

Article

Is Carbon Risk Always Bad News? The Impact of Carbon Risk on Financial Distress Based on China

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Abstract

Global climate challenges and regulatory pressures have strengthened the link between carbon risk and corporate financial distress. We examine the impact of carbon risk on corporate financial distress and its underlying mechanisms using China's accession to the Paris Agreement as an exogenous shock, employing a combination of difference-in-differences and double machine learning approaches. We find that high-carbon firms are significantly less likely to experience financial distress compared to low-carbon firms in China. Mechanism analysis indicates that the relationship between carbon risk and corporate financial distress is positively moderated by the green innovation effect, ESG performance, and media attention. The heterogeneity analysis indicates that carbon risk mitigates financial distress more pronouncedly in high-tech industries, high-pollution industries, competitive markets, and firms with strong environmental governance practices. Furthermore, we investigate whether carbon risk is an effective predictor of financial distress. Based on XGBoost (eXtreme Gradient Boosting, version Python 3.13) and SHAP (Shapley Additive Explanations) value analysis, we find that carbon risk significantly enhances the accuracy and explanatory power of financial distress prediction models. The results provide important guidance for policymakers in creating low-carbon strategies, businesses in improving financial management, and investors in assessing carbon risk.

Keywords: carbon risk; financial distress; financial distress forecasting

1. Introduction

Climate change has become one of the most pressing global challenges of the twenty-first century [1]. Rising global temperatures, more frequent extreme weather events, and increasingly stringent international climate commitments have accelerated the transition toward a low-carbon economy [2,3]. As a major driver of climate-related risk, carbon emissions have prompted governments worldwide to implement a wide range of environmental policies, including carbon taxes, emissions trading systems, and mandatory climate-related disclosure requirements. Because firms are the primary sources of carbon emissions, they face growing regulatory, operational, and reputational pressures during this transition [4]. These pressures can increase operating costs, tighten financing conditions, and undermine long-term financial stability [5], giving rise to carbon risk [6]. Carbon risk is the risk of potential economic loss arising from tighter carbon regulations, changes in policies such as carbon taxes, or a decline in the value of carbon assets (e.g., oil, coal, natural gas) in a company or portfolio as a result of climate change [7,8]. The Paris Agreement represents an important exogenous policy shock that has accelerated this transition and intensified firms' exposure to carbon risk, particularly in carbon-intensive industries. Despite the growing



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importance of carbon risk, its financial consequences remain insufficiently understood. First, does carbon risk significantly affect corporate financial distress? Second, through what mechanisms does carbon risk influence firms' financial distress? Third, can carbon risk, as a key factor, improve the explanatory and predictive power of financial distress models? Addressing these questions is essential for understanding how firms respond to carbon risk and for evaluating the financial implications of the low-carbon transition.

Existing studies attribute corporate financial distress to both internal and external factors. Internal factors include fluctuations in capital structure [9], aggressive corporate strategic decisions, and tunneling behavior by major shareholders [10], all of which substantially increase the likelihood of financial distress. External factors, such as monetary policy adjustments [11], macroeconomic cycles [12], and product market competition [13], also play important roles by increasing firms' exposure to economic uncertainty and financial vulnerability. More recently, the broader corporate finance literature has emphasized external shocks as an important source of corporate financial vulnerability. Prior studies show that bankruptcy events, political risk, and sovereign credit deterioration can weaken firms' financial resilience by affecting financing conditions [14], market liquidity [15], informational efficiency [16], and risk transmission [17]. Together, these studies suggest that external shocks influence firms' financial distress through several common economic channels. Against this backdrop, carbon risk has emerged as a major external shock associated with the global transition to a low-carbon economy. Unlike conventional external shocks, however, carbon risk may affect firms through two competing channels. On the one hand, stricter climate policies increase regulatory compliance costs, tighten financing constraints, and raise the risk of asset impairment, thereby increasing the likelihood of financial distress. On the other hand, transition pressure may encourage green innovation, improve ESG performance, strengthen stakeholder monitoring, and enhance firms' long-term competitiveness, ultimately mitigating financial distress. Despite its growing importance, carbon risk has received limited attention in the financial distress literature. Existing studies continue to focus primarily on internal governance and macroeconomic conditions, while overlooking climate-related transition risk as a source of corporate financial vulnerability. To address this gap, this study examines whether carbon risk affects corporate financial distress, explores the underlying transmission mechanisms, and evaluates its incremental contribution to financial distress prediction.

Theoretically, two opposing views exist regarding the effect of carbon risk on corporate financial distress. The regulatory-cost perspective argues that greater carbon risk increases firms' financial distress through several channels [18,19]. First, compliance with increasingly stringent environmental regulations requires substantial investment, reducing cash flows and profitability [18]. Second, carbon-intensive firms face tighter financing constraints and higher credit risk [20], increasing their financial vulnerability [21]. In addition, carbon pricing uncertainty and stricter climate policies raise the risk of asset impairment and regulatory penalties, further weakening firms' financial resilience [19,22]. In contrast, the regulatory-benefit perspective suggests that carbon risk can improve firms' long-term financial performance [23,24]. Stricter climate policies encourage firms to adopt low-carbon technologies, stimulate green innovation, and strengthen competitiveness [25]. Although compliance costs may increase in the short run, these adjustments can improve operational efficiency, enhance ESG performance, and support long-term profitability. Greater awareness of carbon risk also encourages firms to optimize resource allocation and accelerate green transformation, ultimately reducing the likelihood of financial distress [23,24]. These competing perspectives reflect the ongoing debate surrounding the Porter Hypothesis in the context of corporate financial distress. The regulatory-cost view emphasizes the immediate financial burden imposed by climate policies, whereas the regulatory-benefit view

highlights firms' adaptive responses through innovation and green transformation. As a result, the existing literature provides no clear consensus on whether carbon risk ultimately increases or mitigates corporate financial distress. This unresolved debate motivates our empirical examination of the financial consequences of carbon risk.

China provides a unique institutional setting for addressing these research gaps. As the world's largest developing economy and the largest carbon emitter, China plays a pivotal role in global climate governance. Following its accession to the Paris Agreement in 2016, China accelerated the implementation of its "1 + N" policy framework for carbon peaking and carbon neutrality. The framework placed increasing regulatory pressure on carbon-intensive industries while providing financial subsidies, green credit, and incentives for low-carbon innovation. These policy reforms create a valuable natural setting for examining whether carbon risk exacerbates or mitigates corporate financial distress during the transition to a low-carbon economy.

In this study, we employ a difference-in-differences (DID) approach, using a sample of Chinese A-share listed firms from 2009 to 2020, to identify the causal effect of carbon risk on financial distress. We further incorporate a machine learning framework that combines XGBoost (version Python 3.13) with SHAP (Shapley Additive Explanations) to evaluate the incremental predictive value of carbon risk beyond conventional financial indicators. Our findings reveal a striking and counterintuitive pattern: high-carbon firms are significantly less likely to experience financial distress compared to low-carbon firms following China's participation in the Paris Agreement. This finding suggests that carbon risk may serve not only as a regulatory burden but also as a catalyst for corporate transformation that ultimately enhances financial stability. To further verify the robustness of our findings, we employ a double machine learning (DML) approach, which addresses potential concerns related to high-dimensional controls, model misspecification, and estimator bias. The DML results are consistent with the baseline estimates. In addition, the mitigating effect of carbon risk on financial distress is more pronounced among firms operating in high-tech industries, high-pollution industries, and competitive markets, as well as among firms with stronger environmental governance.

