International Business & Economics Studies
ISSN 2640-9852 (Print) ISSN 2640-9860 (Online)
Vol. 8, No. 3, 2026
www.scholink.org/ojs/index.php/ibes

Original Paper

How does Climate Transition Risk affect Corporate Default Probability: Evidence from Carbon-Intensive Enterprises in China

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Received: June 16, 2025 Accepted: July 28, 2026 Online Published: August 17, 2026

doi:10.22158/ibes.v8n3p316 URL: http://dx.doi.org/10.22158/ibes.v8n3p316

Abstract

Accelerating global climate governance and the deepening of China's "dual carbon" strategy are fundamentally reshaping firms' operating environments through policy tightening, technological disruption, and shifting market preferences. Precisely measuring such macro-level long-term climate transition risk and identifying its impact on micro-level corporate default probability has thus become a critical issue for financial stability and the green transition. Using 2010-2024 panel data of Chinese carbon-intensive listed companies, this study constructs a text-based transition risk index and employs two-way fixed effects and system GMM models. Results show climate transition risk significantly and non-linearly increases default probability, with electricity, heat, and gas sectors most exposed. Risks are higher for large firms and those in eastern/central regions, and are statistically more significant in non-capital-intensive industries. These findings provide micro-evidence for differentiated transition risk governance.

Keywords

climate transition risk, carbon-intensive enterprises, stranded assets, default probability

1. Introduction

The increasing frequency of extreme weather events not only pose a serious threat to natural ecosystems but also directly impacts economic activities in human society [1], with China identified as one of the regions most vulnerable to climate disasters [2]. China's "dual carbon" strategy drives a green transition but brings significant "climate transition risks" [3]. Driven by tightening policies, technological breakthroughs, and shifting market preferences, high-carbon assets face sudden depreciation or obsolescence. This causes fossil fuel asset "stranding" with potential losses of trillions of dollars [4][5], broadly affecting dependent industrial chains and financial assets, triggering asset repricing pressures, and exacerbating corporate liquidity issues[6][7]. Thus, accurately assessing these risks' impact on carbon-intensive enterprises' default probability is crucial. It helps enterprises adjust strategies, assists financial institutions in integrating climate factors into risk management to prevent systemic risks, and provides scientific support for policymakers to design transition pathways balancing emission reduction, development, and security.

Existing research primarily focuses on the impact of transition risks on corporate profitability and asset valuation. These risks affect micro and macro financial stability through policy, technology, and market preferences[8]. Unanticipated mitigation policies cause fossil fuel asset reassessment, value contraction, and balance sheet shrinkage[9]. Tighter emission regulations restrict high-carbon product sales, reducing revenues. Renewable energy advances decrease fossil fuel reliance, causing premature asset obsolescence, and compel production model changes that increase costs and reduce efficiency[10]. Green consumer and investor preferences alter investment structures, affecting capital valuation and risk profiles[11], and indirectly impact fossil fuel assets and supply chain profitability by steering technology and regulation[12].Studies also examine financial institutions' lending relationships. Stress tests show climate risks affect non-performing loan (NPL) ratios via loan collateral value[13] and investment portfolio risk exposure[14][15]. Through financial networks, these risks may trigger "Green Swan" events, threatening market stability[16]. To mitigate these consequences, corporate environmental investments and green innovation are proposed as crucial mechanisms for reducing default rates[17]. Financial institutions are encouraged to quantify environmental risks and integrate them into risk management frameworks[18]. Dynamically linking financing costs to emission-reduction performance creates an "interest rate incentive" mechanism that guides enterprises to reduce carbon emissions, effectively lowering financing costs and default probabilities for green transition projects, providing empirical evidence and viable pathways for micro-level risk management.

However, existing literature rarely delves into the default probability of carbon-intensive enterprises and its transmission channels. Compared to other enterprises, high-carbon-emitting enterprises may be significantly more vulnerable to climate transition risk[19]. Regarding measurement methodologies, mainstream approaches are either difficult to adapt to the Chinese policy context due to their reliance on specific index funds, or they are constrained by missing carbon emission data, which limits the sample size for mechanism testing. Furthermore, existing literature largely assumes linear relationships, failing to account for the sudden, non-linear shocks of climate policies. There is also insufficient analysis of the heterogeneous responses of enterprises across different regions, capital structures, and ownership types.

To address these gaps, this study examines the impact of climate transition risk on the default probability of Chinese listed firms in eight carbon-intensive industries (2010–2024). Using textual analysis of financial reports to proxy transition risk, we explore this relationship theoretically and empirically. We conduct heterogeneity analyses by firm size, region, and capital intensity, and test cost-and revenue-side mediation channels. Ultimately, this research provides decision-making support for enterprises to formulate scientific transition pathways and prevent systemic financial risks.

