Navigating the Carbon Crossroads: Climate Transition Risk and Carbon Emission Efficiency in China's Energy Enterprises

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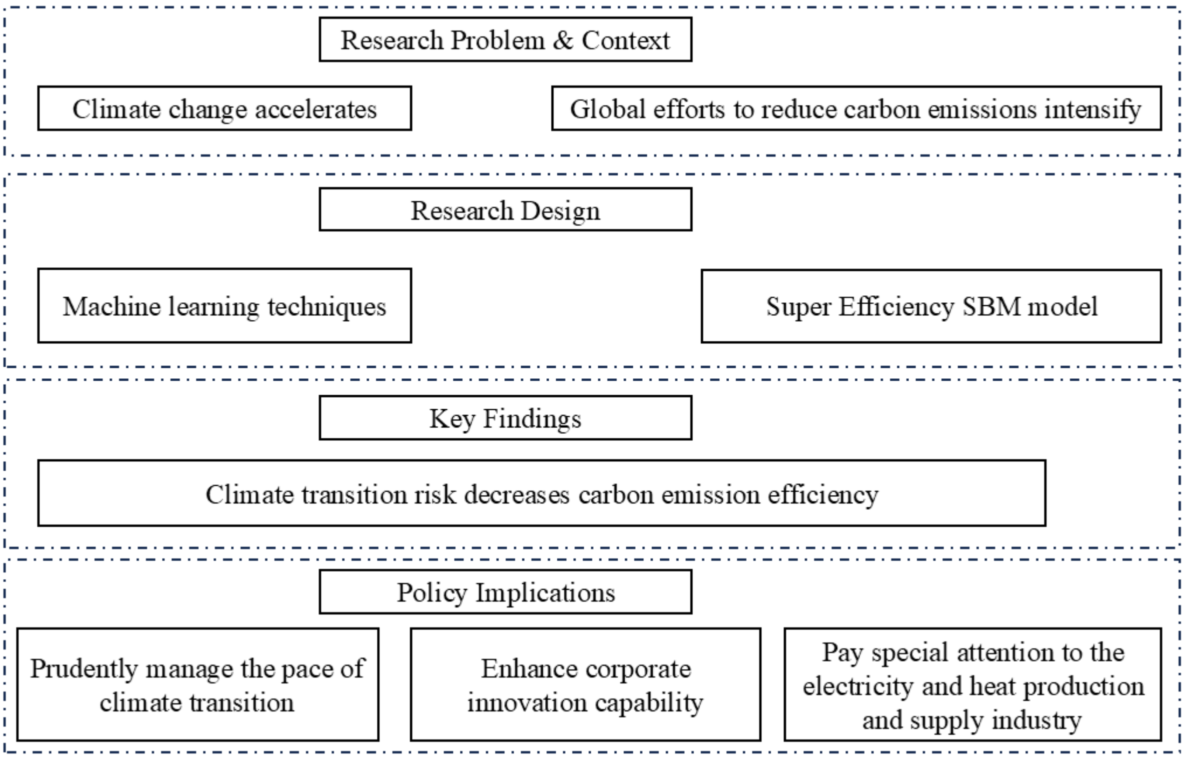
Graphical abstract



ABSTRACT

Climate change acceleration and intensifying global carbon reduction efforts have created an urgent need to understand how climate transition risks affect carbon emission efficiency in energy enterprises. Our study breaks new ground by developing climate risk indicators through machine learning and textual analysis of Chinese A-share listed companies' annual reports (2016-2022). Employing the Super Efficiency SBM model, we explore the complex relationship between transition risk and emission efficiency. Results indicate that transition risk initially hampers efficiency, though we found that robust innovation capabilities can buffer these negative effects. Interestingly, heterogeneity tests reveal that impacts are particularly pronounced within the electricity industry. These findings contribute meaningful insights for environmental policy development while offering practical guidance to energy enterprises grappling with emission reduction challenges.