We examine three potential mechanisms through which carbon risk affects financial distress: green innovation, ESG performance, and media attention. First, we investigate the green innovation channel from two perspectives: executives' green awareness and green innovation, including both disruptive and incremental innovations. We find that higher carbon risk enhances executives' environmental awareness and promotes incremental green innovation, both of which strengthen the mitigating effect of carbon risk on financial distress. By contrast, disruptive green innovation does not exhibit a significant moderating effect, likely because of its long development cycle and substantial investment requirements. Second, ESG performance strengthens the mitigating effect of carbon risk on financial distress. Specifically, improvements in the environmental (E) and social (S) dimensions significantly reduce the likelihood of financial distress, whereas the governance (G) dimension does not produce a significant short-term effect. These findings suggest that the different dimensions of ESG contribute unevenly to firms' financial resilience. Third, higher carbon risk attracts greater media attention to high-carbon firms. Increased public scrutiny reduces managerial opportunism and information asymmetry, thereby enhancing firms' ability to withstand financial distress.

Our results show that carbon risk plays an important role in corporate financial distress. However, existing financial distress prediction models rarely incorporate this factor, limiting their ability to capture the financial pressures and transition challenges associated with increasingly stringent climate policies. Incorporating carbon risk not only improves the predictive performance of financial distress models but also helps firms better manage

the risks associated with the low-carbon transition. In addition, it provides policymakers with a more effective tool for identifying firms that are vulnerable to financial distress. To demonstrate the predictive value of carbon risk, we develop an XGBoost (eXtreme Gradient Boosting, version Python 3.13)–based financial distress prediction model. Incorporating carbon risk significantly improves both predictive accuracy and model interpretability. SHAP (Shapley Additive Explanations) analysis further shows that carbon risk is among the most important predictors of financial distress, highlighting its value as a forward-looking indicator of corporate financial vulnerability.

The marginal contributions of this study can be categorised into four parts.

First, this study extends the literature on the relationship between carbon risk and corporate financial distress by providing new evidence on the net effect of carbon risk on firms' financial stability. To the best of our knowledge, only two studies—Nguyen et al. [26] and Ding et al. [27]—have directly examined this relationship. Based on evidence from developed economies, Nguyen et al. [26] find that carbon risk exacerbates financial distress and compels firms to reduce financial leverage. Likewise, using data on Chinese listed firms from 2008 to 2018, Ding et al. [27] show that higher carbon emissions are associated with greater financial distress. In contrast, using a sample of Chinese listed firms from 2009 to 2020, drawn from the world's largest emerging economy, we find that carbon risk significantly reduces the likelihood of financial distress. This counterintuitive result suggests that the economic consequences of carbon risk are not inherently negative but depend on the policy and institutional environment in which the low-carbon transition unfolds. Our findings demonstrate that the relationship between carbon risk and corporate financial distress is context-dependent rather than universally predetermined, providing new insights into the heterogeneous effects of carbon risk across different economic settings. Furthermore, by showing that carbon transition pressure can improve firms' financial resilience in an appropriate institutional environment, our study provides empirical support from an emerging economy for the applicability of the Porter Hypothesis to corporate financial outcomes.

Second, this study is the first to deeply integrate econometric methods with machine learning models, constructing an analytical framework for corporate financial distress that combines explanatory power with predictive capability. We employ the DID design, which exploits China's accession to the Paris Agreement as an exogenous policy shock, allowing us to identify the causal effect of carbon risk on financial distress. We further develop an XGBoost-based financial distress prediction model and use SHAP values to quantify the contribution of individual features, thereby evaluating the incremental predictive value of carbon risk. This integrated framework offers two key advantages. First, the DID approach mitigates endogeneity concerns and omitted variable bias, providing credible causal evidence on the effect of carbon risk. Second, the machine learning model effectively handles high-dimensional data and captures complex nonlinear relationships and feature interactions that are difficult to identify using conventional econometric methods.

Third, this study develops an integrated strategic adaptation framework to explain the mechanisms through which carbon risk influences corporate financial distress. Rather than treating green innovation, ESG performance, and media attention as independent channels, we conceptualize firms' responses to carbon risk as three complementary forms of strategic adaptation. Specifically, firms respond through technological adaptation, reflected in greater green innovation, which enhances resource efficiency and long-term competitiveness. They also undertake governance adaptation, reflected in improved ESG performance, which strengthens stakeholder trust and financing capacity. In addition, firms engage in informational adaptation, reflected in increased media attention, which improves information transparency and external monitoring. By integrating these three

complementary dimensions, our framework provides a more systematic understanding of how firms strategically adapt to carbon risk and how these adaptations jointly enhance financial resilience and reduce the likelihood of financial distress.

Lastly, this study extends the practical application of carbon risk by demonstrating its value in machine learning-based financial distress prediction. Unlike existing studies that primarily treat carbon risk as an explanatory factor, we show that it also serves as a powerful forward-looking predictor of corporate financial distress. By incorporating carbon risk into an XGBoost-based prediction model and evaluating feature importance using SHAP values, we demonstrate that carbon risk is among the most influential predictors of financial distress and significantly improves both predictive accuracy and model interpretability. These findings broaden the practical application of carbon risk from causal analysis to risk prediction, providing a more effective tool for investors, corporate managers, and policymakers to identify financially vulnerable firms in the low-carbon transition.

The remainder of this study is structured as follows. Section 2 presents the theoretical analysis and develops the research hypotheses. Section 3 delineates the primary variables, data types, and the methodology for model creation. Section 4 delineates the results of empirical studies. Section 5 performs a mechanism analysis, examining the moderating effects of corporate green innovation, ESG performance, and media attention. Section 6 examines the prediction efficacy of financial distress models after the integration of carbon risk indicators. Section 7 presents conclusions and implications.

2. Theoretical Analysis and Research Hypothesis

According to signaling theory, firms can use the low-carbon transition initiated by the Paris Agreement to signal their commitment to sustainable development and environmental responsibility. To comply with increasingly stringent environmental regulations, firms are likely to increase investment in green technologies and environmental initiatives. These actions signal to investors, creditors, and other stakeholders that the firm is adaptable and well-positioned for long-term growth, thereby improving access to external financing and reducing the likelihood of financial distress [28]. In addition, stronger environmental commitment enhances corporate reputation and market competitiveness, further strengthening firms' financial resilience. From the perspective of externality theory, however, rising carbon risk may internalise the environmental costs previously borne by society, increasing firms' operating and compliance costs [29,30]. These additional costs place greater financial pressure on firms, particularly those in high-carbon-emitting industries, by reducing cash flow and weakening financing capacity. Consequently, carbon risk can either alleviate or exacerbate financial distress, depending on how firms respond to transition pressures. Firms that proactively adapt through green transformation are more likely to strengthen their financial resilience and reduce the likelihood of financial distress, whereas firms that fail to adjust may experience deteriorating financial conditions as a result of higher compliance costs and adverse market responses.