This paper makes three primary contributions. First, focusing on eight representative carbon-intensive industries, this study provides firm-level evidence that climate transition risk significantly and non-linearly increases enterprise default probability. This addresses existing literature's over-reliance on banking-sector spillovers, thereby diversifying research perspectives on climate transition risk.

Second, heterogeneity analyses reveal that transition risk impacts vary significantly across firms. Large enterprises face higher default risks than small and medium-sized ones, and firms in eastern and central regions are more sensitive to transition risk than those in the west. Notably, non-capital-intensive firms are statistically more vulnerable than capital-intensive ones, indicating that these numerous enterprises warrant equal attention during the transition process.

Third, we investigate cost and revenue side transmission mechanisms. Transition risk elevates default probability both directly and indirectly by eroding operating revenues and raising capital costs. Notably, transition support that lowers capital costs may inadvertently induce over-financing and increase default risk. These findings provide a basis for targeted regulatory policies to enhance resilience and mitigate default risks across diverse carbon-intensive sectors.

The remainder of this paper is structured as follows: Section 2 discusses the channels through which climate transition risk affects carbon-intensive enterprises. Section 3 measures the climate transition risk of carbon-intensive enterprises across different industries. Section 4 presents the empirical analysis and discusses the results. Section 5 concludes the paper and provides policy recommendations.

2. Transmission Channel Analysis of Climate Transition Risk on the Default Probability of Carbon-intensive Enterprises

Climate transition risk increases the default probability of carbon-intensive enterprises through complex, multidimensional mechanisms involving both micro-level financial deterioration and macro-level industry contagion. Specifically, these effects operate through four main transmission channels.

2.1 Financing Cost Channel

Rising financing costs are the primary mechanism by which transition risk elevates default probability. As the low-carbon transition progresses, investors demand higher risk premiums for high-carbon assets. Equity costs rise sharply due to market sensitivity to climate risk, while debt costs increase moderately through credit rationing and higher interest rates. This "dual-track" cost escalation erodes profit margins and weakens debt-servicing capacity.

2.2 Asset Impairment and Stranding Channel

Asset impairment losses represent another key transmission pathway. During the transition, unexploitable fossil fuel reserves ("unburnable carbon") and traditional infrastructure face premature retirement or devaluation. These stranded assets shrink enterprise asset size, reducing net asset values and potentially triggering debt covenants, which further exacerbates liquidity crises.

2.3 Operating Revenue and Profitability Channel

Declining operating revenue growth exacerbates default risk from the income side. Transition risk shifts consumer preferences toward green products, suppressing demand for high-carbon goods. This structural shift erodes market share and stalls sales growth. Combined with rising costs, this "scissors differential" severely compresses profit margins, straining firms' ability to meet fixed debt obligations.

2.4 Industry Spillover and Contagion Channel

Climate transition risk propagates across industries through production and financial networks, creating systemic risk. Through trade chains, risks from upstream carbon-intensive sectors transmit to downstream industries; sharp price fluctuations or supply constraints trigger cascading default risks.

In financial networks, contagion is even faster. As primary creditors, banks absorb risks from deteriorating carbon-intensive assets, leading to higher non-performing loan ratios and tighter credit. Meanwhile, investor sentiment and "herding effects" accelerate equity market sell-offs and valuation declines, further amplifying corporate default probabilities.

3. Measurement of Climate Transition Risk

3.1 Measurement of Climate Transition Risk

Based on existing literature, three primary methods measure climate transition risk. The first uses regional carbon emission intensity as a proxy, but spatial mobility and incomplete corporate data prevent precise firm-level characterization. The second constructs stranded asset portfolios to reflect risk at the firm level, yet lacks multi-dimensional analysis. Accordingly, this study adopts the third approach, calculating the frequency of transition risk seed words in corporate financial reports to capture individual firms' exposure.

This paper screens transition risk seed words from Sautner et al. [20] and combines them with Du's [21] extended set. Using annual reports of listed firms in eight carbon-intensive industries (2010-2024), we calculate the frequency of these seed words in financial reports to measure climate transition risk.

$$CCE_{i,t}=\frac{1}{B_{i,t}}\sum C_i$$

where $CCE_{i,t}$ denotes the climate transition risk of firm *i* in year *t*, $B_{i,t}$ represents the frequency of occurrence of seed words in the financial report of firm *i* in year *t*, and C_i is the total number of words in the financial report of firm *i* in that year.

