its formal ratification by China’s National People’s Congress Standing Committee in late August 2016 marked a shift toward a more stringent climate-policy regime, elevating firms’ expectations of tighter future regulations. Because specific regulatory details remained unclear, the period featured a heightened, economy-wide policy shock alongside substantial uncertainty about the timing and stringency of implementation. Following Seltzer et al. [67], we estimate the following model:

$$GI_{i,t} = \alpha + \beta_1 Sens_{i,t-1} + \beta_2 Sens_{i,t-1} \times post_t + \gamma Controls_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (4)$$

where $post_t$ equals 1 from 2016 onward and 0 otherwise. *GI* denotes green innovation. All specifications include firm and year fixed effects, and the explanatory variables are lagged by one year, consistent with our baseline and mechanism analyses.

The regression results are presented in Table 16. The coefficient for the interaction term $Sens \times post$ is −0.017 and is not statistically significant. The coefficient for $Sens_Pos \times post$ is 0.032, which is also not statistically significant. By contrast, the coef-

ficient for $Sens_Neg \times post$ is -0.048 and is significant at the 5 percent level. This suggests that following the ratification of the Paris Agreement, negative sensitivity is associated with an additional decline in green innovation of approximately 4.8 percent relative to other firms. Taken together, these findings suggest that a heightened, economy-wide policy shock amplifies the negative effect of climate transition risk on green innovation.

Table 16. Policy shock analysis.

	(1) <i>GI</i>	(2) <i>GI</i>	(3) <i>GI</i>
<i>Sens</i>	−0.001 (−0.05)		
<i>Sens × post</i>	−0.017 (−0.91)		
<i>Sens_Pos</i>		0.056 *** (2.79)	
<i>Sens_Pos × post</i>		0.032 (1.00)	
<i>Sens_Neg</i>			−0.055 *** (−2.77)
<i>Sens_Neg × post</i>			−0.048 ** (−1.96)
<i>Constant</i>	−7.486 *** (−15.07)	−7.513 *** (−15.10)	−7.499 *** (−15.11)
<i>Controls</i>	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Observations</i>	35,023	35,023	35,023
<i>Adj.R²</i>	0.73	0.73	0.73

Note: ** and *** represent significance at the 5 and 1 percent levels, respectively.

This finding is consistent with real options theory and the managerial cognition perspective [23,36]. The regulatory uncertainty during the announcement and ratification period increased the value of the “option to wait”. Confronted with the perceived certainty of higher compliance costs, managers are likely to adopt more conservative strategies, prioritizing short-term financial stability and cash-flow resilience over long-term, sunk-cost-intensive green innovation investments in settings that are characterized by negative sensitivity. Consequently, the heightened policy shock exacerbates the dampening effect of climate transition risk on green innovation.

8. Conclusions and Implications

The literature on the climate risk–innovation nexus remains divided, with some studies reporting negative effects and others documenting positive effects, but it lacks a unified theoretical explanation [12,18]. We reconcile these conflicting results by proposing a firm-level sensitivity framework that distinguishes firms with positive sensitivity to public climate attention from those with negative sensitivity.

Drawing on an integrated framework centered on option-theoretic perspectives (real and growth options) [23,24], we posit that corporate green innovation reflects a complex trade-off between short-term costs and long-term benefits, and between conservative and proactive strategies. This theoretical foundation provides a coherent account of how sys-

tematically opposing firm-level responses can, in aggregate, yield an overall null effect in our setting and in the prior studies.

Our analysis reveals a statistically insignificant aggregate relationship between climate transition risk and corporate green innovation, which helps to reconcile the conflicting evidence in the literature [9,13]. Decomposing the aggregate effect shows that a one-unit increase in positive sensitivity (*Sens_Pos*) is associated with an approximately 5.4 percent increase in green innovation, whereas a comparable increase in negative sensitivity (*Sens_Neg*) is associated with a 5.0 percent reduction. These opposing patterns are consistent with our theoretical expectations: evidence for positive sensitivity (*Sens_Pos*) accords with growth options [24], whereas evidence for negative sensitivity (*Sens_Neg*) accords with real options and agency costs [23]. This polarization effect is robust across instrumental-variables analyses, alternative measurements, and alternative sample constructions, and it underscores that ignoring firm-level heterogeneity may bias inference.

