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Does Climate Risk Drive Green Transformation? Evidence from the Chinese Energy Enterprises

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ABSTRACT: Against the backdrop of the global climate governance paradigm shifting from "consensus building" to "action implementation", how climate risk drives the green transformation of energy enterprises has become a critical research topic. Based on a sample of Chinese A-share listed energy enterprises from 2016 to 2024, this paper systematically examines the impact of climate risk on green transformation and the mediating role of R&D innovation. This study finds that climate risk accelerates the green transformation of energy enterprises, and this conclusion remains robust after replacing the measurement approaches of core variables. Second, mechanism tests indicate that R&D innovation serves as a potential mediating pathway through which climate risk drives green transformation. Third, heterogeneity analysis reveals significant industry boundaries: climate risk significantly drives green transformation in new energy enterprises but not in traditional ones constrained by carbon lock-in. Fourth, both high and low-resilience enterprises, as well as large and small-size enterprises, achieve green transformation, and small-size enterprises exhibit relatively higher response elasticity. The findings offer decision-support insights for energy system planners to differentiate transition strategies between incumbent fossil fuel enterprises and emerging renewable enterprises.

KEYWORDS: Climate risk; green transformation; energy enterprises; corporate resilience

JEL Classification: G32; Q54; Q58; O33

1 Introduction

With the full implementation of the Paris Agreement and the stringent constraints of China's "dual-carbon" goals, high-carbon-emitting industries face unprecedented pressure to transform [1,2]. As the most carbon-intensive economic sector, energy enterprises' green transformation is not only an inevitable requirement for addressing climate change but also a strategic pivot for reshaping industrial competitiveness and gaining long-term capital favor. However, existing literature lacks a systematic exploration of how climate risk drives green transformation in energy enterprises. Core questions remain unanswered: When climate risk shifts from an "externality" to a "perceived pressure" within enterprises, through what pathways does it promote substantive green transformation? What differences exist in risk response among enterprises with different resilience levels?

Existing climate finance research primarily focuses on the financial consequences of climate risk, such as rising capital costs [3], stock price crash risk [4], and regional energy transition barriers [5]. These studies implicitly assume that "climate risk equals negative shock", overlooking its potential role as a catalyst for strategic transformation. More importantly, traditional metrics rely on lagging indicators such as carbon emission intensity, which fail to capture management's forward-looking perception of climate risk and strategic adjustments. In recent years, text-based approaches for measuring corporate climate risk exposure [4,6] have provided new possibilities for identifying underlying mechanisms, but their application in the energy sectors of transition economies remains to be explored.

This paper extends the climate finance analytical framework to the field of corporate green transformation. Unlike general environmental regulations, climate risk is characterized by high uncertainty and stranded asset expectations [7], reshaping corporate investment incentives through the "financing cost channel" and the "investor preference channel" [8]. Enterprises with high climate risk exposure face greater brown asset discounts and refinancing constraints, forcing them to undergo green transformation to reset market expectations and reduce capital costs. However, this transformation effect is not automatic: the uncertainty of climate risk and the long-cycle nature of green investment require enterprises to possess sufficient resource redundancy and dynamic adaptation capabilities to support strategic R&D investment. Based on this, this paper examines the micro-mechanisms by which climate risk drives green transformation using a sample of Chinese A-share-listed energy enterprises from 2016 to 2024.

This paper addresses three interrelated questions. First, does climate risk significantly promote the green transformation of energy enterprises? Second, does R&D investment serve as a mediating mechanism transmitting climate risk into green transformation? Third, does this effect differ systematically across industries—specifically, between renewable and traditional energy enterprises—and across enterprises with varying levels of resilience and size? These analyses are expected to shed light on the micro-mechanisms of climate finance and inform the design of targeted climate policies.

The marginal contributions of this paper are as follows: First, it expands the theoretical boundaries of climate finance. While existing research focuses on market penalties for short-term financial performance (such as brown discounts), this paper incorporates climate risk into the analytical framework of corporate strategic transformation, revealing potential micro-mechanisms through which climate risk may drive green transformation in connection with R&D innovation. Second, it identifies heterogeneous effects across enterprise types, confirming that the promoting effect of climate risk on green transformation depends on enterprises' resource bases and dynamic capabilities. This finding has important implications for the design of climate finance policy.

The rest of this article proceeds as follows. Section 2 reviews the literature and develops theoretical hypotheses. Section 3 introduces research design, variable measurement, and model specification. Section 4 presents the empirical findings, together with mechanism and heterogeneity analyses. Section 5 discusses the findings and Section 6 concludes.

2 Literature Review and Theoretical Hypotheses

2.1 Research Background

The energy industry is the most carbon-intensive core sector, and its green transformation is essential for achieving global carbon-neutrality goals. Unlike general manufacturing, traditional energy enterprises face deep carbon lock-in dilemmas: massive sunk costs in fossil fuel infrastructure (coal power, oil and gas pipelines, refining facilities) exhibit long-cycle, high-specificity characteristics, resulting in strong technological path dependence and transformation inertia [9,10]. This existing endowment of "brown assets" exposes energy enterprises to stranded asset risks under climate policy shocks, while also suggesting that their green transformation requires overcoming more rigid organizational barriers and technological bottlenecks.