Table 1. Climate Transition Risk Seed Word Set

Seed Words	
Word Set	Energy saving, Energy, Clean, Fuel, Ecology, Water saving, Environment, Green, Transition, Solar energy, Upgrading, Recycling, Retrofitting, Utilization rate, Nuclear power, Wind power, Natural gas, Efficiency enhancement, Fuel oil, Efficiency, Recycling, Regeneration, High efficiency, Photovoltaic, Emission reduction, Consumption reduction (26)
Expanded Words	
Word Set	Energy saving, Energy, Clean, Ecology, Environment, Transition, Solar energy, Upgrading, Recycling, Utilization rate, Nuclear power, Wind power, Natural gas, Efficiency enhancement, Fuel oil, Efficiency, Regeneration, Emission reduction, Environmental protection, Green, Low carbon, Consumption reduction, Fuel, Water saving, Photovoltaic, High efficiency, Retrofitting, Fuel consumption, Electricity consumption, Energy consumption, Wind power, Photovoltaic, Efficacy, Intensive (34)

3.2 Climate Transition Risk of Carbon-intensive Enterprises

As shown in Figure 1, which depicts the climate transition risk of eight carbon-intensive industries, despite significant heterogeneity across industries, the majority of industries exhibited varying degrees of increase in climate transition risk over the period from 2010 to 2024, with an overall fluctuating upward trend.

Among all industries, the electricity and gas industries experienced the most pronounced risk increases. Driven by carbon neutrality goals and renewable energy advancements, the electricity sector's risk rose sharply after 2015, approaching 0.75 by 2024 due to asset stranding and transition costs. Similarly, despite being cleaner, the gas industry faced peak risks in 2010-2013 and 2017-2019 with an overall upward trend, reflecting market uncertainty and transition pressures under net-zero targets.

In addition, the petrochemical industry exhibited the most pronounced risk fluctuations, driven by its characteristics and external shocks. Transition risk peaked in 2016 following the Paris Agreement and new environmental laws, and again in 2021 due to "dual carbon" goals and global ESG growth. This volatility stems from high policy sensitivity and the contradiction between inelastic short-term demand for oil and long-term low-carbon substitution. Additionally, geopolitical conflicts affecting strategic resources like oil and coal further amplified this risk.

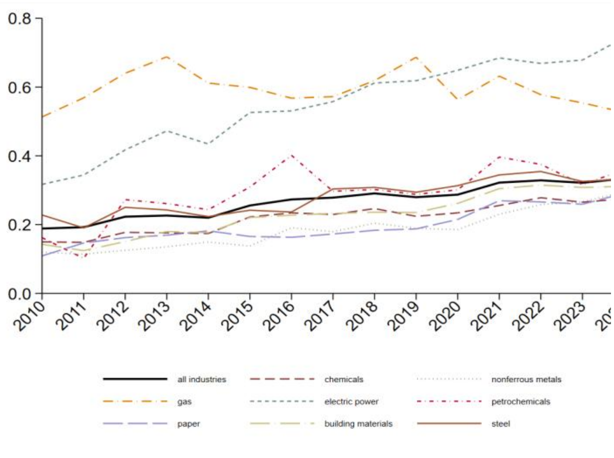

Figure 1. Climate Transition Risk for Carbon-intensive Enterprises

4. Analysis of the Impact of Transition Risk on the Default Probability of Carbon-intensive Enterprises

4.1 Research Design

4.1.1 Sample Selection and Data Sources

Following the Listed Company Industry Classification Guidelines promulgated by the China Securities Regulatory Commission (CSRC) in 2012 and drawing on existing studies by domestic and international scholars, we select eight key industries—paper (C22), petrochemicals (C25), chemicals (C26), building materials (C30), steel (C31), nonferrous metals (C32), electric power (D44), and gas (D45)—as representatives of carbon-intensive industries. Using the annual financial statement data of listed companies in these industries from the CSMAR database over the period 2010–2024, we construct our sample to analyze the transition risk of carbon-intensive industries in the context of the low-carbon transition. To enhance the validity and representativeness of the empirical results, we perform the following preprocessing steps on the original sample:

(1) To mitigate the influence of industry-specific anomalies, we exclude sample observations of firms designated as ST (special treatment) or *ST (delisting risk).

(2) We exclude sample observations with missing data for key variables.

(3) To avoid the influence of extreme values on the empirical results, we winsorize all variables at the 1% and 99% levels.

All other data in this study are sourced from the WIND database and the CSMAR database. After applying the above procedures, we obtain an unbalanced panel dataset comprising 4,876 firm-year observations across 526 enterprises over the period 2010–2024.