Beyond establishing this core finding, our study clarifies the mechanisms through which these effects operate. We show that financing constraints and R&D investment serve as important channels that operate in opposite directions for different sensitivity types. Positive sensitivity is associated with eased financing constraints and higher R&D expenditures, thereby promoting green innovation, whereas negative sensitivity is associated with tighter financing conditions and lower R&D investment, thereby dampening innovation. These mechanism results are consistent with the financing constraints and R&D investment channels developed in Section 2.

Additional heterogeneity analyses reveal that these effects are particularly pronounced in specific contexts. The impact is stronger among manufacturing firms, non-state-owned enterprises, firms without financial backgrounds, and firms located in less-developed central-western regions, as well as in low-marketization provinces. These patterns suggest that firms facing greater transition pressures or operating under tighter constraints exhibit more distinctive responses to climate risk signals. In addition, our analysis of the policy shock around the Paris Agreement, which represents a plausibly exogenous shift in the regulatory environment, shows that increased regulatory uncertainty amplifies the negative effect that is associated with negative sensitivity, consistent with the higher value of the “option to wait” predicted by real options theory [23].

Collectively, this study provides an integrated theoretical and empirical framework that reconciles the inhibition-versus-promotion debate by introducing a directional sensitivity perspective. Our findings carry important implications for policy and practice. First, policymakers should move beyond uniform, “one-size-fits-all” climate policies. Regulatory frameworks should be designed to account for firm-level heterogeneity. For instance, opportunity-perceiving firms may respond best to innovation-led incentives like R&D grants, while threat-perceiving firms may require risk-mitigation support to overcome initial barriers. Second, governments should enhance green finance infrastructure to alleviate identified constraints, focusing on expanding instruments like green loans and sustainability bonds. These financial initiatives address the identified constraints and provide the necessary capital for firms that are committed to green initiatives, thereby reducing the inclination for “wait-and-see” behavior and ensuring a smoother transition to sustainable practices. Third, at the corporate level, managers must integrate climate-related risks and opportunities into their strategic planning and focus on enhancing internal financial resilience. This entails prioritizing R&D investment and ensuring access to capital for proactive transition strategies. Strengthening internal financial buffers is essential to help firms manage climate-related market volatility and to ensure that they are better prepared to navigate future regulatory and market changes.

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Appendix A

Keywords About Climate Transition Risk

Following Chen et al. [26], we group keywords into three categories related to climate transition risk. Chinese keywords are listed first; English translations appear in parentheses. These keywords are used to construct the daily public climate attention index.

- (i) **Regulatory attention category:** 低碳经济, 减少碳排放, 节能减排, 低碳, 减排, 节能, 碳关税, 碳汇, 碳排放, 碳中和, 碳交易, 碳足迹, 双碳, 碳达峰 (low-carbon economy, carbon-emission reduction, energy conservation and emission reduction, low carbon, emission reduction, energy conservation, carbon border tax, carbon sink, carbon emissions, carbon neutrality, carbon trading, carbon footprint, dual-carbon goals and carbon peak).
- (ii) **Opportunity attention:** 能源管理, 绿色能源, 绿色金融, 清洁能源, 可再生能源, 再生资源, 能源危机, 氢能, 生物燃料, 生物质能, 太阳能, 新能源, 风能, 核能, 潮汐能, 地热能, 光伏, 电动汽车, 新能源汽车 (energy management, green energy, green finance, clean energy, renewable energy, renewable resources, energy crisis, hydrogen energy, biofuel, biomass energy, solar energy, new energy, wind power, nuclear power, tidal energy, geothermal energy, photovoltaic, electric vehicle and new-energy vehicle).
- (iii) **Climate commission category:** International agreements and conferences: 巴黎协定, 哥本哈根气候大会, 京都协议书/京都议定书, 联合国气候大会, 气候变化研究进展, 气候峰会 (Paris Agreement, Copenhagen Climate Change Conference, Kyoto Protocol, United Nations climate conference, progress in climate research and climate summit).

Appendix B

Table A1. Variable definitions.

Type	Symbol	Definition and Construction
Dependent variable	<i>GI</i>	The number of green patents measuring the quality of firms' green innovation, using the natural logarithm of the number of green patents applied plus 1. Source: CNRDS

Table A1. Cont.