The regulatory benefit perspective suggests that carbon risk can reduce the likelihood of corporate financial distress. According to the Porter Hypothesis, environmental regulations encourage firms to undertake green transformation, thereby enhancing innovation capability and long-term competitiveness [31]. As carbon risk intensifies, firms face increasingly stringent climate-related regulations, including carbon taxes, emissions trading systems, and other regulatory pressures. In response, many firms invest in green technologies to improve resource efficiency, reduce carbon emissions, and lower compliance costs [32]. Such technological innovation not only enhances production efficiency but also creates new market opportunities and revenue sources, thereby strengthening firms' financial resilience and reducing the likelihood of financial distress. Governments

also play an important role in facilitating firms' low-carbon transition. To encourage green transformation, governments often provide policy support through R&D subsidies, tax incentives, free carbon allowance allocations, and green finance initiatives [24]. These policies reduce the financial burden associated with technological upgrading, ease financing constraints, and improve firms' liquidity, enabling them to better absorb the costs of carbon transition [33]. As a result, government support helps mitigate the financial risks associated with increasingly stringent climate policies. In addition, the successful implementation of low-carbon strategies sends a positive signal to capital markets. Firms that demonstrate strong environmental commitment and superior ESG performance are more likely to gain the confidence of investors and creditors because they are perceived as better positioned to manage transition risks and achieve sustainable long-term growth [26]. Improved market confidence enhances firm value and reduces financing costs, further strengthening financial resilience. Consequently, firms that proactively respond to carbon risk through green transformation are better able to reduce the likelihood of financial distress.

The regulatory cost perspective suggests that carbon risk increases the likelihood of corporate financial distress. According to the dynamic trade-off theory of capital structure, firms determine their optimal capital structure by balancing the tax benefits of debt against the expected costs of financial distress [34]. More stringent climate regulations increase firms' compliance costs and transition-related expenditures, raising the expected costs of financial distress and reducing the relative attractiveness of debt financing [35]. At the same time, creditors incorporate carbon risk into their risk assessments by demanding higher risk premiums from carbon-intensive firms [8]. As a result, these firms face higher financing costs, tighter financing constraints, and reduced financial flexibility, making them more vulnerable to adverse economic shocks. Carbon risk also increases the costs and uncertainty associated with green technological innovation. Developing and commercializing green technologies requires substantial investment in research and development, testing, and deployment, whereas financial returns often materialize only over the long term [36]. Moreover, innovation projects are inherently uncertain, and unsuccessful investments may lead to unrecoverable expenditures, declining competitiveness, and financial losses. These risks are particularly pronounced for firms with limited financial resources or high leverage, increasing their likelihood of financial distress [37]. In addition, carbon risk may accelerate the emergence of stranded assets, causing carbon-intensive assets to lose economic value before the end of their expected useful lives [38]. Under increasingly stringent climate policies, traditional energy infrastructure, high-emission production facilities, and fossil fuel reserves are especially vulnerable to becoming stranded assets. Asset impairment weakens firms' balance sheets, reduces collateral value, and may trigger debt covenant violations, thereby restricting access to external financing and increasing default risk. The resulting decline in profitability and financial flexibility further heightens the likelihood of financial distress.

The following competing hypotheses are derived from the above analysis:

H1a. *Carbon risk promotes the likelihood of financial distress.*

H1b. *Carbon risk reduces the likelihood of financial distress.*

3. Methodology

3.1. Model Design

Following Nguyen et al. [26] and the industry classification developed by the Carbon Disclosure Project (CDP), we classify firms into treatment and control groups based on the carbon-intensity and energy-consumption characteristics of their industries. Specifically,

firms operating in carbon-intensive industries are assigned to the treatment group, whereas firms in all other industries serve as the control group. The treatment group includes firms engaged in electricity, heat and gas production and supply; oil and gas extraction; non-metallic and non-ferrous metal mining; ferrous and non-ferrous metal smelting and rolling processing; chemical raw materials, chemical fibers and chemical products manufacturing; petroleum processing, coking and nuclear fuel processing; metal and non-metallic mineral products manufacturing; construction and civil engineering; housing construction; wood processing; paper manufacturing; wood, bamboo, rattan, palm, grass and paper products manufacturing; and machinery and equipment repair.

This study uses the DID model to evaluate the impact of carbon risk on firm financial distress, using China's accession to the Paris Agreement as a quasi-natural experiment. The signing of the Paris Agreement is an exogenous event for firms. Meanwhile, firms are classified based on their industry's carbon emission characteristics. The Paris Agreement primarily targets carbon-intensive industries, which are directly affected by its implementation, while low-carbon-emitting firms are unaffected. Therefore, carbon-intensive and low-carbon-emitting industries provide ideal treatment and control groups. To strengthen the identification strategy, we estimate the model with firm and year fixed effects. Firm fixed effects absorb all time-invariant firm characteristics, such as inherent differences in industry attributes, ownership structure, and managerial style, while year fixed effects control for common macroeconomic and policy shocks. In addition, we include a comprehensive set of firm-level control variables to account for observable differences in firm characteristics. Therefore, the estimated coefficient is identified from within-firm changes following the Paris Agreement rather than from permanent differences between high-carbon and low-carbon firms. Here is the specific model:

$$Zscore_{i,t} = \alpha + \beta Carbon_i Post_t + \delta Carbon_i + \varphi Post_t + \sigma X_{i,t-1} + \eta_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

In Equation (1), the subscript i denotes the firm, and t denotes the year. The dependent variable, the $Zscore$, measures financial distress. A higher $Zscore$ indicates better financial health, reducing the likelihood of financial distress. The key independent variable is $CarbonPost$, and its coefficient β captures the net change in financial distress between the treatment group (high-carbon emitting firms) and the control group (low-carbon emitting firms) after an increase in carbon risk. A positive β indicates a decrease in financial distress by increasing carbon risk. $X_{i,t-1}$ represents the control variables, which are lagged by one period to ensure robustness and avoid endogeneity issues [19,26]. A firm-fixed effect (η_i) and a year-fixed effect (γ_t) are included in the model to control for omitted variable bias. Random error terms ($\varepsilon_{i,t}$) are incorporated into all regressions, with standard errors clustered at the firm level.