4.1.2 Variable Selection

(1) Debt default risk

To investigate the impact of climate transition risk on the default probability of carbon-intensive enterprises, we select the debt default risk (DP) of firms as the dependent variable. Drawing on the approach proposed by Bharath et al.[22] for estimating corporate loan default probability through distance-to-default, we first calculate the distance-to-default (DD) for each firm, with the formula specified as follows:

$$DD_{it} = \frac{\log\left(\frac{Equity_{it} + Debt_{it}}{Debt_{it}}\right) + \left(r_{i,t-1} - \frac{\sigma_{Vit}^2}{2}\right) \times T_{it}}{\sigma_{Vit} \times \sqrt{T_{it}}} \tag{1}$$

where DD_{it} denotes the distance-to-default of firm i in period t, which measures the distance between the firm's asset level and the default threshold. A smaller value of this indicator implies a higher likelihood of default. $Equity_{it}$ represents the total market capitalization of firm i in period t, calculated as the product of the total number of shares outstanding and the year-end market price. $Debt_{it}$ denotes the debt of firm i in period t, which equals the sum of year-end short-term liabilities and one-half of year-end long-term liabilities. $r_{i,t\text{-}1}$ is the one-year lagged annual return of the firm's stock. T_{it} represents the debt maturity of firm i, which is conventionally set to 1. $\sigma_{V_{it}}$denotes the asset volatility of firm i in period t, which is derived from $\sigma_{E_{it}}$.$\sigma_{E_{it}}$denotes the volatility of stock returns, calculated as the standard deviation of the firm's monthly return data over the previous year. The formula for $\sigma_{V_{it}}$ is as follows:

$$\sigma_{V_{it}} = \frac{Equity_{it}}{Equity_{it} + Debt_{it}} \times \sigma_{E_{it}} + \frac{Debt_{it}}{Equity_{it} + Debt_{it}} \tag{2}$$

Based on Equation (1) and Equation (2), we can compute the distance-to-default DD_{it}, and then derive the corporate default probability through the standard cumulative normal distribution function:

$$DP_{it} = Normal(-DD_{it}) \tag{3}$$

(2) Control variables

Following the studies of ALI et al.[23] and LI et al.[24], we select firm size (Size), leverage ratio (Lev), return on assets (ROA), price-to-book ratio (PB), and book-to-market ratio (BM) as control variables. The specific definitions of these variables are presented in Table 2.

Table 2. Main Variables and Explanations

Variable Nature	Variable Symbol	Variable Name	Variable Definition
Explained Variable	*DP*	Corporate Default Probability	The likelihood that a company cannot repay loans or fulfill obligations upon maturity
Explanatory Variable	*CCE*	Transition Risk Coefficient	The ratio of the frequency of transition risk seed words to the total number of words in the company's current financial report
Control Variable	*Size*	Corporate Asset Size	The logarithmic value of the sum of a company's fixed assets and current assets

Lev	Leverage Ratio	The ratio of a company's total liabilities to its total assets
ROA	Return on Assets	The ratio of a company's total profit to its total assets
PB	Price-to-Book Ratio	The ratio of price per share to net assets per share
BM	Book-to-Market Ratio	The ratio of a company's total assets to its market value

4.1.3 Benchmark Regression

To examine the impact of transition risk on carbon-intensive enterprises, we employ a two-way fixed effects model with both firm and year fixed effects for the regression:

$$DP_{it}=\alpha+\beta_1 CCE_{it}+\sum\beta_n Con_{it}+\lambda_i+\mu_t+\varepsilon_{it}$$

where DP_{it} denotes the default probability of firm i in period t, CCE_{it} denotes the transition risk of firm i in period t, Con_{it} represents a vector of control variables, λ_i denotes firm fixed effects, μ_t denotes time fixed effects, and ε_{it} denotes the random error term.

4.2 Empirical Analysis

4.2.1 Descriptive Statistics

Table 3 shows that the dependent variable, corporate default probability (DP), has a mean of 0.006, indicating most firms have low default risk. The explanatory variable, transition risk coefficient (CCE), averages 0.282, showing considerable variation across firms. Among controls, firm size (Size) averages 22.64 with moderate heterogeneity, while leverage (Lev) averages 0.441, indicating moderate debt levels. Return on assets (ROA) averages 0.043 but includes negative values (min=-0.118), reflecting some poor profitability. The book-to-market ratio (BM) averages 0.699 (below 1), whereas the price-to-book ratio (PB) averages 2.562, indicating high market valuations and considerable variability for some firms.