From an institutional environment perspective, Chinese energy enterprises face dual institutional pressures: "dual-carbon" goal constraints and supply guarantees for energy security [11].

On one hand, regulatory tools such as coal power capacity elimination, renewable portfolio standards (RPS), and emissions trading systems (ETS) continue to tighten. On the other hand, energy enterprises bear the political mission of ensuring national energy security. This unique institutional setting constitutes the contextual premise of this paper: the green transformation of energy enterprises is not a pure market choice, but a strategic trade-off between policy coercion and supply-security obligations.

2.2 Climate Risk Measurement

Research on the economic impacts of climate risk has undergone a paradigm shift from macro-aggregation and sector-level analyses to micro-level enterprises identification. Early literature primarily focused on the aggregate effects of climate change on macroeconomic output [12] or relied on sector-level panel data to infer climate impacts on regional productivity [13]. However, the "fallacy of aggregation" inherent in both macro indicators and sector-level averages fails to capture firm-level heterogeneity in exposure and strategic adaptation, particularly by ignoring the distributional differences in transition risk across enterprises. Recent studies have thus moved toward micro-identification, utilizing firm-level data to quantify heterogeneous climate risk exposure [14].

In recent years, the urgency of measuring climate risk exposure at the firm and system levels has motivated a growing literature, ranging from network-based stress-testing of institutional portfolios [15] to more recent text-based analytical methods [4,6]. Sautner et al. [6] based on earnings call texts, construct firm-level climate exposure measures and document that such exposure is priced in equity and options markets and predicts green innovation and hiring. Following Lin and Wu [4], annual report risk metrics capture the extent of corporate climate risk disclosure and reflect management's attention to climate issues. This heterogeneity in risk attention is particularly critical among energy enterprises: the same climate policy signal (such as carbon price increase expectations) may trigger vastly different strategic responses in enterprises with different governance structures, technological bases, and resource endowments—some viewing it as a threat, others as an opportunity [6,16]. The existing literature has not adequately addressed how management's risk perception translates into substantive green transformation actions through internal resource allocation.

2.3 Theoretical Framework

The impact of climate risk on corporate green transformation theoretically involves two seemingly contradictory yet fundamentally complementary explanatory threads: the "constraint logic" and the "promotion logic". Clarifying the relationship between them is the prerequisite for constructing the core mechanism of this paper.

The constraint perspective draws on resource dependence theory, arguing that climate risk crowds out enterprises' long-term green investment by increasing financing constraints and redirecting resources toward short-term environmental compliance [17]. In particular, energy enterprises face brown-to-green asset reset pressures, requiring massive capital expenditures and sunk costs in the short term [10], which may divert funds from R&D under tight cash flow constraints. Empirically, He et al. [17] establish that atypical weather patterns erode green innovative capacity, as firms reallocate R&D expenditures in response to thermal shocks. Climate risk perception may also prompt managers to reduce accounting conservatism [18].

The "promotion view" is based on the Porter hypothesis. This view emphasizes that climate risk, as an external pressure, can induce enterprises to improve efficiency and competitiveness through innovation offsets [19]. Meta-analytic evidence synthesizing studies across developed and developing countries further confirms that environmental regulation generally exerts a positive effect on green innovation, particularly under command-and-control instruments [20]. In this dynamic process, heightened climate exposure strengthens societal climate risk perception and accelerates corporate digital transformation, thereby enhancing the efficiency of green innovation across both the R&D and outcome-conversion stages [21]. Concurrently, climate risk disclosure enhances the green innovation premium by promoting internal resource integration—such as market share expansion and inflows of technical talent—and by attracting external market attention from investors and the media [22]. Moreover, enterprises exposed to greater climate risk tend to have lower leverage ratios, thereby improving financial flexibility and facilitating green innovation [23]. For enterprises in the auto industry, transition risk constitutes a "policy window", with carbon-pricing policies inducing clean-technology innovation through path-dependent mechanisms [24]. These theoretical predictions are consistent with cross-country evidence showing that well-crafted environmental regulation fosters green productivity growth within an optimal stringency range [25].

The above two logics are not in simple opposition; rather, they respectively reveal the "cost side" and the "benefit side" of how climate risk affects corporate green transformation. This paper posits that climate risk affects green transformation through a trade-off mechanism: the "cost of inaction" vs. "transformation capability" at the firm-level. The core assets of energy enterprises (mines, power plants, pipeline networks) have ultra-long depreciation cycles and high specificity, thereby constituting a typical "carbon lock-in". When climate risk rises, the opportunity cost of maintaining existing brown asset portfolios increases sharply. At this point, enterprises face not a free choice of "whether to transform" but a survival choice between "active transformation" and "passive stranding". This means climate risk in the energy industry does not play a general "external cost" role but rather serves as a mandatory asset reallocation signal. The textual disclosure density of management's climate risk perception essentially reflects the depth of risk reassessment for existing asset portfolios. When this risk perception reaches a threshold, enterprises must hedge against the depreciation risk of existing assets through green technology investment (renewable energy substitution, CCUS retrofitting), thereby forming a positive "risk-transformation" relationship. Thus, we propose:

H1: *Climate risk perception significantly promotes the green transformation of energy enterprises.*

2.4 Mediating Mechanism

The core mechanism through which climate risk drives green transformation lies in alleviating financing constraints and inducing innovation. On the one hand, enterprises exposed to high carbon-transition risk face greater brown asset discounts [26], while enterprises located in climate-vulnerable regions face tighter debt financing constraints [27]. These pressures may incentivize enterprises to undergo green transformation, thereby improving their environmental performance and reducing capital costs. On the other hand, the policy signaling effect of climate risk prompts enterprises to tilt resources toward clean technology fields, accumulating green technology capabilities through R&D investment to achieve innovation offsets [19,25]. Energy enterprises' green transformation critically depends on technological breakthroughs (such as CCUS, hydrogen energy, energy storage), with R&D expenditure serving as the key hub connecting "risk perception" and "transformation action".

H2: *The impact of climate risk on green transformation is transmitted through enhanced R&D intensity, indicating an innovation-mediated channel.*

2.5 Boundary Conditions

Corporate resilience determines whether enterprises merely absorb shocks or adapt dynamically, reflecting enterprises' absorptive and adaptive capabilities [28]. High-resilience enterprises can rapidly reallocate resources in response to climate risk shocks, turning pressure into efficiency advantages for clean technology investment. Low-resilience enterprises (with stagnant or declining TFP growth) are trapped in organizational inertia and resource misallocation, unable to bear the high adjustment costs of green transformation. High TFP growth implies that enterprises possess excellent resource reallocation efficiency, organizational learning, and technology absorption capabilities. Facing climate risk shocks, high-resilience enterprises can quickly identify clean technology investment opportunities, converting pressure into opportunities for "creative destruction". In contrast, low-resilience enterprises, trapped in organizational inertia and resource misallocation, even if they perceive risks, cannot bear the high transformation costs, ultimately falling into the dilemma of "wanting to transform but being unable to do so". Therefore, the promoting effect of climate risk is highly dependent on enterprises' resilience foundation: resilience is not only a "stress resistance" capability but also a "transformation capability" that converts external shocks into internal transformation opportunities. Thus, we propose:

H3: *For enterprises with stronger resilience, the promoting effect of climate risk on green transformation is stronger.*

3 Variables, Model, and Data

3.1 Sample Selection and Data Sources

This paper uses Chinese A-share listed energy enterprises from 2016 to 2024 as the research sample. Energy enterprises are defined according to the China Securities Regulatory Commission (CSRC) 2012 industry classification standard. Following Liu et al. [29], this paper identifies the following industries as energy enterprise samples: coal mining and washing (industry code B06), oil and gas extraction (B07), mining auxiliary activities (B11), petroleum processing, coking, and nuclear fuel processing (C25), electricity and heat production and supply (D44), gas production and supply (D45), water production and supply (D46) and ecological protection and environmental governance (N77). These industries are further divided into traditional and renewable (new) energy enterprises. Since there is no unified industry classification standard for the renewable energy industry, this paper follows He et al. [30] and classifies an enterprise as renewable energy if its main business involves renewable energy sources—including solar, hydro, wind, geothermal, and biomass energy—or if it operates within the renewable energy value chain. Specifically, the electricity, heat, gas, and water production and supply industry (D44–D46) and the ecological protection and environmental governance industry (N77) are categorized as renewable energy enterprises because their business activities are closely tied to renewable energy development and the energy transition ecosystem (e.g., biomass energy utilization, waste-to-energy projects, and environmental services for clean energy infrastructure). The remaining industries are classified as traditional energy enterprises. The sample screening follows these principles: (1) excluding enterprises with abnormal financial conditions such as ST(Special Treatment), *ST(Special Treatment with Delisting Risk), and PT(Particular Transfer); (2) excluding observations with missing key variables; (3) winsorizing all continuous variables at the 1% level to mitigate extreme value effects. The final sample consists of 1517 firm-year observations. All data are from the CSMAR and CNRDS databases.

3.2 Variable Definitions

The Dependent Variable is Green Transformation (GTIndex). Following Qian and Cao [31], the listed company green transformation index uses a text analysis method, selecting keywords related to green transformation, searching annual reports of listed companies, and counting the frequency of all green transformation keywords in the reports. The total word frequency plus 1 is then natural logarithm transformed.

The core explanatory variable is Climate Risk (CR_I1). Following Lin and Wu [4], this paper uses a text-based approach to construct climate risk metrics based on annual report climate risk-related word frequencies, summing climate risk word frequencies, and dividing by total annual report word count to obtain the climate risk index. For robustness, this paper also uses the unstandardized raw word frequency (CR_W1) as an alternative measure.