Type	Symbol	Definition and Construction
Independent variables	<i>Sens</i>	Indicator variable that equals 1 if a firm's stock excess return is sensitive to public climate attention, and 0 otherwise. Source: Self-constructed
	<i>Sens_Pos</i>	Indicator variable that equals 1 if a firm's stock excess return is positively sensitive to public climate attention, and 0 otherwise. Source: Self-constructed
	<i>Sens_Neg</i>	Indicator variable that equals 1 if a firm's stock excess return is negatively sensitive to public climate attention, and 0 otherwise. Source: Self-constructed
Mechanism variables	<i>RD</i>	The natural logarithm of R&D expense. Source: CSMAR
	<i>FC</i>	The Whited–Wu [54] index of financing constraints. Source: CSMAR
Control variables	<i>Size</i>	The natural logarithm of total assets. Source: CSMAR
	<i>Lev</i>	The ratio of liabilities to total assets. Source: CSMAR
	<i>Fixed</i>	The ratio of fixed assets to total assets. Source: CSMAR
	<i>Board</i>	The natural logarithms of the number of directors. Source: CSMAR
	<i>Indep</i>	Ratio of independent directors: independent directors divided by number of directors. Source: CSMAR
	<i>Dual</i>	A dummy variable that is equal to 1 when the CEO serves as board chairperson (duality), and 0 otherwise. Source: CSMAR
	<i>Balance</i>	Ratio of shares held by the second-largest shareholder to those held by the largest shareholder. Source: CSMAR

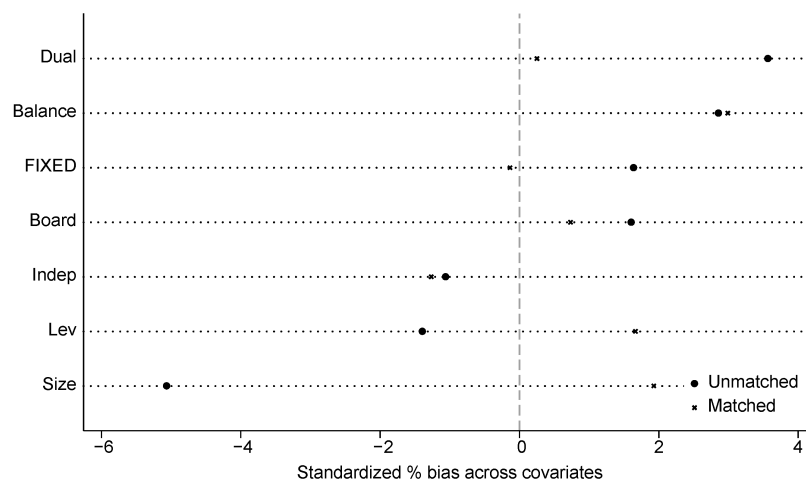


Figure A1. Differences before and after sample matching.

Table A2. PSM test.

Variable	Unmatched/ Matched	Mean		<i>t</i>	<i>p</i> > <i>t</i>
		Treated	Control		
<i>Size</i>	U	22.26	22.32	−2.870	0.004
	M	22.26	22.23	0.810	0.418
<i>Lev</i>	U	0.421	0.424	−0.800	0.423
	M	0.421	0.418	0.700	0.486

Table A2. Cont.

Variable	Unmatched/ Matched	Mean Treated	Mean Control	<i>t</i>	<i>p</i> > <i>t</i>
<i>Fixed</i>	U	0.208	0.205	0.930	0.350
	M	0.208	0.208	−0.060	0.954
<i>Board</i>	U	2.115	2.112	0.900	0.368
	M	2.115	2.114	0.310	0.759
<i>Indep</i>	U	37.75	37.81	−0.590	0.554
	M	37.75	37.82	−19.50	−0.530
<i>Dual</i>	U	0.308	0.291	2.020	0.044
	M	0.308	0.306	0.100	0.917
<i>Balance</i>	U	0.378	0.369	1.610	0.107
	M	0.378	0.369	1.240	0.214

Table A3. *t*-tests results based on the FC index.

Group	N	Mean	Std.Dev	T-Stat	<i>p</i> -Value (One-Tailed)
Without financial background	816	0.46	0.28	3.83	0.001
With financial background	1494	0.41	0.28		

Note: The FC index is a widely used measure of financing constraints, with higher values indicating tighter constraints. This analysis is conducted on the subsample of firms that are statistically sensitive to climate transition risk.

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