Keywords: Climate transition risk, Carbon emission efficiency, Energy enterprises, Machine learning, Super Efficiency SBM model

1. Introduction

The unprecedented challenges posed by global climate change continue to threaten economic stability and development trajectories. Extreme weather events have inflicted substantial losses worldwide (Goklany, 2012; Steinfeld, 2001). GERMANWATCH[1] reports that between 2000 and 2019, more than 11,000 extreme weather incidents caused economic damages exceeding $2.56 trillion. This mounting threat has driven governments, financial institutions, and the investment community to integrate climate risk considerations into their risk management frameworks (Afshan et al., 2023; Amar et al., 2022).

As a key global player, China has implemented various energy-saving and emission-reduction policies to tackle climate change challenges (Lei, 2024; Wang et al., 2024). Recent scholarship demonstrates that these policies significantly influence corporate ESG performance (Lei, 2024) and reshape regional carbon emission patterns (Wen et al., 2024). While the government has outlined specific initiatives to strengthen climate response and promote green, low-carbon circular development, businesses—particularly in the energy sector—face growing climate risks during their low-carbon transition journeys (Yu et al., 2022).

Given that the energy sector generates over 90% of China's total emissions, enhancing carbon efficiency within energy enterprises remains critical for achieving reduction targets (B. Li et al., 2024). However, policy and regulatory uncertainties inherent in low-carbon transitions create substantial climate risks. Early in energy transitions, fossil fuel production equipment may become stranded assets, while still-maturing low-carbon technologies often lead to output reductions and cost increases—potentially undermining enterprises' carbon emission efficiency.

The scholarly conversation has typically centered on macro-level determinants affecting regional or industry-wide carbon emissions. In contrast, research examining carbon emission efficiency at the enterprise level remains scarce, with even fewer studies addressing climate transition risks specifically. This notable gap presents a valuable opportunity for our investigation.

[1] https://www.germanwatch.org/en/cri

Our research examines how climate transition risks influence carbon emission efficiency in energy enterprises. We make two key contributions:

First, we focus explicitly on the micro-level impacts of climate transition risks on energy enterprises' carbon emission efficiency—addressing a significant gap in current literature.

Second, our methodology employs enterprise output rather than operating income when estimating carbon emission efficiency. This approach better reflects carbon emissions since production processes generate carbon dioxide regardless of whether products are ultimately sold.

Through these analytical lenses, our study offers valuable insights into the complex dynamic between climate transition risk and carbon emission efficiency, providing theoretical support for environmental policy development while guiding energy enterprises through their emission reduction challenges.

2. Literature Review

The growing severity of global climate challenges has pushed climate transition risk to the forefront of scholarly inquiry and policy discourse (Li & Pan, 2022; Wu & Wan, 2023; Yang et al., 2023). Such risk encompasses potential economic and social disruptions stemming from climate policies, technological shifts, and market transformations.

A substantial body of work examines how macroeconomic policies, international trade patterns, energy price fluctuations, and technological breakthroughs shape carbon emission profiles across regions and industries (Cheng et al., 2023; Faccini et al., 2023; Fried et al., 2022; Reboredo & Ugolini, 2022; Zhou et al., 2023). Benedetti et al. (2021) investigated how government interventions in fossil fuel markets affect carbon emission portfolios (Benedetti et al., 2021). Their findings suggest that while such interventions effectively reduce risk exposure for fossil fuel stocks, they yield statistically ambiguous results regarding risk-return tradeoffs. In a different vein, Pilpola and Lund (2018) conducted a case study of Finland's energy system transition (Pilpola & Lund, 2018), highlighting the critical importance of integrating energy efficiency measures and renewable technologies into climate policy frameworks.