Table 3. Descriptive Statistics

Variable	N	Mean	SD	Min	Max
DP	4876	0.00600	0.0380	0	0.320
CCE	4876	0.282	0.210	0.0360	1.038
Size	4876	22.64	1.369	20.31	26.36
Lev	4876	0.441	0.183	0.0790	0.825
ROA	4876	0.0430	0.0520	-0.118	0.219
BM	4876	0.699	0.255	0.172	1.266

PB	4876	2.562	1.868	0.512	11.05

4.2.2 Correlation Analysis

The results of the correlation analysis are presented in Table 4. The coefficient between climate transition risk (CCE) and corporate default probability (DP) is significantly positive at the 1% level, which preliminarily suggests that higher climate transition risk is associated with a higher level of debt default risk among carbon-intensive enterprises.

Table 4. Correlation Analysis

Variables	(DP)	(CCE)	(Size)	(Lev)	(ROA)	(BM)	(PB)
DP	1.000						
CCE	0.135***	1.000					
Size	0.227***	0.380***	1.000				
Lev	0.238***	0.210***	0.505***	1.000			
ROA	-0.122***	-0.049***	-0.039***	-0.393***	1.000		
BM	0.212***	0.293***	0.609***	0.374***	-0.291***	1.000	
PB	-0.131***	-0.231***	-0.437***	-0.129***	0.201***	-0.808***	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

4.2.3 Multicollinearity Test

The results of the multicollinearity test are presented in Table 5. The variance inflation factor (VIF) values for all variables are below 10, indicating that there is no severe multicollinearity issue among the variables in this study, and thus subsequent regression analysis can be conducted.

Table 5. Multicollinearity Test

Variable	VIF	1/VIF
BM	4.230	0.236
PB	3.210	0.311
Size	2.220	0.451
Lev	1.810	0.552
ROA	1.390	0.722
CCE	1.180	0.849
Mean	2.340	

4.2.4 Benchmark Regression

Table 6 presents benchmark regression results for carbon-intensive enterprises. Column (1) shows that transition risk (CCE) has a positive and statistically significant (1% level) impact on default probability (DP). Column (2), incorporating full controls, confirms this finding: CCE remains positive and significant at the 1% level, indicating that increased climate transition risk significantly elevates the debt default probability of carbon-intensive enterprises.

Table 6. Analysis of Baseline Regression Results

	(1)	(2)
VARIABLES	DP	DP
CCE	0.0241***	0.0228***
	(3.255)	(3.092)
Size		0.0055***
		(3.065)
Lev		0.0208***
		(3.183)
ROA		-0.0304**
		(-2.553)
BM		0.0093*
		(1.782)
PB		0.0009*
		(1.684)
Constant	-0.0008	-0.1427***
	(-0.383)	(-3.437)
Observations	4,876	4,876
R-squared	0.305	0.314
id fe	yes	yes
year fe	yes	yes

4.3 Endogeneity and Robustness Tests

4.3.1 Endogeneity Tests

The preceding analysis demonstrates that climate transition risk increases the default probability of carbon-intensive enterprises. However, potential endogeneity concerns remain. We employ the following two approaches to address possible endogeneity issues.

(1) Instrumental variable approach

We use the mean climate transition risk level of firms in the same industry within the same municipal district as the instrumental variable and estimate the model using the two-stage least squares (2SLS) method. The first-stage regression results are presented in Column (1) of Table 7, which indicate that the instrumental variable passes both the weak instrument test and the under-identification test. The second-stage regression results, reported in Column (2) of Table 7, show that the coefficient of climate transition risk (CCE) remains positive and significant at the 1% level, confirming that our findings remain robust after accounting for endogeneity concerns.

(2) System GMM approach

Column (3) in table 7 presents system GMM estimation results. The climate transition risk (CCE) coefficient remains positive and significant at the 1% level, confirming that increased transition risk raises default risk. Diagnostic tests validate the model: the AR(1) test is significant (p=0.0002), while the AR(2) test (p=0.491) and Hansen test (p=0.208) confirm the absence of second-order serial correlation and instrument validity, respectively. With control variables consistent with expectations, these results demonstrate the robustness of our conclusions after addressing endogeneity and dynamic omitted variable bias.