The Mechanism Variable is firm Innovation. This paper uses two approaches to measure R&D innovation. First is R&D expenditure ratio (RDeapoinr), measured as the ratio of enterprise R&D investment to operating revenue, reflecting the firm's ability to convert climate risk into innovation investment. Second is the number of green innovation patents (Green1).

Grouping Variable: Corporate Resilience (Res). Following Ackah et al. [32], total factor productivity (TFP) as a comprehensive measure of resource allocation efficiency can effectively capture dynamic performance in both dimensions. Output Y is measured by main business revenue (OPREV), capital K by net fixed assets (PPE), labor L by number of employees (STAFF), and intermediate input M by cash paid for purchasing goods and receiving services (PGS). The resulting residual σ_{it} is the enterprise's total factor productivity. This paper first estimates firm TFP using the Cobb-Douglas production function:

$$\ln VA_{it} = \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln M_{it} + \sigma_{it}$$

where VA_{it} is firm i's total sales revenue in year t, K_{it} is net fixed assets, L_{it} is total employees, and M_{it} is cash paid for purchasing goods and receiving services. Firm i's total factor productivity level in year t is derived from the regression residual (σ_{it}). Corporate resilience is then defined as the annual change rate of *TFP*:

$$Res = TFP_{it} - TFP_{i,t-1}$$

The economic meaning of this indicator is that, when enterprises face external shocks such as climate risk, the *TFP* growth rate reflects their ability to achieve "adaptive evolution" through technical efficiency improvements, resource optimization, allocation, and organizational learning. Positive values indicate that enterprises have improved resource allocation efficiency amid volatility, while negative values suggest that shocks have caused efficiency losses or resource misallocation. Using *TFP* change rates rather than levels can effectively eliminate inherent productivity differences among enterprises, thereby capturing marginal dynamic adaptation capabilities.

To alleviate omitted-variable bias, this paper controls for a series of firm and governance characteristics that may affect green transformation. Specifically, the variables include: (1) Independent director ratio (InDrcRat), measured as the ratio of independent directors to total board members, reflecting corporate governance supervision intensity; (2) Firm size (Size), measured as the natural logarithm of total assets, controlling for the impact of firm resource endowment and political connections; (3) Asset-liability ratio (Lev), measured as the ratio of total liabilities to total assets, controlling for the impact of financial constraints on transformation investment; (4) Inventory turnover (Ivtyto), measured as the ratio of operating costs to average inventory balance, controlling for operational efficiency and short-term performance pressure; (5) Ownership concentration (LrgHldRt), measured as the shareholding ratio of the largest shareholder, controlling for the intervention of controlling shareholders in long-term strategic investment; and (6) Firm age (Age), measured as the years since IPO (initial public offering), controlling for the impact of organizational inertia and path dependence.

Table 1 reports the descriptive statistics of the main variables. The mean value of the green transformation index (GTIndex) is 3.117, with a standard deviation of 0.883, indicating that the overall green transformation level of sample enterprises is relatively low with significant individual differences. The gap between the minimum value of 0.693 and the maximum value of 5.375 provides ample room for green transformation improvement. The mean value of the climate risk index (CR_I1) is 1.908, with a standard deviation of 1.337 and a maximum value of 9.730, indicating significant heterogeneity in climate risk exposure across different enterprises. Some enterprises have incorporated climate risk into their strategic agenda, while most remain in a passive response stage.

Table 1: Descriptive statistics.

	Count	Mean	SD	Min	Max
GTIndex	1517	3.116967	0.883075	0.6931	5.3753
CR_I1	1517	1.907954	1.33691	0	9.73
InDrcRat	1517	38.56817	9.442215	8.3333	62.5
Size	1517	23.40424	1.540685	20.37937	27.6366
Lev	1517	0.5301286	0.166445	0.1162	0.9021
Ivtyto	1517	18.89852	31.06422	0.4395	221.8321
LrgHldRt	1517	39.97398	16.02842	10.14	77.29
Age	1517	23.20066	5.784124	9	36
RDeapoinr	1517	2.028467	2.137019	0	10.62
Green1	1517	26.76316	63.72438	0	447

Notes: All variables are defined in Appendix A Table A1.

Regarding R&D investment, the mean value of RDeapoinr is 2.0284, indicating a right-skewed distribution where a few high-R&D enterprises pull up the overall level. This is consistent with the capital-intensive, technologically mature industrial attributes of the energy sector. The standard deviation of green patent(Green1) (63.724) is much larger than the mean (26.763), with numerous zero values, indicating uneven distribution of green innovation activities among sample enterprises, where a few industry leaders account for the majority of green patent output.

3.3 Model Setting

We construct the following two-way fixed effects model to empirically test the impact of climate risk on green transformation:

$$\mathrm{GTIndex}_{it} = \beta_0 + \beta_1 \mathrm{CR\_I1}_{it} + \beta_2 Control_{it} + \mu_i + t_i + \varepsilon_{it}, \tag{1}$$

where $\mathrm{GTIndex}_{it}$ denotes the green transformation, and subscripts *i* and *t* respectively denote the enterprise and year. $\mathrm{CR\_I1}_{it}$ represents the climate risk. t_i represents the time fixed effect (FE) and u_i denotes the individual fixed effect (FE). β_0 is the constant term, and ε_{it} is the random error term.