Recent scholarship has further broadened our grasp of climate-related financial impacts. Lei and Xu (2025) delved into how extreme weather events drive energy cost fluctuations (Lei & Xu, 2025), while Zeng et al. (2025) scrutinized tail risk contagion patterns within green finance markets (Zeng et al., 2025). Taking yet another approach, Li and Lei (2024) explored the nexus between climate change and green total factor productivity through a circular economy lens (Li & Lei, 2024).

Despite this rich macro-level scholarship, research focusing on micro-level carbon emission efficiency—particularly within energy enterprises—remains surprisingly sparse. Nevertheless, studies in this domain carry significant practical weight for achieving meaningful carbon reductions at the enterprise level. Zhu et al. (2024) drew on data from Chinese energy firms to examine how factors such as enterprise scale, ownership structures, and industry characteristics influence emission efficiency (Zhu et al., 2024). Their work revealed that both scale and ownership significantly shape emission efficiency, while industry effects exhibit more nuanced patterns. These insights offer valuable direction for crafting targeted carbon reduction strategies.

Similarly scarce is literature specifically addressing climate transition risk, though some researchers have begun exploring how climate policy shifts affect enterprises and financial markets. Markard et al. (2020) examined the European Emissions Trading System's impact on corporate strategies and policy positions (Markard & Rosenbloom, 2020), suggesting that ETS might serve as a "Trojan horse"—enabling firms to mitigate climate change while potentially hindering more ambitious climate policy implementation. In another noteworthy contribution, Huisingh et al. (2015) investigated how climate-related disclosure practices influence enterprise carbon risks (Huisingh et al., 2015), finding that enhanced disclosure requirements help firms navigate carbon policy uncertainties.

While existing literature offers valuable insights at the macroeconomic level, enterprise-level research on carbon emission efficiency remains underdeveloped. Our study addresses this gap by focusing specifically on the interplay between enterprise-level climate transition risk and carbon emission efficiency, thereby complementing and extending current scholarship.

3. Theoretical Analysis and Research Hypotheses

In the face of mounting climate challenges, governments worldwide have introduced increasingly stringent carbon emission controls. These policies aim to push energy firms toward greater research and application of emission-reduction technologies and clean energy solutions—ultimately enhancing carbon efficiency and facilitating energy system transformation. Yet in the early phases of energy transition, measures like elevated carbon taxes on fossil fuels and direct quantity restrictions often trigger significant energy price spikes, particularly in petroleum, natural gas, coal mining, and adjacent sectors (Hongsong Wang et al., 2022; Shankar et al., 2003).

This transition risk frequently translates into rising input costs for firms. Recent evidence suggests that external shocks—including extreme weather events—can profoundly disrupt corporate activities (Lei & Xu, 2024), with particularly pronounced effects on R&D investments and innovation capabilities. Moreover, carbon-intensive energy enterprises may be forced to alter production methods to control costs, potentially rendering existing equipment obsolete and creating stranded assets (Y.-H. H. Chen et al., 2023). Compounding these challenges, government-imposed emission restrictions may compel companies dependent on fossil fuel combustion to abandon functioning production infrastructure altogether (G. Chen et al., 2023).

Taken together, these forces may substantially increase costs while decreasing output, thereby undermining carbon emission efficiency. This reasoning leads to our first hypothesis:

H1: During initial energy transition phases, heightened climate transition risk correlates with diminished carbon emission efficiency in energy enterprises.

Endogenous growth theory offers a countervailing perspective, suggesting that economic growth can be sustained through internal technological advancement rather than external forces (Ha & Howitt, 2007; Izushi, 2008; Pan & Xuan-Thang, 2016). This theoretical framework emphasizes the crucial roles of technological progress and human capital—factors that can be enhanced through deliberate decisions by enterprises and policymakers.

Through this lens, appropriate policies might motivate energy firms to pursue technological breakthroughs. Such innovation could significantly improve resource utilization efficiency, enabling substantial conservation and recycling while reducing energy intensity at any given output level. Put differently, adopting cutting-edge energy-saving technologies and cleaner production processes might lower carbon intensity and boost emission efficiency.