3.2. Variable Definitions

Corporate financial distress is the dependent variable. According to Altman [39] and Ji et al. [40], we use the Zscore as a measure of financial distress. Financial distress and the Zscore have a negative relationship, meaning that a higher Zscore denotes a decreased likelihood of financial distress. A Zscore beyond 2.67 signifies excellent financial health; a Zscore below 1.81 denotes financial distress; and a Zscore ranging from 1.81 to 2.67 suggests a precarious financial position with a heightened likelihood of financial distress.

$$Zscore = 1.2 \frac{\text{Working capital}}{\text{Total assets}} + 1.4 \frac{\text{Retained earnings}}{\text{Total assets}} + 3.3 \frac{\text{Earnings before interest and taxes}}{\text{Total assets}} + 0.6 \frac{\text{Market value of equity}}{\text{Book value of total liabilities}} + 0.999 \frac{\text{Net sales}}{\text{Total assets}} \quad (2)$$

Table 1 presents the definitions of other key variables used in this study, including firm size (Size), leverage ratio (Lev), return on assets (ROA), market-to-book ratio (MB),

cash flow from operations (CFO), liquidity level (Liq), the shareholding of the largest shareholder (Top), dual roles of the chairman and managing director (Dual), management shareholding (Mhldn), and firm age (Age). Additionally, the study controls for firm-fixed effects and year-fixed effects.

Table 1. Variable definitions.

Variables	Definition
Zscore	The Zscore is used to measure corporate financial distress. A firm is less likely to experience financial distress if its Zscore is greater.
Carbon	The dummy variable for the experimental group is assigned a value of one if the firm is carbon-intensive, and zero otherwise.
Post	The time dummy variable is set to zero for years before the Paris Agreement and to one for years after the agreement.
Size	The natural logarithm of the total assets.
Lev	Financial leverage is calculated as the ratio of total liabilities to total assets.
ROA	The ratio of net income to the average total assets.
MB	The ratio of the market value of equity to the book value of equity.
CFO	The ratio of net operating cash flow to the book value of assets.
Liq	Liquidity is expressed as the ratio of current assets to total assets.
Top	The ownership stake of the largest shareholder, or the proportion of shares held by the largest shareholder.
Dual	A dummy variable that equals one if the chairman and the general manager are the same individual, and zero otherwise.
Mhldn	The ownership stake held by management, or the proportion of shares owned by the management team.
Age	The age of the business is represented as the natural logarithm of the number of years since its establishment.

3.3. Sample Selection

This study selects A-share listed companies from 2009 to 2020 as the initial sample. After excluding financial and insurance firms, ST companies, and those with incomplete data, a final sample of 26,130 observations is achieved. The financial data for all listed companies are obtained from the China Stock Market & Accounting Research Database (CSMAR) and the China National Research Data Service Platform (CNRDS). To mitigate the impact of extreme values, all continuous variables are Winsorized at the 1% lower and upper percentiles.

Table 2 presents the descriptive statistics for the key variables in the model, with an average Zscore of 5.1834 and a standard deviation of 10.0594. On average, listed companies in China have relatively high Zscores, suggesting a lower likelihood of financial distress. Even so, some firms still face a higher likelihood of financial distress, which requires caution.

Table 2. Descriptive statistics.

Variables	N	Mean	SD	Min	P50	Max
Zscore	26,130	4.5377	4.8126	−0.0404	2.9856	37.7534
Carbon	26,130	0.2371	0.4253	0	0	1
Post	26,130	0.6201	0.4854	0	1	1

Table 2. *Cont.*

Variables	N	Mean	SD	Min	P50	Max
CarbonPost	26,130	0.1413	0.3483	0	0	1
Size	26,130	22.1298	1.2803	19.7341	21.9505	26.045
Lev	26,130	0.4352	0.2044	0.0502	0.4311	0.8692
ROA	26,130	0.0421	0.0659	−1.8591	0.0381	0.6754
MB	26,130	2.1487	1.5466	0.4690	1.6674	10.3312
CFO	26,130	0.0461	0.0709	−0.1685	0.0451	0.2443
Liq	26,130	0.5617	0.2064	0.092	0.5761	0.964
Top	26,130	0.3494	0.1492	0.0886	0.3298	0.7489
Dual	26,130	0.2412	0.4278	0	0	1
Mhldn	26,130	0.1186	0.1914	0	0.0012	0.6929
Age	26,130	2.8646	0.3082	1.9459	2.8904	3.5264

3.4. Univariate Tests

The results of the univariate tests for financial distress before and after increasing carbon risk for high- and low-carbon emitting firms are presented in Table 3. The findings indicate that high-carbon-emitting firms' Zscore increased after carbon risk increased, indicating a lower likelihood of financial distress, with a mean difference of 0.5912. Low-carbon-emitting firms experience a decrease in the likelihood of financial distress, although the decline is less pronounced than that seen among high-carbon-emitting firms. Low-carbon-emitting firms have better financial conditions before and after the carbon risk shock. As a result, the difference between the two groups is 1.6643 before the increase in carbon risk and 1.5726 afterward. It is evident from these results that high-carbon-emitting firms' financial distress decreased significantly after the rise in carbon risk, supporting Hypothesis H1b.

Table 3. Univariate tests.

Variables	Carbon (1)		Carbon (0)		t-Test		
	Mean	SD	Mean	SD	Mean Diff (1–0)	T-Value	p-Value
Post (0)	3.5924	10.1615	5.2567	8.5823	−1.6643	−8.0151 ***	[0.0000]
Post (1)	4.1836	7.9077	5.7562	11.2906	−1.5726	−7.9054 ***	[0.0000]
Mean Diff (1–0)	0.5912		0.4996				
T-value	−2.5726 ***		−3.2911 ***		0.0916	3.0533 ***	[0.0000]
p-value	[0.0000]		[0.0000]				

Notes: *** represent significance at 1% level.

4. Empirical Results

4.1. Baseline Regression

Table 4 reports the baseline regression results. Column (1) presents the estimates without control variables, while Column (2) reports the results after incorporating the full set of controls. In both specifications, the coefficient on CarbonPost is positive and statistically significant at the 1% level. Following the Paris Agreement, firms in the treatment group (high-carbon-emitting firms) exhibit significantly higher Zscores than those in the control group (low-carbon-emitting firms), indicating a lower likelihood of financial distress. These findings support Hypothesis H1b and highlight the importance of incorporating carbon risk into analyses of corporate financial stability.

Table 4. Baseline regression.

Variables	(1)	(2)
	Zscore	Zscore
CarbonPost	0.1858 *** (0.0439)	0.0466 ** (0.0316)
Carbon	−0.4775 *** (0.0472)	−0.0579 * (0.0288)
Post	−0.2176 *** (0.0476)	−0.2264 *** (0.0342)
Size		−0.0679 *** (0.0107)
Lev		−1.9339 *** (0.0790)
ROA		1.6143 *** (0.1375)
MB		0.1037 *** (0.0238)
CFO		1.6085 *** (0.1389)
Liq		1.1864 *** (0.0533)
Top		0.1615 ** (0.0662)
Dual		−0.0538 ** (0.0218)
Mhldn		−0.2042 *** (0.0723)
Age		0.0641 * (0.0361)
Constant	2.2161 *** (0.0496)	3.2876 *** (0.2784)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	26,130	26,130
Pseudo R ²	0.0448	0.4450

Notes: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

The finding that carbon risk increases the Zscore, thereby reducing the likelihood of firms' financial distress, may appear counterintuitive because carbon regulation is commonly regarded as a source of additional compliance costs and operational pressure. From the perspective of traditional environmental economics, stricter carbon constraints are expected to increase production costs, reduce cash flows, and consequently exacerbate financial distress. However, this conventional prediction does not fully capture the institutional characteristics of China's government-led low-carbon transition.