4 Empirical Analysis

4.1 Baseline Regression

Column (1) of Table 2 reports the baseline results controlling only for two-way fixed effects. The coefficient of the climate risk (CR_I1) is 0.219, significantly positive at the 1% level, indicating that one-unit increase in climate risk raises the enterprise green transformation index by 0.219 points. Column (2) adds control variables, the CR_I1 coefficient is 0.193, with a significance level unchanged. A potential concern is reverse causality: enterprises already active in green transformation may strategically emphasize climate risk in annual reports. To address the issue, Column (3) reports the results using one-period-lagged climate risk (lCR_I1) as the explanatory variable. The coefficient is 0.071, significant at the 10% level, indicating that climate risk identified in year_{t-1} promotes green transformation in year_t. Among control variables, firm size is positively associated with green transformation, suggesting that larger enterprises possess resource advantages in environmental upgrading. Firm age, conversely, exhibits a significantly negative coefficient, indicating that older enterprises may suffer from organizational inertia that hinders green adjustment. These results confirm Hypothesis 1.

Table 2: Baseline regression results.

	(1) GTIndex	(2) GTIndex	(3) GTIndex
CR_I1	0.219***	0.193***	
	(5.625)	(4.840)	
InDrcRat		−0.001	−0.000
		(−0.734)	(−0.043)
Size		0.118*	0.147
		(1.680)	(1.637)
Lev		0.013	0.133
		(0.050)	(0.418)
Ivtyto		−0.000	0.000
		(−0.436)	(0.465)
LrgHldRt		−0.004	−0.006
		(−1.298)	(−1.568)
Age		−0.146***	−0.088
		(−3.377)	(−1.642)
lCR_I1			0.071*
			(1.855)
_cons	2.699***	3.588*	1.823
	(36.313)	(1.824)	(0.713)
ID FE	YES	YES	YES
YEAR FE	YES	YES	YES
N	1517	1517	1205
R^2	0.858	0.861	0.862

Note: *$p < 0.1$, ***$p < 0.01$. t-statistics in parentheses.

4.2 Robustness Tests

To enhance the reliability of conclusions, this paper conducts a series of robustness tests. First, column (1) of Table 3 replaces the climate risk (CR_I1) with the word frequency indicator (CR_W1), confirming the core conclusion remains robust. Next, column (2) uses green transformation word frequency as the dependent variable instead of GTIndex. The results remain consistent with the baseline regression.

Table 3: Robustness tests.

Variable	(1) Alt.X	(2) Alt.Y
CR_W1	0.000***	
	(4.584)	
CR_I1		7.033***
		(4.665)
InDrcRat	−0.001	0.034

(Continued)

Table 3 (continued)

Variable	(1) Alt.X	(2) Alt.Y
	(−0.576)	(0.784)
Size	0.109	2.152
	(1.531)	(1.050)
Lev	0.040	6.478
	(0.155)	(0.961)
Ivtyto	−0.000	−0.006
	(−0.328)	(−0.305)
LrgHldRt	−0.005	−0.235**
	(−1.420)	(−2.232)
Age	−0.136***	−3.539**
	(−3.030)	(−2.595)
_cons	3.667*	55.925
	(1.806)	(0.977)
ID FE	YES	YES
YEAR FE	YES	YES
N	1517	1517
R^2	0.861	0.926

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. t-statistics in parentheses.

Concerned about common-source bias in our text-based measures: If enterprises with stronger green disclosure tendencies also report higher climate risk, the observed correlation may reflect disclosure style rather than actual behavior. To test this, we use the logarithm of environmental protection investment (EPInvest) as an alternative dependent variable. Table 4 presents the results. Column (1) shows no significant association between climate risk and environmental investment. Column (2) uses one-period-lagged climate risk(lCR_I1); the coefficient is positive and significant at the 10% level. This pattern corroborates our main findings.

Table 4: Alternative dependent variable.

	(1) EPInvest	(2) EPInvest
CR_I1	−0.236	
	(−0.511)	
InDrcRat	0.006	0.005
	(0.508)	(0.471)
Size	0.312	−0.136
	(0.481)	(−0.285)
Lev	−1.889	−1.528
	(−0.767)	(−1.041)
Ivtyto	−0.006	−0.012
	(−0.696)	(−1.606)
LrgHldRt	0.011	−0.038***
	(0.344)	(−2.631)

(Continued)

Table 4 (continued)

	(1) EPInvest	(2) EPInvest
Age	0.272	0.402***
	(1.384)	(3.378)
lCR_I1		0.557*
		(1.695)
_cons	−4.372	3.771
	(−0.235)	(0.286)
ID FE	YES	YES
YEAR FE	YES	YES
N	340	279
R^2	0.825	0.857

Note: *$p < 0.1$, ***$p < 0.01$. t-statistics in parentheses.