However, technological progress exhibits dual effects on energy consumption and carbon emissions. On one hand, it may actually increase both by stimulating economic growth and shifting behavioral patterns among enterprises and consumers—potentially undermining expected efficiency gains through what scholars term the "rebound effect." On the other hand, robust enterprise innovation capabilities might buffer the negative impact of transition risk on carbon efficiency. This dynamic informs our second hypothesis:

H2: During initial energy transition phases, enterprise innovation capabilities moderate the negative relationship between climate transition risk and carbon emission efficiency.

4. Materials and Methods

4.1. Data Sources

Our study examines annual reports from Chinese energy industry A-share listed companies spanning 2016-2022. Climate risk data was extracted through textual analysis and machine learning techniques applied to these reports. Additional metrics were sourced from multiple databases: CSMAR, CNRDS, WIND, and RESSET.

To account for the distinctive operational characteristics within the energy sector, we classified enterprises into five categories following the 2012 national industry classification framework: electricity production and supply; heat production and supply; coal mining and washing; gas production and supply; petroleum and natural gas extraction; and petroleum processing, coking, and nuclear fuel processing.

The multi-source approach to data collection ensured both breadth and reliability. Climate risk indicators stemmed from textual analysis of annual reports obtained via WIND. Carbon emission calculations followed IPCC 2006 guidelines, utilizing energy consumption data from CNRDS. Financial and operational metrics came from CSMAR, while RESSET provided the market data elements.

Our data workflow involved several stages: first downloading and converting annual reports from PDF to TXT format; then applying the Chinese "JIEBA" library for word segmentation and stopword removal; subsequently integrating additional research variables from Guotai An; and finally excluding anomalous data points from ST and *ST companies and samples with incomplete information.

4.2. Variable Description

Dependent Variable (Carbon Emission Efficiency): Carbon emissions accounting typically follows one of several methodologies—input-output analysis, material balance calculations, life cycle assessment, or direct measurement. Efficiency metrics fall into either single-factor or multi-factor approaches. Single-factor metrics simply express emissions relative to one input variable, while total-factor efficiency considers the relationship between actual and optimal emissions while accounting for multiple inputs like labor, capital, and energy alongside outputs like GDP and carbon levels.

Given China's lack of mandatory carbon disclosure requirements and the selective nature of voluntary reporting (which skews toward better performers), accessing comprehensive enterprise-level emissions data remains challenging. Following established approaches (Shen & Huang, 2019), we estimate enterprise carbon footprints using industry-level emissions data calculated from industry energy consumption figures (CNRDS database) using the IPCC 2006 methodology.

For our efficiency calculations, we employ the Super Efficiency SBM model, incorporating capital input, employee headcount, and operating costs as input indicators, with enterprise output as the expected output and CO_2 emissions as the undesired output.

Independent Variable (Climate Transition Risk): Climate risk encompasses global environmental threats with far-reaching and potentially irreversible consequences (Chichilnisky, 2000). The TCFD framework distinguishes between physical risks (both acute and chronic) and transition risks associated with the shift toward low-carbon economies, including policy, technological, market, and reputational factors. Our study focuses specifically on transition risks from a policy perspective—the challenges energy enterprises face when balancing carbon reduction compliance with performance objectives.

With no standardized measurement approach for climate transition risk in the literature, we build on Li's (2024) textual analysis methodology, which tracked keywords in US company earnings calls (Q. Li et al., 2024). Following Hu et al. (2021) and others, we analyze annual reports of all A-share listed Chinese energy companies from 2016-2022 (Hu et al., 2021; Q. Li et al., 2024). Our approach, drawing on Du's (2023) work and input from digital experts (Du et al., 2023), employs 98 vocabulary terms across risk categories to construct our climate transition risk index (Table 1).