Table 7. Endogeneity Analysis

	Instrumental Variable First-Stage Regression	Instrumental Variable First-Stage Regression	System GMM
	(1)	(2)	(3)
VARIABLES	CCE	DP	DP
mean_CCE	0.8909***		
	(38.405)		
L.DP			0.2183***
			(0.00)
CCE		0.0229***	0.0164***
		(2.780)	(0.00)
Size	0.0089*	0.0055***	0.0024***
	(1.893)	(3.051)	(0.00)
Lev	0.0006	0.0208***	0.0191***
	(0.037)	(3.186)	(0.00)
ROA	0.0370	-0.0304**	-0.0338***
	(1.423)	(-2.556)	(0.00)
BM	-0.0073	0.0093*	0.0094***
	(-0.739)	(1.781)	(0.00)
PB	-0.0001	0.0009*	0.0014***

	(-0.123)	(1.680)	(0.00)
Constant			0.0000
			(0.00)
rk LM statistic	92.735		
	[0.0000]		
rk Wald F statistic	1474.950		
	[16.38]		
AR1			0.0002
AR2			0.491
Hansen			0.208
Observations	4,876	4,876	4,080
R-squared	0.710	0.017	
id fe	yes	yes	
year fe	yes	yes	
Number of id			589

4.3.2 Robustness Tests

We conduct the following three approaches to test the robustness of the model: replacing the dependent variable, controlling for industry fixed effects, and performing subsample regressions.

(1) Replacement of the dependent variable

Following Xu[25], we construct a dummy variable, Violate, based on the difference between prior-year short-term borrowings (including those due within one year) and current-year repayments. Violate equals 1 if the difference is positive (indicating default) and 0 otherwise. Re-estimating the model using Violate as the dependent variable (Table 8, Model 1) yields a positive and significant CCE coefficient at the 1% level, confirming the robustness of our findings.

(2) Controlling for industry fixed effects

Given that different industries exhibit distinct characteristics, we further control for industry fixed effects. The results, reported in Column (2) of Table 8, show that the coefficient of climate transition risk (CCE) remains positive and significant at the 1% level, again supporting the robustness of our conclusions.

(3) Subsample regression

Given that the four municipalities directly under the central government—Beijing, Shanghai, Tianjin, and Chongqing—differ from other cities in terms of political economy and resource endowments, we exclude firms located in these four municipalities and re-run the regression. The results, presented in Column (3) of Table 8, show that the coefficient of climate transition risk (CCE) remains positive and significant at the 1% level, further confirming the robustness of our regression results.

Table 8 Robustness test

	Replace Variable (1)	Control Industry Fixed Effects (2)	Subsample Regression (3)
VARIABLES	Violate	Violate	DP
CCE	0.1267**	0.0228***	0.0236***
	(2.194)	(3.092)	(3.098)
Size	-0.0392**	0.0055***	0.0058***
	(-2.037)	(3.065)	(3.053)
Lev	0.1106	0.0208***	0.0213***
	(1.636)	(3.183)	(3.135)
ROA	-0.2047*	-0.0304**	-0.0316***
	(-1.753)	(-2.553)	(-2.643)
BM	0.0584	0.0093*	0.0053
	(1.133)	(1.782)	(1.008)
PB	0.0034	0.0009*	0.0007
	(0.648)	(1.684)	(1.148)
Constant	0.8539**	-0.1427***	-0.1449***
	(2.021)	(-3.437)	(-3.349)
Observations	4,421	4,876	4,263
R-squared	0.368	0.314	0.313
Ind fe	no	yes	no
id fe	yes	yes	yes
year fe	yes	yes	yes

4.4 Heterogeneity Analysis

4.4.1 Firm Size Heterogeneity

Classifying firms by size per the Statistical Classification of Large, Medium, Small, and Micro Enterprises (2017), we conduct subsample regressions (Table 9). The climate transition risk (CCE) coefficient is positive and significant at the 1% level for large-scale enterprises but statistically insignificant for small-to-medium-scale ones. This confirms significant firm size heterogeneity, with the impact of climate transition risk on default probability being more pronounced for large-scale carbon-intensive enterprises.

This size heterogeneity stems from the higher adjustment costs and complex risk exposures of large-scale enterprises. First, regarding assets, large firms face severe balance sheet shocks from "stranded assets" and impairment losses due to their substantial asset bases, whereas smaller firms are less burdened and can easily curtail operations. Second, regarding financing, large firms carry heavier debt burdens and face higher refinancing difficulties as climate risks increase financing costs and trigger ESG-related investment aversion, leading to liquidity crises. Third, regarding regulation, large enterprises face stricter supervision and significantly higher compliance costs (e.g., carbon accounting and allowances) compared to smaller firms, which often remain at the regulatory periphery.