4.3 Mechanism Analysis

Table 5 tests the transmission mechanism through which climate risk promotes green transformation via firm innovation. Column (1) uses R&D expenditure ratio (RDeapoinr) as the dependent variable, with the CR_I1 coefficient of 0.198 and significantly positive, indicating that climate risk significantly enhances enterprises' R&D investment intensity. Column (2) replaces contemporaneous climate risk with its one-period lag; the coefficient remains positive and significant (0.197, $p < 0.05$), suggesting that prior climate risk exposure drives current innovation input rather than reverse causation. Following Tian et al. [33] and Lu et al. [34], we use green patent applications(Green1) to measure of green innovation. Column (3) further regresses on green innovation, with the CR_I1 coefficient as high as 10.828 and significant at the 5% level, indicating that climate risk not only stimulates R&D investment but also substantially transforms into green innovation output. Combined with the baseline regression results, the positive association between climate risk and both R&D intensity and green patent output is consistent with innovation investment serving as a potential mediating pathway. The coefficients on firm size and age reverse sign when the dependent variable shifts from the green transformation index to R&D intensity, suggesting that larger and older enterprises invest more heavily in R&D relative to revenue despite lower baseline green transformation levels. In sum, Hypothesis 2 is supported.

Table 5: Mechanism analysis.

Variable	(1) RDeapoinr	(2) RDeapoinr	(3) Green1
CR_I1	0.198**		10.828**
	(2.525)		(2.292)
InDrcRat	0.000	0.000	0.183*
	(0.046)	(0.044)	(1.798)
Size	−0.322*	−0.365*	2.053
	(−1.966)	(−1.905)	(0.572)
Lev	−0.006	0.093	−27.920**
	(−0.012)	(0.157)	(−2.016)
Ivtyto	−0.005***	−0.006***	−0.069**

(Continued)

Table 5 (continued)

Variable	(1) RDeapoinr	(2) RDeapoinr	(3) Green1
	(−5.115)	(−2.882)	(−2.497)
LrgHldRt	0.010	0.006	0.031
	(1.296)	(0.665)	(0.159)
Age	0.203**	0.269***	5.198
	(2.293)	(2.774)	(1.034)
lCR_I1		0.197**	
		(1.976)	
_cons	4.169		−154.777
	(0.945)		(−1.148)
ID FE	YES		YES
YEAR FE	YES		YES
N	1517		1517
R^2	0.853		0.841

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. t-statistics in parentheses.

4.4 Heterogeneity Analysis

Table 6 splits the sample into high- and low-resilience groups based on the median of corporate resilience (Res). In Column (1), the high-resilience group has a CR_I1 coefficient of 0.212, significant at the 1% level. In Column (2), the low-resilience group has a coefficient of 0.180, also significant at the 1% level. Although the high-resilience estimate is slightly higher, a formal difference test (Fisher's permutation test, p-value = 0.406) shows that the difference is not statistically significant. Therefore, climate risk significantly promotes green transformation in both groups, but the promoting effect is comparable in magnitude.

Table 6: Corporate resilience.

Variable	(1) High_res	(2) Low_res
CR_I1	0.212***	0.180***
	(3.908)	(3.669)
InDrcRat	−0.001	−0.001
	(−0.548)	(−0.446)
Size	0.096	0.143
	(1.334)	(1.306)
Lev	0.080	−0.187
	(0.251)	(−0.570)
Ivtyto	0.001	−0.002*
	(0.878)	(−1.839)
LrgHldRt	−0.000	−0.013***
	(−0.036)	(−3.106)
Age	−0.027	−0.158***
	(−0.459)	(−3.555)
_cons	0.998	3.881

(Continued)

Table 6 (continued)

Variable	(1) High_res	(2) Low_res
	(0.441)	(1.330)
ID FE	YES	YES
YEAR FE	YES	YES
N	762	685
R^2	0.856	0.906

Note: *$p < 0.1$, ***$p < 0.01$. t-statistics in parentheses.

This paper divides the sample into new energy enterprises and traditional energy enterprises according to the CSRC 2012 industry classification standard. In Table 7 Column (1) for the new energy group, the CR_I1 coefficient is 0.208 and significant at the 1% level. In Column (2) for the traditional energy group, the coefficient is 0.194 but not significant (t = 1.660). This divergence reveals the essential differences between the two types of industries: new energy enterprises are already on the green transformation track, and the regulatory signals and market opportunities related to climate risk are highly aligned with their strategic direction, leading to more acute responses. Traditional energy enterprises, constrained by existing asset specificity, technological path dependence, and vested interests, find it difficult to make substantive adjustments even when facing the same climate risk shocks, presenting a dilemma of "wanting to transform but being unable to do so". This result has important implications for industry policy under the "dual-carbon" goals: the promoting effect of climate risk has significant industry boundaries, and the transformation of traditional energy enterprises requires mandatory policy interventions beyond market incentives to resolve stranded asset risks and break path dependence.

Table 7: Industry heterogeneity analysis.