Table 1. Lexicon Categorized by Risk Type

Risk Type	Lexicon
Severe Risks	disaster, earthquake, typhoon, tsunami, drought, flood, extreme, harsh, internal, strong wind, sandstorm, frost, hail, freeze, water disaster, storm, mudslide, landslide, ice flood, snow disaster, drought disaster, flood disaster, rainstorm, tornado, ice hail, flood disaster, rain and snow, blizzard, freeze disaster, drought, drought condition, heavy rainfall, flood, severe cold, wind and sand (34)
Chronic Risks	climate, weather, humidity, water temperature, cooling, cold, temperature, rainfall, rain, rainy season, rain situation, precipitation, gloomy, heavy rain, extreme cold, winter, flood season, high humidity, water condition, water level, light, water shortage, high cold, cold wave, subsidence, groundwater, flood situation, surface, water storage (30)
Transaction Risks	energy saving, energy, clean, ecological, environment, transformation, solar energy, upgrade, recycling, utilization rate, nuclear power, wind power, natural gas, efficiency increase, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low carbon, energy consumption reduction, fuel, water conservation, photovoltaic, high efficiency, transformation, fuel consumption, electricity consumption, energy consumption, wind power, photovoltaic efficiency (34)

Other Variables: Following established practice, we control for company size (SIZE), leverage (LEV), return on assets (ROA), firm age (AGE), largest shareholder proportion (HS), and turnover rate (TO). For examining relationship dynamics, we include innovation capability (GA) as a moderating variable. Year and industry fixed effects are incorporated throughout. Table 2 provides comprehensive variable definitions and measurement approaches. All data originate from CNRDS, CSMAR, and RESSET databases.

Table 2. Definition of Main Variables

Variable	Definition	Measurement Method
CEF	Carbon Emission Efficiency	Calculated using the super-efficiency SBM model
CTR	Climate Transition Risk	Derived from machine learning and text analysis
SIZE	Firm Size	Natural logarithm of total assets
ROA	Return on Assets	Ratio of net profit to average total assets
LEV	Leverage	Total liabilities / Total assets
AGE	Firm Age	Natural logarithm of the number of years since the firm's establishment
HS	Largest Shareholder Ownership	Proportion of shares held by the largest shareholder at the end of the year
TO	Turnover Rate	The proportion of shares traded during the year to the total number of shares
GA	Innovation Capability	Natural logarithm of the number of patents applied for in the current year
Year	Year	Year dummy variable
Industry	Industry	Industry dummy variable

4.3. Model Specification

Based on our theoretical framework, we construct baseline regression and moderation effect models to examine how climate transition risk influences carbon emission efficiency in energy enterprises:

$$CEF_{i,t} = \alpha_0 + \alpha_1\ CTR_{i,t} + \sum \beta_i X_{i,t} + \sum Industry_i + \sum Year_t + \varepsilon_{i,t} \qquad (1)$$

$$CEF_{i,t} = \alpha_0 + \alpha_1\, CTR_{i,t} + \alpha_2\, CTR_{i,t} \times GA_{i,t} + \alpha_3 GA_{i,t} + \sum\beta_i X_{i,t} + \sum Industry_i + \sum Year_t + \varepsilon_{i,t} \quad (2)$$

In these equations, $CEF_{i,t}$ captures carbon emission efficiency for enterprise i at time t, while $CTR_{i,t}$ measures climate transition risk and GA represents innovation capability through patent applications. Control variables (X), industry fixed effects, and year fixed effects address unobserved heterogeneity, with $\varepsilon_{i,t}$ denoting the random disturbance term.

5. Results

5.1. Exploratory Data Analysis

Table 3 presents descriptive statistics for our sample of 849 observations. Carbon emission efficiency (CEF) exhibits notable variation (mean: 0.190, SD: 0.350), highlighting substantial efficiency differences across enterprises. Climate transition risk (CTR) shows a more concentrated distribution (mean: 0.164, SD: 0.141), though some outliers face considerably higher risk exposure.