The conventional view implicitly treats carbon risk primarily as a regulatory burden that increases firms' operating costs and financial pressure. This perspective views carbon risk as an external constraint while overlooking firms' strategic responses to regulatory change. In contrast, dynamic capabilities theory and the Porter Hypothesis suggest that carbon risk can stimulate organizational transformation by encouraging firms to reconfigure resources, upgrade production technologies, and improve managerial practices. Accordingly, the economic consequences of carbon risk depend not only on the direct costs of regulatory compliance but also on firms' ability to adapt during the low-carbon transition. China's government-led low-carbon transition provides a supportive institutional environment in which such adaptive responses are more likely to emerge. Rather than relying

solely on regulatory mandates, China's transition strategy combines mandatory environmental regulation with complementary policy instruments, including green finance, fiscal subsidies, tax incentives, and innovation support policies. These institutional arrangements reduce the costs of organizational transformation, strengthen firms' incentives and capacity to adapt, and enable carbon risk to generate positive effects on firms' financial resilience.

Accordingly, our findings suggest that carbon risk should not be conceptualized merely as an exogenous regulatory shock. Instead, in an appropriate institutional environment, carbon risk can become a catalyst that stimulates firms to build stronger technological capabilities, governance quality, and organizational resilience. Consequently, the relationship between carbon risk and corporate financial distress should be understood as the net outcome of the interaction between regulatory pressure and firms' adaptive transformation rather than the direct consequence of compliance costs alone.

Our findings are contrary to those of Nguyen et al. [26], which emphasize that carbon risk raises the likelihood of financial distress in developed countries like Australia. Australia belongs to a typical market-oriented environmental governance model, and rising carbon risk implies stricter carbon pricing, emission limits, and increased policy uncertainty, which in turn leads to rising financial distress. The Chinese government, in promoting the process of carbon peaking and carbon neutrality, adopts more government-led policies and will give more financial subsidies, emphasizing a smooth transition and avoiding shocks to the markets. This reflects the differing mechanisms by which the impact of carbon risk on financial distress differs in developed and developing countries.

Our findings differ from those of Ding et al. [27], who argue that higher carbon emissions aggravate corporate financial distress. The divergence arises mainly from four aspects. First, Ding's sample ends in 2018 and therefore captures only the initial cost pressures of the Paris Agreement. By contrast, our study extends to 2020 and reflects the period when policies were gradually implemented and supporting mechanisms improved. Second, our parallel trend tests reveal a clear policy lag. The effects became evident only three years after implementation, which shorter observation windows were unable to capture. Third, by examining mechanisms such as green innovation, ESG performance, and media attention, we demonstrate that the results are grounded in behavioral and institutional logic rather than statistical artifacts. Fourth, we employ rigorous robustness checks—including PSM-DID, placebo tests, and double machine learning—that consistently confirm our conclusions. Therefore, our study does not contradict prior research but rather complements and extends the understanding of how carbon risk affects financial distress across different policy phases and institutional contexts.

4.2. Parallel Trend Test

To identify policy effects, the DID method presumes that, before the adoption of the policy, the Zscore trends for the treatment group and the control group do not change over time and that the overall trend remains the same. Specifically, before the enactment of the Paris Agreement, there were no notable disparities in financial distress (Zscores) between high-carbon-emitting and low-carbon-emitting companies. We evaluate the accuracy of this assumption by employing the event study methodology [41]. If the parallel trend assumption is valid, we anticipate that the computed coefficients for the period 2009–2014 will not considerably deviate from zero. Figure 1 presents the computed coefficients and the 95% confidence intervals for the parallel trend test. In the treatment and control groups, there are no statistically significant differences in financial distress (Zscores) before the Paris Agreement. Furthermore, from the third year onward, the Zscore of the treatment group shows a significant upward trend, indicating a substantial decrease in the likelihood of financial distress.

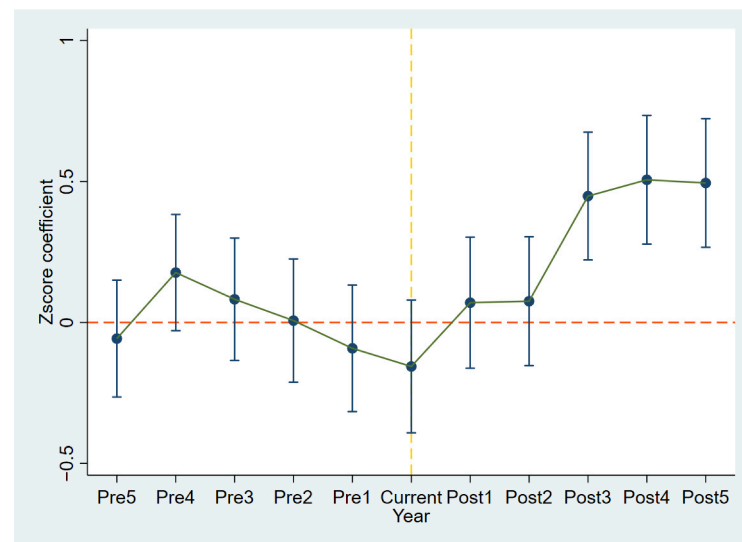


Figure 1. Parallel Trend Test. The dots denote the estimated coefficients, and the error bars represent 95% confidence intervals. The vertical dashed line marks the policy implementation year, while the horizontal dashed line indicates the zero-effect benchmark.

The delayed policy effect observed in Figure 1 is consistent with the gradual transmission of carbon transition policies. Although the Paris Agreement marked the beginning of China's low-carbon transition, the implementation of related policies required time to be transmitted through governments, regulators, and firms. Meanwhile, firms also needed time to adjust their production strategies, undertake green investments, and implement technological upgrading, all of which involve relatively long investment and payoff cycles. In addition, supportive measures such as green finance, fiscal incentives, and preferential credit policies were introduced progressively, allowing firms to gradually improve their financing conditions, operational efficiency, and risk management capabilities. Consequently, the benefits of low-carbon transformation accumulated over time and became statistically significant approximately three years after the Paris Agreement, as reflected by the increase in the Zscore and the corresponding reduction in the likelihood of financial distress. Generally, our findings confirm the efficacy of the DID method in identifying policy effects, as predicted by the parallel trend test.

In recent literature, however, it has been suggested that pre-treatment trend tests have failed to provide valid empirical evidence in support of the parallel trends assumption [42]. The statistical power of pre-treatment trend tests is low, which may lead to estimates that are biased or distorted. To address this issue, Rambachan [43] developed a method for testing when parallel trends are violated. The method involves constructing confidence intervals for point estimates after treatment and conducting sensitivity analyses. It consists of two parts: first, determining the maximum deviation from the parallel trends assumption ($Mbar$); and second, calculating the confidence interval for the post-treatment point estimates corresponding to the above deviation. Under the maximum deviation scenario, a confidence interval that excludes zero indicates that the treatment effect is robust to deviation from parallel trends. Following the approach of Biasi [44], we set the maximum deviation $Mbar = 1 \times \text{standard error}$. After the policy implementation, sensitivity tests should be conducted for periods when the policy effect significantly deviates from zero. Therefore, this study conducts sensitivity tests for the third, fourth, and fifth periods following the policy implementation. Figure 2 illustrates the results of the parallel trend sensitivity analyses for the year of policy implementation, considering both a relative deviation constraint and a smoothing constraint. The results indicate that even with some

deviation from the parallel trend assumption, the Paris Agreement policy significantly contributes to reducing the risk of corporate financial distress.