4.4.2 Regional Heterogeneity

Classifying firms by region (eastern, central, and western) to account for geographic disparities, we conduct subsample regressions (Table 9). The climate transition risk (CCE) coefficient is positive and significant at the 5% level for firms in the eastern and central regions but statistically insignificant for those in the western region. These results indicate significant regional heterogeneity, with the impact of climate transition risk on default probability being more pronounced in the eastern and central regions.

The greater impact of climate transition risk in the eastern and central regions stems from their high concentration of carbon assets, financial sensitivity, and strict regulation. First, industrial structure differs: the eastern and central regions rely heavily on high-carbon industries, incurring high transition costs, whereas the western region faces smaller shocks due to lower industrialization and renewable energy progress. Second, financial markets vary: institutions in the east and central regions react rapidly to risk by raising financing costs, causing liquidity stress; conversely, the western region's less sensitive financial sector creates a transmission lag, reducing short-term debt pressure. Third, policy enforcement is stricter in the east and central regions, while the west enjoys a regulatory "buffer period" to support regional development, resulting in lower default probabilities for western firms.

5.4.3 Industry Heterogeneity

Following Yin[26] and Lu[27], we classify firms into capital-intensive and non-capital-intensive groups based on the fixed asset ratio and conduct separate regressions (Table 9, Models 6 and 7). Results indicate that for non-capital-intensive firms, the CCE coefficient is positive and significant at the 1% level (0.0221**), whereas for capital-intensive firms, it is only marginally significant at the 10% level (0.0522). Although the larger coefficient magnitude for capital-intensive firms likely reflects higher asset specificity and transition costs, the impact of climate transition risk on default probability is statistically more stable for non-capital-intensive enterprises, highlighting significant industry heterogeneity.

Table 9. Heterogeneity Analysis

	Large Enterprises	Medium & Small Enterprises	Eastern Region	Central Region	Western Region	Capital-Intensive	Non-Capital-Intensive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)

VARIABLES	DP	DP	DP	DP	DP	DP	DP
CCE	0.0320***	0.0060	0.0213**	0.0353**	0.0288	0.0522*	0.0221***
	(3.316)	(1.129)	(2.097)	(2.449)	(1.345)	(1.729)	(2.984)
Size	0.0049**	0.0022	0.0068**	0.0023	0.0034	0.0052	0.0047**
	(2.175)	(1.010)	(2.426)	(0.984)	(0.866)	(1.430)	(2.235)
Lev	0.0247***	-0.0005	0.0166**	0.0215**	0.0246	0.0315**	0.0202***
	(3.180)	(-0.214)	(2.200)	(2.231)	(1.583)	(2.030)	(2.953)
ROA	-0.0473***	-0.0015	-0.0337**	0.0047	-0.0773*	-0.0266	-0.0352***
	(-3.098)	(-0.227)	(-2.274)	(0.275)	(-1.823)	(-0.871)	(-2.925)
Growth	0.0016	0.0023	0.0007	-0.0056*	0.0110	0.0000	0.0024
	(0.517)	(0.876)	(0.258)	(-1.936)	(1.124)	(0.002)	(0.914)
FirmAge	0.0260	0.0058	0.0134	0.0122	0.0318	-0.0341	0.0243
	(1.481)	(1.077)	(0.811)	(0.641)	(1.068)	(-1.461)	(1.622)
Mfee	-0.0002	-0.0001	0.0001	-0.0002	-0.0016	-0.0001	-0.0002
	(-1.321)	(-1.112)	(0.325)	(-0.754)	(-1.314)	(-0.495)	(-1.625)
Board	0.0000	0.0226	0.0014	-0.0031	0.0044	-0.0110	0.0029
	(0.003)	(1.363)	(0.161)	(-0.232)	(0.261)	(-1.099)	(0.407)
Indep	0.0001	0.0008	0.0003	-0.0002	-0.0000	-0.0002	0.0002
	(0.443)	(1.372)	(1.217)	(-0.652)	(-0.035)	(-0.525)	(0.888)
Top1	0.0329**	-0.0053	0.0203	0.0347	0.0200	0.0313	0.0240*
	(2.306)	(-0.989)	(1.415)	(1.559)	(0.743)	(1.487)	(1.897)
Constant	-0.2173***	-0.1409	-0.2209***	-0.0961	-0.2002*	-0.0176	-0.2068***
	(-3.184)	(-1.302)	(-2.779)	(-1.304)	(-1.909)	(-0.283)	(-3.180)
Observatio-ns	3,763	1,113	2,954	981	941	601	4,275
R-squared	0.316	0.517	0.359	0.354	0.242	0.311	0.320
id fe	yes	yes	yes	yes	yes	yes	yes
year fe	yes	yes	yes	yes	yes	yes	yes