Table 3. Descriptive Statistics

Variable	Size	Mean	SD	Min	Max
CEF	849	0.190	0.350	0.001	1.980
CTR	849	0.164	0.141	0.011	0.744
SIZE	849	22.408	1.341	19.226	27.910
ROA	849	0.035	0.034	-0.063	0.190
LEV	849	0.530	0.170	0.013	0.960
AGE	849	3.219	1.609	2.197	3.714
HS	849	0.430	0.170	0.003	0.900
TO	849	4.250	2.450	0.010	8.490
GA	849	0.030	0.100	0.001	1.000

Firm size (SIZE) displays relative homogeneity (mean: 22.408, SD: 1.341), while return on assets (ROA) approaches zero, suggesting fairly balanced asset returns across the sample. Leverage (LEV) exceeds 0.5 on average, pointing to high debt levels throughout the sector. Firm age (AGE) clustering indicates similar establishment periods, while largest shareholder proportion (HS) averages near 0.5, suggesting concentrated ownership structures. Stock trading activity (TO) shows substantial variability, and innovation capability (GA) averages near zero, though with notable exceptions demonstrating stronger innovative capacity.

5.2. Correlation Analysis

Figure 1 illustrates key variable relationships, revealing a significant negative correlation between climate transition risk (CTR) and carbon emission efficiency (CEF) at the 1% confidence level. This preliminary finding aligns with hypothesis H1, suggesting that heightened transition risk may indeed hamper efficiency.

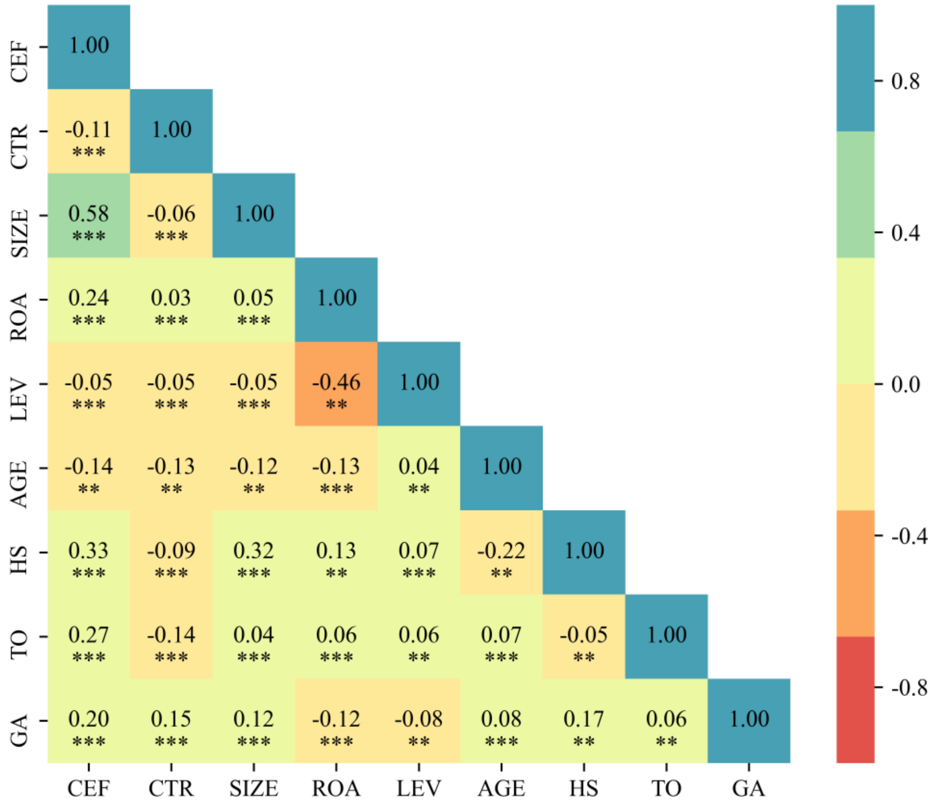


Figure 1. Correlation Analysis

Several control variables—ROA, LEV, HS, AGE, and TO—demonstrate statistically significant correlations with carbon emission efficiency. These patterns enrich our understanding of efficiency determinants and provide groundwork for subsequent regression analyses.