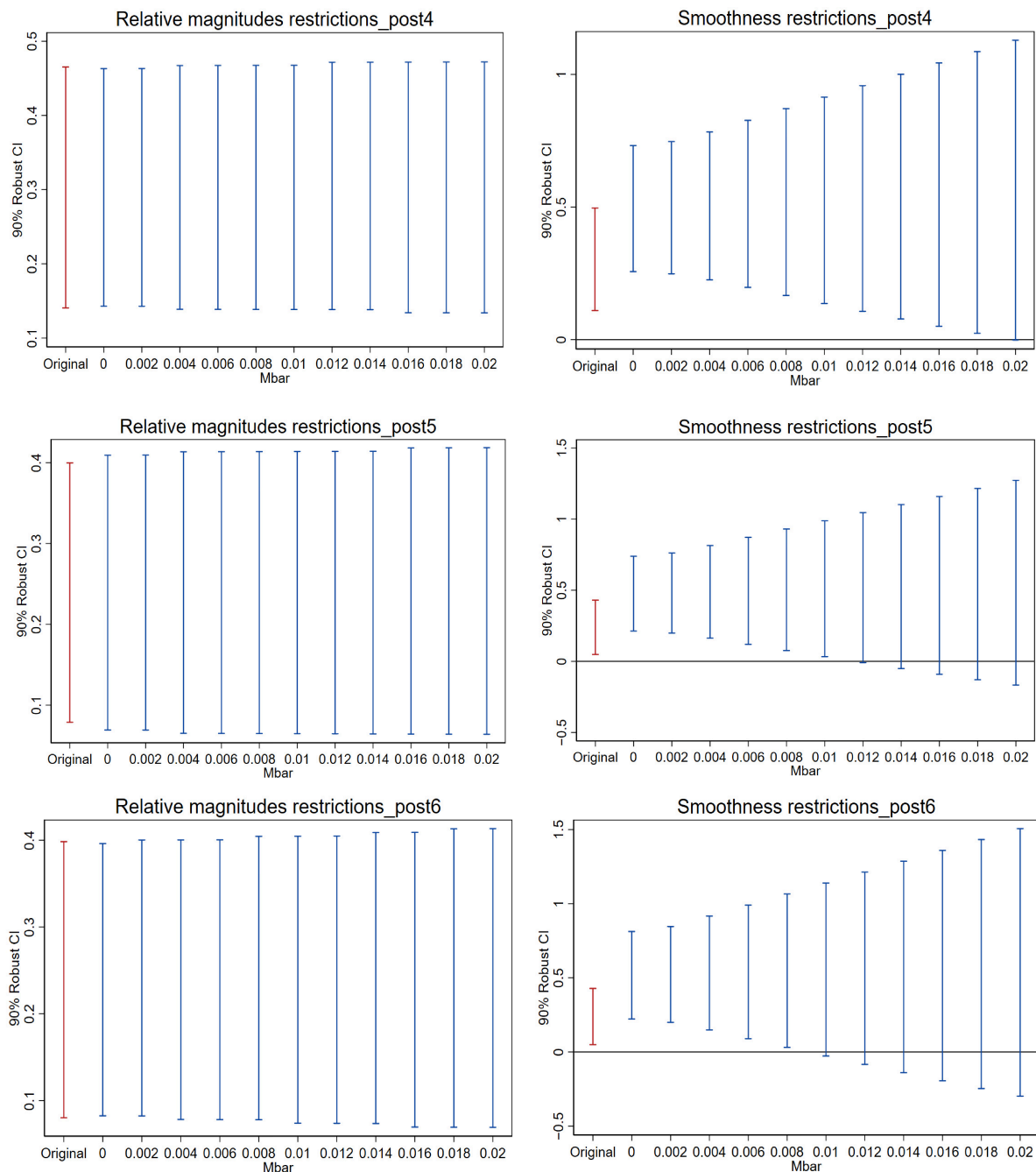


Figure 2. Parallel Trend Sensitivity Test. The red error bar represents the original estimation result, while the blue error bars represent the estimation results after allowing for different maximum deviations (Mbar) from the parallel trends assumption.

4.3. Robustness Test

4.3.1. Placebo Test

We implement a placebo test to evaluate the influence of unobservable firm characteristics. According to Rahat [45], the placebo test is performed in two ways. Our first step is to advance the Paris Agreement implementation by 3–5 years as a pseudo-policy shock period. In the second step, we create pseudo-treatment groups and multiply them by the Post variable to create pseudo-policy-effect variables. This procedure runs 5000 times, providing 5000 pseudo-policy effect variables.

In Table 5 and Figure 3, the policy effect for the advanced Paris Agreement implementation time is not significant, and the estimated coefficients of the 5000 pseudo-policy effect variables are normally distributed around zero. This result shows a clear difference from the 0.0466 reported in the baseline regression, consistent with the expectations of the placebo test. Based on these results, we suggest that using DID in this study is a valid approach and that our results are robust.

Table 5. Robustness test: placebo test.

Variables	(1)	(2)	(3)
	2010	2011	2012
	Zscore	Zscore	Zscore
CarbonPost	0.0871 (0.0662)	0.0594 (0.0553)	−0.0555 (0.0482)
Constant	2.6241 *** (0.4343)	2.5916 *** (0.4441)	2.3849 *** (0.4439)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	9956	9956	9956
Pseudo R ²	0.5110	0.5109	0.5110

Notes: *** represent significance at 1% level.

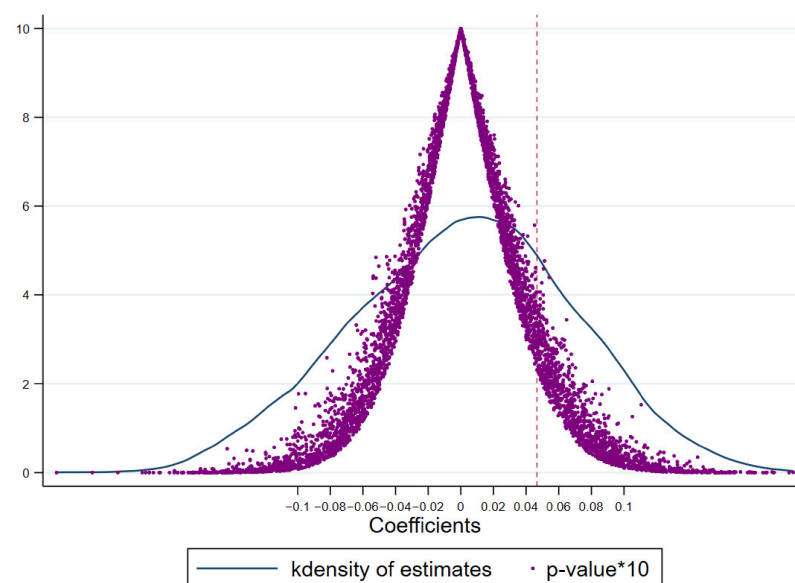


Figure 3. Placebo test.