4.5 Mediation Mechanism Tests

To further explore the transmission channels through which climate transition risk affects corporate default probability, we follow Xu[25] and conduct channel analysis from both the revenue side and the cost side, examining the mediating roles of operating revenue growth rate (*Growth*) and weighted average cost of capital (*Cost*). The specific test results are as follows:

Table 10. Mechanism Test

Variable	(1) Growth	(2) DP	(3) Cost	(4) DP
CCE	-0.0545**	0.00856**	-0.244**	0.0114**
	(0.0218)	(0.00343)	(0.121)	(0.00498)
Growth		-0.00845**		
		(0.00098)		
Cost				-0.000848**
				(0.000401)
Size	-0.00864*	0.00246***	-0.136***	0.00259***
	(0.00464)	(0.000719)	(0.0259)	(0.000840)
Lev	0.310***	0.0269***	0.409**	0.0200***
	(0.0299)	(0.00394)	(0.174)	(0.00431)
ROA	2.324***	-0.0304***	-0.157	-0.0216***
	(0.108)	(0.00827)	(0.535)	(0.00770)
BM	0.0562	0.0166***	-0.192	0.0138***
	(0.0345)	(0.00348)	(0.205)	(0.00386)
PB	0.0224***	0.000651**	-0.0279	0.000756**
	(0.00473)	(0.000284)	(0.0252)	(0.000331)
_cons	0.0205	-0.0759***	8.768***	-0.0707***
	(0.0922)	(0.0149)	(0.520)	(0.0179)
N	4876	4876	4876	4876
id fe	yes	yes	yes	yes
year fe	yes	yes	yes	yes
R-sq	0.156	0.082	0.019	0.079

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01.

Mechanism tests reveal that climate transition risk (CCE) significantly suppresses operating revenue growth (Growth) at the 5% level (-0.0545) while directly increasing default probability (DP) at the 5% level (0.00856). Furthermore, Growth negatively impacts DP at the 1% level (-0.00845). These results indicate that transition risk elevates default risk both directly and indirectly by weakening revenue growth. Regarding control variables, firm size (Size), leverage (Lev), ROA, PB, and BM show significant associations with default probability, confirming satisfactory model control.

Mechanism tests reveal that the transition risk coefficient (CCE) negatively affects the weighted average cost of capital (Cost) at the 5% level (-0.244). This counterintuitive reduction in capital costs likely stems from government green subsidies and a forced shift toward bank borrowing. Furthermore, lower capital costs significantly increase default probability (DP) at the 5% level (-0.000848), as cheap funds may induce over-leverage and entail higher liquidity risks. Since CCE negatively affects Cost, which in turn negatively affects DP, the indirect effect is positive and aligns with the direct effect. This confirms that the weighted average cost of capital partially mediates the positive impact of transition risk on default probability.

5. Conclusion and Suggestions

Based on panel data of listed enterprises in China's eight carbon-intensive industries from 2010 to 2024, this study constructs a transition risk indicator through textual analysis and employs a two-way fixed effects model and the system GMM approach for empirical testing. The following core conclusions are drawn:

Climate transition risk significantly elevates the debt default probability of carbon-intensive enterprises, exhibiting nonlinear cumulative characteristics where risk accelerates as exposure expands. This impact is most pronounced in the electricity and gas supply industries due to high asset specificity and strong transition path dependence. The effect demonstrates significant heterogeneity regarding firm size and geography: large-scale enterprises face higher default risks than smaller ones, and firms in eastern and central regions are more sensitive to transition risk, whereas the effect is statistically insignificant in the western region. Furthermore, while capital-intensive industries show high sensitivity coefficients due to large transition sunk costs, the impact on non-capital-intensive industries is statistically more significant and stable. This challenges the traditional focus on heavy emitters, suggesting that non-capital-intensive industries also face severe survival pressures and cumulative financial risks due to limited asset buffers and weaker policy protection.

To mitigate climate transition risks and avoid systemic shocks from a "one-size-fits-all" approach, this paper proposes three key recommendations. First, regulators should implement differentiated oversight based on firm size, industry, and region, closely monitoring financial sectors linked to carbon-intensive enterprises to prevent systemic defaults. Second, financial institutions must conduct regular climate stress tests, integrate climate factors into credit and pricing processes, and develop hedging instruments like climate insurance to enhance system resilience. Finally, carbon-intensive enterprises should systematically replace high-carbon assets with low-carbon investments, adapt management models to their organizational structures, and ensure timely environmental disclosure. These measures are essential for preventing debt defaults during the green transition.

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