5.3. Baseline Regression

To test hypothesis H1 while addressing potential endogeneity concerns, we examined both contemporaneous and lagged relationships between climate transition risk and carbon emission efficiency.

Table 4, column (1) reveals that current climate transition risk negatively affects carbon emission efficiency (coefficient: -0.38, t-value: -1.83, $p < 0.10$), supporting hypothesis H1. More strikingly, column (2) shows that lagged climate transition risk exerts an even stronger negative effect (coefficient: -0.62, t-value: -2.96, $p < 0.01$).

Table 4. CTR and CEF Regression Results

Variable	*CEF* (1)	*CEF* (2)	*CEF* (3)
CTR	-0.38* (-1.83)		-0.72*** (-2.92)
CTR_{t-1}		-0.62*** (-2.96)	
Constant	0.05 (0.36)	0.22 (1.36)	0.26* (1.68)
Controls	Y	Y	Y
Year	Y	Y	Y
Industry	Y	Y	Y
N	849	685	685
R^2	0.49	0.51	0.45

To further mitigate endogeneity concerns, particularly reverse causality, we lagged both the explanatory variable and all controls by one period. Results in column (3) confirm our findings—the climate transition risk coefficient remains negative and significant (coefficient: -0.72, t-value: -2.92, $p < 0.01$), reinforcing the robust negative relationship between transition risk and efficiency.

5.4. Robustness Checks

We conducted alternative variable testing to further validate our findings. First, we redefined the dependent variable as the ratio of corporate revenue to carbon emissions. Table 5, column (1) shows that the core relationship remains significantly negative at the 1% level, reinforcing our baseline findings.

Table 5. Robustness Check

Variable	*CEF* (1)	*CEF* (2)
CTR	-2.51***	-0.02*
	(-3.01)	(-1.93)
Controls	Y	Y
Constant	0.14***	0.03
	(36.95)	(0.26)
Year	Y	Y
Industry	Y	Y
N	849	849
R^2	0.86	0.49

Additionally, we constructed a more nuanced measure of climate transition risk by applying entropy-weighted averaging to keyword frequencies. Regression results with this alternative measure (Table 5, column (2)) again yield a negative coefficient at the 10% significance level, further supporting our primary conclusions.

These robustness checks confirm the stability of our findings across different variable specifications and measurement approaches, strengthening confidence in the identified relationship between climate transition risk and carbon emission efficiency.

6. Discussion

6.1. Mechanism Analysis

To unpack the mechanisms through which climate transition risk affects carbon emission efficiency, we examined the moderating role of corporate innovation capabilities. Table 6, column (2) reveals a significantly positive interaction between innovation capability and climate transition risk ($p < 0.01$), supporting hypothesis H2.

Table 6. Mechanism analysis

Variable	*CEF* (1)	*CEF* (2)
CTR	-0.38* (-1.83)	-0.57** (-2.55)
CTR×GA		0.28*** (2.62)
Controls	Y	Y
Constant	0.05 (0.36)	0.04 (1.05)
Year	Y	Y
Industry	Y	Y
N	849	849
R^2	0.49	0.52

This finding suggests that robust innovation capabilities can buffer the negative efficiency impacts of transition risk. Enterprises with stronger innovation orientations appear better equipped to navigate transition challenges, possibly because technological advancement enhances operational efficiency in high-carbon enterprises, boosting overall value and offsetting stranded asset effects.

These insights resonate with recent work by Shen et al. (2024) on climate investment and green finance interconnections in China (Shen et al., 2024), as well as Zhang et al.'s (2024) emphasis on green technology innovation for high-quality industrial development under China's dual circulation strategy (Zhang et al., 2024).