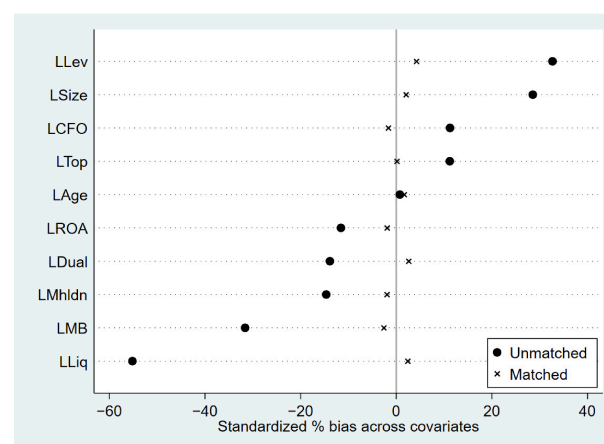
4.3.2. PSM-DID

To address the issue of sample selection bias, we use PSM–DID for robustness checks. First, we compute propensity scores for each firm in the treatment groups by employing firm-level control variables as covariates. Next, we perform matching for each year using kernel matching and Mahalanobis distance matching methods. Table 6 presents the regression results. The results show that the baseline regression remains robust. The balance test is shown in Figure 4. There is a large bias between the treatment and control groups before matching. The bias between the treatment and control groups is reduced to less than 10% after matching. In Table 6, the significant reduction in bias before and after matching confirms the satisfactory quality of the matching.

Table 6. Robustness test: PSM-DID.

Variables	(1)	(2)
	Kernel	Mahalanobis
	Zscore	Zscore
CarbonPost	0.0458 ** (0.0231)	0.0466 ** (0.0235)
Constant	3.2815 *** (0.2782)	3.2876 *** (0.2784)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
N	26,124	26,130
Pseudo R ²	0.4445	0.4450

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

**Figure 4.** Balance Test.

4.3.3. Double Machine Learning

To address the endogeneity issue arising from omitted variables, we re-examine the data using the double machine learning method, which was suggested by Chernozhukov et al. [46] and Bodory et al. [47]. Double machine learning provides superior variable selection and model design compared to traditional causal inference methods [48]. On the one hand, by using regularization algorithms, the double machine learning method avoids the curse of dimensionality caused by high-dimensional redundancy and provides reliable estimates; On the other hand, the advantage of double machine learning also lies in its ability to handle nonlinear relationships among variables, which helps mitigate model specification bias arising from nonlinear interactions in the economic system.

We use the double machine learning method to re-examine the causal relationship between carbon risk and corporate financial distress. The sample splitting ratio is 1:4. To avoid subjective selection in model specification, we use a general interactive double machine learning model and apply a neural network prediction method. In column (1) of Table 7, the coefficients are significant at the 1% level. We adjust the sample splitting ratio to 1:2 and 1:7. Columns (2) and (3) indicate that regression coefficients remain significant at the 1% level. These results suggest that the findings of the study remain robust.

Table 7. Robustness test: double machine learning.

Variables	(1)	(2)	(3)
	Nnet kfold = 5	Nnet kfold = 3	Nnet kfold = 8
	Zscore	Zscore	Zscore
CarbonPost	0.506 *** (0.036)	0.510 *** (0.038)	0.505 *** (0.037)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26,130	26,130	26,130

Notes: *** represent significance at 1% level.

4.3.4. Heterogeneous Treatment Effect Test

De [49] asserts that the DID model estimates are a weighted average of treatment effects for all treated individuals. The model may exhibit instability when a significant number of negative weights are present alongside heterogeneous treatment effects. According to the results, 103 weights are positive, and one is negative out of 104. Positive weights equal 1, and negative weights equal 0. The little presence of negative weights indicates that heterogeneous treatment effects do not substantially influence the baseline regression outcomes, hence ensuring their robustness.

4.3.5. Other Robustness Tests

Some other robustness tests were carried out.

First, we adjust the baseline model's standard errors. To overcome potential issues with the sample distribution, we apply the Bootstrap method to adjust the standard errors of the baseline model. Using Bootstrap, we perform resampling with replacement on the basic regression sample to generate subsamples for estimation. The procedure is executed 1000, 2500, and 5000 times to determine the model's standard errors. Table 8 indicates that the regression results exhibit no significant alterations, thus affirming the robustness of the baseline regression and bolstering the trustworthiness of the conclusions.

Table 8. Robustness test: adjustment standard errors.

Variables	(1)	(2)	(3)
	1000	2500	5000
	Zscore	Zscore	Zscore
CarbonPost	0.0514 ** (0.0255)	0.0514 ** (0.0241)	0.0514 ** (0.0251)
Constant	3.5618 *** (0.2456)	3.5618 *** (0.2506)	3.5618 *** (0.2482)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	26,130	26,130	26,130
Pseudo R ²	0.4417	0.4417	0.4417

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

Next, we change the sample period. At the end of 2019, the COVID-19 pandemic profoundly impacted the global economy and enterprises. Many companies experienced a sharp decline in performance, faced immense financial pressures, and confronted the likelihood of financial distress or even bankruptcy during the pandemic. To mitigate the

liquidity shock induced by the pandemic and to prevent any distortion in the analysis of financial distress, we omit the sample from the year 2020. Additionally, because the Paris Agreement was adopted on 12 December 2015 and implemented on 4 November 2016, we exclude the sample for 2016 to mitigate any noise caused by its implementation. As shown in Table 9, excluding these years does not have a significant impact on any of the regression results, thereby validating the robustness of the baseline regression model.

Table 9. Robustness test: adjustment sample period.

Variables	(1)	(2)
	Excluding the 2020 Sample	Excluding the 2016 Sample
	Zscore	Zscore
CarbonPost	0.0316 ** (0.0150)	0.0555 ** (0.0264)
Constant	3.5147 *** (0.3058)	3.2294 *** (0.2709)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
N	22,929	23,812
Pseudo R ²	0.4426	0.4459

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

Third, we replace the dependent variable. There are two methods for estimating financial distress in the literature. One method uses accounting-based data (such as the Zscore) [39], while the other uses market-based data (such as distance to default) [50]. Based on the approach of Bharat [50], we calculate the probability of default for each firm and use it as a proxy for financial distress. Financial distress is more likely to be experienced by a firm with a higher probability of default. Table 10 confirms the robustness of the baseline results.

Table 10. Robustness test: replacement of the dependent variables.

Variables	EDFvalue
CarbonPost	−0.0105 *** (0.0038)
Constant	−0.4156 *** (0.0294)
Firm FE	Yes
Year FE	Yes
Controls	Yes
N	26,130
Pseudo R ²	0.1266

Notes: *** represent significance at 1% level.