Variable	(1) New	(2) Old
CR_I1	0.208***	0.194
	(5.371)	(1.660)
InDrcRat	−0.002	−0.001
	(−0.981)	(−0.446)
Size	0.140*	0.109
	(1.847)	(0.704)
Lev	−0.381	0.531
	(−1.489)	(1.148)
Ivtyto	−0.001*	0.003
	(−1.730)	(0.989)
LrgHldRt	−0.003	−0.006
	(−0.766)	(−1.031)
Age	−0.134***	−0.666
	(−3.529)	(−1.125)
_cons	3.118	14.486
	(1.536)	(1.096)
ID FE	YES	YES
YEAR FE	YES	YES

(Continued)

Table 7 (continued)

Variable	(1) New	(2) Old
N	1072	445
R^2	0.885	0.709

Note: *$p < 0.1$, ***$p < 0.01$. t-statistics in parentheses.

Finally, we split the sample into large-firm and small-firm subsamples according to the median value of firm size (Size). In Table 8 Column (2), representing the small-size group, the CR_I1 coefficient is 0.361, which is approximately 2.15 times greater than the 0.168 reported in Column (1) for the large-scale group. This result indicates that smaller enterprises exhibit higher responsiveness. A formal test of between-group differences (Fisher's Permutation test) yields a p-value of 0.005, suggesting the observed difference is statistically significant. This outcome, herein referred to as the "scale paradox", contrasts with prior literature that asserts large enterprises assume greater environmental responsibility. The paradox is particularly relevant in the energy industry, as small-size energy enterprises typically operate as specialized service providers or as emerging technology enterprises, characterized by streamlined structures, lower transformation costs, and greater agility in responding to climate risk policy signals and market opportunities. Conversely, large-scale enterprises, despite possessing financial resources, face considerable existing asset obligations and complex stakeholder interests, resulting in relatively slower transitions. Accordingly, these findings imply that climate policies should not uniformly target large enterprises alone. The potential competitive advantage of small-size enterprises in adapting to climate policy merits equivalent consideration.

Table 8: Size heterogeneity analysis.

Variable	(1) High_size	(2) Low_size
CR_I1	0.168***	0.361***
	(4.006)	(5.293)
InDrcRat	−0.002	−0.000
	(−1.293)	(−0.163)
Lev	0.088	0.021
	(0.207)	(0.065)
Ivtyto	−0.000	0.000
	(−0.299)	(0.182)
LrgHldRt	−0.004	−0.005
	(−0.798)	(−0.955)
Age	−0.158**	−0.059
	(−2.077)	(−0.879)
_cons	6.853***	3.971***
	(3.745)	(2.748)
ID FE	YES	YES
YEAR FE	YES	YES
N	788	716
R^2	0.832	0.903

Note: **$p < 0.05$, ***$p < 0.01$. t-statistics in parentheses.

5 Further Discussion

5.1 Dual Attributes of Climate Risk: Pressure and Opportunity

The results indicate a positive association between climate risk and the green transformation of energy enterprises. This finding reflects the dual nature of climate risk as both an external pressure and a market signal. On the one hand, climate risk increases financing costs and regulatory expectations for high-carbon assets, creating tangible cost pressure [3]. On the other hand, it signals forthcoming policy windows and technological transitions, prompting enterprises to reallocate resources toward clean technology. The mechanism analysis confirms that this transformation is not merely discursive: climate risk translates into concrete R&D investment and green patent output, suggesting that energy enterprises respond through substantive innovation rather than symbolic disclosure. This aligns with the Porter Hypothesis, which posits that appropriately stringent environmental pressures can induce innovation offsets [19,25].

5.2 Corporate Resilience

The result reveals that both high- and low-resilience enterprises exhibit significant positive responses to climate risk, with no statistically significant difference between groups. This indicates that the promoting effect of climate risk on green transformation is pervasive rather than conditional on resilience levels. In the energy industry, the asset specificity and long depreciation cycles of brown assets create a universal "cost of inaction" that compels transformation regardless of internal adaptive capacity. Consequently, resilience appears to sustain transformation momentum—both groups maintain significant innovation responses—but does not amplify their intensity. This suggests that climate risk functions as a mandatory asset-reallocation signal that enterprises cannot easily ignore, rather than an opportunity that only high-capability enterprises can exploit.

5.3 Re-Examining the Scale Paradox

This paper finds a "scale paradox": small-size enterprises demonstrate significantly stronger responsiveness to climate risk than large-scale enterprises, and the group difference is statistically significant. This contrasts with conventional findings that large enterprises bear greater environmental responsibility [35]. In the energy sector, small enterprises—often specialized service providers or emerging technology enterprises—benefit from streamlined structures, lower asset-specificity burdens, and shorter decision chains, enabling agile responses to climate policy signals. Conversely, large enterprises face considerable sunk costs in existing infrastructure and complex stakeholder coordination, resulting in slower adjustment despite superior financial resources. This divergence implies that the transformation potential of climate risk is distributed unevenly across the firm-size distribution.