6.2. Heterogeneity Analysis

Our industry-specific analysis reveals striking variations in how climate transition risk influences carbon emission efficiency across energy subsectors (Table 7). In electricity, heat production and supply, gas production and supply, and petroleum processing sectors, transition risk significantly dampens efficiency—most pronouncedly in the electricity and heat production segment, strongly supporting hypothesis H1.

Table 7. Heterogeneity Analysis

Variable	Electricity, Heat Production, and Supply	Gas Production and Supply	Petroleum Processing, Coking, and Nuclear Fuel Processing	Coal Mining and Washing	Oil and Natural Gas Extraction
	CEF	*CEF*	*CEF*	*CEF*	*CEF*
	(1)	(2)	(3)	(4)	(5)
CTR	-0.64**	-0.08	-0.01	0.06	2.29
	(-2.01)	(-0.50)	(-0.22)	(0.29)	(0.15)
Controls	Y	Y	Y	Y	Y
Constant	-0.09	0.04	-0.01***	0.06	-1.41*
	(0.49)	(0.63)	(14.09)	(0.83)	(-1.70)
Year	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
R^2	0.53	0.35	0.79	0.91	0.27
N	444	137	83	148	37

This pattern likely reflects how China's economic structural transformation has reduced traditional energy demand, affecting costs, outputs, and pricing dynamics in these industries and consequently reducing carbon efficiency.

Curiously, in coal mining and petroleum/natural gas extraction, transition risk exhibits a counterintuitive positive relationship with efficiency. This unexpected finding might reflect these industries' short-term responses—namely, accelerating resource exploitation within expected reserve lifespans (10-30 years) while improving extraction efficiency. This pattern suggests that while these sectors may face long-term challenges, short-term transition pressures might paradoxically drive more efficient resource utilization.

7. Conclusions and Policy Implications

7.1. Conclusions

Our research provides compelling evidence that climate transition risk significantly impacts enterprise carbon emission efficiency, with particularly strong effects in the electricity sector. Several key implications emerge:

First, the negative relationship between transition risk and efficiency underscores the need for carefully calibrated transition management. Policymakers should consider gradual implementation of carbon reduction targets, allowing enterprises adequate adaptation time for operational shifts and clean technology investments.

Second, innovation capability's moderating effect highlights its crucial buffering role. This finding suggests that government R&D support for low-carbon technologies could substantially mitigate transition disruptions.

Third, the heterogeneous sectoral impacts point to the necessity of tailored policy approaches. The electricity sector, with its pronounced vulnerability, may require specialized support mechanisms to maintain operational viability during transition periods.

Finally, our novel methodological framework—integrating machine learning with traditional efficiency measures—offers a valuable template for climate risk assessment that could be adapted across industries and contexts.

7.2. Policy Implications

Based on our findings, we propose three primary policy recommendations:

(1) **Calibrate transition pacing:** While carbon reduction represents an irreversible trend for energy enterprises, overly aggressive government pressure during early transition stages may impose unsustainable economic burdens and potentially hamper growth. Policymakers must balance emissions reduction targets with economic vitality, evaluating policy rationality, feasibility, and effectiveness to achieve sustainable development.

(2) **Foster enterprise innovation:** Given innovation's demonstrated buffering effect, energy enterprises should prioritize R&D investments in low-carbon and energy-saving technologies. Structured technology development roadmaps can ensure that low-carbon advances complement rather than disrupt core operations, enabling increased output amid transition pressures.

(3) **Prioritize electricity sector support:** With its heightened vulnerability to transition risks, the electricity and heat production industry—the first sector incorporated into China's national carbon trading market—requires special attention. Small coal-fired generators face particularly acute compliance challenges. Targeted policy interventions, financial support mechanisms, and gradual transition pathways can help build sectoral resilience and foster virtuous development cycles despite transition pressures.

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