5.4 The "Lock-in Effect" of Traditional Energy

The industry-heterogeneity analysis in this paper reveals the structural limitations of climate risk transformation effects: the insignificant coefficient for traditional energy enterprises indicates that climate risk cannot automatically overcome industry-level path dependence. The insignificant coefficient for traditional energy enterprises suggests that climate risk alone cannot automatically overcome industry-level path dependence. There are three possible interpretations of this. First, from a technological perspective, the accumulation of high-carbon technologies may create path dependence, and green substitution could face learning costs and complementary asset constraints. Second, from an institutional perspective, existing energy pricing mechanisms, grid dispatch rules, and infrastructure investment systems may tilt toward traditional energy, thereby creating institutional path dependence [9]. Third, from a cognitive perspective, managers and engineering teams may experience ‘cognitive lock-in’, harboring doubts about the urgency of climate risks and the feasibility of green transformation, which can delay responses.

The policy implication of this finding is that transformation targeting traditional energy enterprises cannot rely solely on market incentives and information disclosure; more forceful policy interventions are needed. Specifically, first establish total control and trading markets for carbon emissions to internalize the social costs of climate risk through price signals, compressing the profit space of traditional energy. Second, design differentiated transformation timelines and technological roadmaps, allowing enterprises to autonomously choose transformation paths but clarifying final compliance deadlines to avoid efficiency losses from “one-size-fits-all” approaches. Third, establish stranded asset risk-resolution mechanisms to support asset impairment restructuring and employee retraining for traditional energy enterprises through policy-based financial tools, thereby reducing social resistance to transformation.

6 Conclusion

Based on a sample of Chinese A-share listed energy enterprises from 2016 to 2024, this paper systematically examines the impact of climate risk on corporate green transformation and the mediating role of R&D innovation. The findings are consistent with the view that climate risk may serve as a catalyst for the green transformation of energy enterprises. And this conclusion remains robust after replacing the measurement approaches of core explanatory and dependent variables. Secondly, mechanism tests suggest that R&D innovation may serve as a mediating pathway linking climate risk to green transformation. Climate risk is positively associated with enhanced R&D investment intensity and increased green patent output. Thirdly, the promoting effect of climate risk on green transformation is statistically significant for new energy enterprises but insignificant for traditional energy enterprises. This divergence indicates that, constrained by asset specificity and path dependence, traditional energy enterprises face a “carbon lock-in” dilemma—where the driving effect of climate risk struggles to penetrate the heavy burdens of existing assets and the complex interest coordination mechanisms that prevent it from translating into actual green transformation behaviors, despite potential transformation willingness. Fourth, both high- and low-resilience enterprises, as well as large-scale and small-size enterprises, demonstrate statistically significant green transformation responses under climate risk pressures. Small-size enterprises exhibit relatively higher response elasticity (larger coefficient magnitudes).

The theoretical contribution of this paper lies in connecting climate economics with corporate strategic management research, revealing the micro-mechanisms through which climate risk, as an external shock, drives corporate green transformation, and expanding the applicability of the “Porter Hypothesis” in the energy industry. It also introduces the corporate resilience perspective, clarifying the moderating role of dynamic capabilities in risk-opportunity conversion, providing a new analytical dimension for understanding heterogeneous corporate environmental responses.

The policy implication of this paper is that the promoting effect of climate risk is neither automatic nor homogeneous, but depends on enterprises’ internal resource base and the external industry structure. This means that achieving “dual-carbon” goals cannot rely solely on market incentives and information disclosure. Mandatory transformation policies and stranded asset risk resolution mechanisms need to be designed to address traditional energy enterprises’ path dependence, while recognizing the green innovation potential of small-size enterprises to avoid efficiency losses from excessive policy resources concentrated on large enterprises.

A limitation of this paper is that both the climate risk index and the green transformation index are constructed from annual report texts. While this approach has advantages in data availability and cross-enterprise comparability, it carries “greenwashing” risks: enterprises may create green images through strategic information disclosure rather than substantive environmental performance improvement. Furthermore, the gap between textual disclosure and substantive performance widens when enterprises face mandatory environmental regulations or ESG rating pressures. Future research can expand to cross-national samples to test the institutional dependence of climate risk transformation effects, providing empirical evidence for differentiated policy design in global climate governance.

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Appendix A

Table A1: Variable definitions.

Variable	Definition	Measurement	Source
GTIndex	Green transformation index	ln (1 + total frequency of green transformation keywords in annual reports)	CNRDS
CR_I1	Climate risk index	Climate risk-related word frequency/total word count in annual reports	CNRDS
Rdeapoinr	R&D expenditure ratio	R&D investment/operating revenue × 100	CNRDS
Green1	Green innovation output	Number of green innovation patents	CNRDS
Res	Corporate resilience	Annual change rate of TFP (total factor productivity)	Calculated
InDrcRat	Independent director ratio	Independent directors/total board members × 100	CSMAR
Size	Firm size	ln(total assets)	CSMAR
Lev	Leverage	Total liabilities/total assets	CSMAR
Ivtyto	Inventory turnover	Operating costs/average inventory balance	CSMAR
LrgHldRt	Ownership concentration	Shareholding ratio of the largest shareholder (%)	CSMAR
Age	Firm age	Years since IPO	CSMAR

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