Fourth, we change the classification criterion for high-carbon firms. We conduct an additional robustness test by redefining high-carbon firms based on firm-level carbon emission intensity. Specifically, firms with carbon emission intensity above the sample median are classified as high-carbon firms, while those below the median are classified as low-carbon firms. Table 11 confirms the robustness of the baseline results.

Table 11. Robustness test: changing the classification criterion for high-carbon firms.

Variables	Zscore
CarbonPost	0.0300 ** (0.0135)
Constant	3.1197 *** (0.3197)
Firm FE	Yes
Year FE	Yes
Controls	Yes
N	26,130
Pseudo R ²	0.4814

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

Fifth, we add higher-dimensional fixed effects. We additionally control for industry–year fixed effects and province–year fixed effects in the baseline specification. Table 12 confirms the robustness of the baseline results.

Table 12. Robustness test: add higher dimensional fixed effects.

Variables	Zscore	Zscore
CarbonPost	0.0479 ** (0.0215)	0.0221 ** (0.0104)
Constant	7.8954 *** (2.6322)	10.5332 *** (2.5827)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry × year FE	Yes	No
Province × year FE	No	Yes
Controls	Yes	Yes
N	26,130	26,130
Pseudo R ²	0.6676	0.6539

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

4.4. Heterogeneity Analysis

We analyze the differential impact of increased carbon risk on corporate financial distress across various external environments, considering dimensions such as the emphasis on environmental governance, the technological level of the industry, the degree of industry pollution, and the extent of industry regulation.

4.4.1. Emphasis on Environmental Governance

Under China’s environmental accountability system, local governments retain considerable discretion in implementing environmental policies. As a result, firms face varying degrees of regulatory pressure across regions, reflecting differences in local governments’ emphasis on environmental governance. Regions that place greater emphasis on environmental protection typically impose more stringent environmental regulations on carbon-intensive firms, providing stronger incentives for green transformation and organizational adaptation. Consequently, firms in these regions are more likely to reduce the likelihood of financial distress. According to Chen et al. [48], we use the frequency of keywords associated with “environmental protection” as a proxy for environmental governance in local government work reports.

As shown in Columns (1) and (2) of Table 13, rising carbon risk leads to a significantly greater increase in the Zscore for firms located in regions with a high emphasis on environmental governance than for those in regions with a low emphasis, indicating a

larger reduction in the likelihood of financial distress. A stronger environmental governance environment is typically associated with more stringent environmental regulation and regulatory enforcement. These conditions provide stronger incentives for firms to undertake green transformation by improving environmental compliance, investing in green technologies, and adopting more resource-efficient production processes. As a result, firms are better positioned to cope with the regulatory and market uncertainties associated with carbon risk, thereby strengthening their financial resilience. In addition, regions with stronger environmental governance generally provide more favorable institutional support for low-carbon innovation through R&D subsidies, policy incentives, and other green development initiatives. Such institutional support facilitates firms' technological upgrading, improves resource efficiency, lowers carbon-related compliance costs, and ultimately reduces the likelihood of financial distress.

Table 13. Heterogeneity analysis.

Variables	Emphasis on Environmental Governance		Industry Technological Level		Industry Pollution Intensity		Industry Regulation Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High	Low	High	Non-High	High	Non-High	Competitive	Regulated
	Zscore	Zscore	Zscore	Zscore	Zscore	Zscore	Zscore	Zscore
Carbon Post	0.5077 ** (0.2255)	0.3027 (0.1859)	0.0460 *** (0.0164)	0.0248 (0.1268)	0.1444 ** (0.0586)	−0.0197 (0.0548)	0.0754 ** (0.0354)	0.0244 (0.0382)
Constant	2.5207 *** (1.5781)	2.6557 *** (0.4499)	6.1449 *** (1.6444)	1.0634 *** (1.0471)	2.8143 *** (0.4662)	3.4122 *** (0.3424)	3.2200 *** (0.4548)	2.6192 *** (0.3393)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5719	5749	10,556	15,574	7920	18,210	19,046	7084
Pseudo R ²	0.5046	0.5095	0.5178	0.4643	0.5638	0.3799	0.3800	0.4897

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

4.4.2. Industry Technological Level

High-tech firms generally possess stronger innovation capabilities, higher value-added production, and greater access to financial and technological resources, enabling them to respond more effectively to the challenges associated with carbon risk. These advantages facilitate technological upgrading and organizational adaptation, thereby strengthening financial resilience and reducing the likelihood of financial distress. To examine whether the effect of carbon risk differs by technological intensity, we divide the sample into high-tech and non-high-tech industries.

As shown in columns (3) and (4) of Table 13, compared with non-high-tech companies, high-tech companies experience a larger increase in the Zscore as carbon risk rises, indicating a greater reduction in the likelihood of financial distress. High-tech firms generally possess stronger innovation capabilities and greater R&D capacity, enabling them to respond more effectively to changes in environmental regulations. Their technological advantages facilitate the development and adoption of energy-efficient and environmentally sustainable products and production processes, thereby accelerating green transformation. In addition, high-tech firms are typically more advanced in digitalization and information technologies, allowing them to optimize production processes, improve resource efficiency, and reduce energy consumption and carbon emissions. These improvements lower operating costs while enhancing firms' ability to adapt to carbon risk. Moreover, high-tech firms are better positioned to seize emerging opportunities associated with the low-carbon

transition, including the development of green products and participation in rapidly growing sustainable markets. Consequently, they are more capable of transforming regulatory pressure into competitive advantages, strengthening financial resilience and reducing the likelihood of financial distress.

4.4.3. Industry Pollution Intensity

High-pollution industries, due to their critical position in the economy, enjoy government policy support, strong market bargaining power, and ample financing resources, which effectively mitigate financial pressure and reduce the likelihood of financial distress. Therefore, we categorize the sample companies into high-pollution and non-high-pollution industries. As shown in columns (5) and (6) of Table 13, the results indicate that rising carbon risk leads to a significantly larger increase in the Zscore for firms in high-pollution industries than for firms in non-high-pollution industries, suggesting a greater reduction in the likelihood of financial distress. This finding appears counterintuitive because highly polluting firms generally face stricter environmental regulations and higher compliance costs. Conventional wisdom suggests that these firms should experience greater financial pressure under carbon risk. However, from the perspective of the Porter Hypothesis, firms facing the greatest regulatory pressure are also those with the strongest incentives to undertake green transformation. Compared with low-pollution firms, highly polluting firms generally have greater scope for technological upgrading and operational restructuring. Consequently, climate policies not only increase compliance costs but also induce substantial improvements in production efficiency, resource allocation, and innovation capability. Moreover, highly polluting industries are the primary targets of environmental regulation and therefore receive more policy support during the transition process, including green finance, technological subsidies, and emission-reduction incentives. These supportive policies help offset the initial compliance costs and accelerate firms' transition toward more efficient production, thereby improving financial resilience and reducing the likelihood of financial distress. By contrast, firms operating in low-pollution industries are already relatively compliant with environmental regulations and therefore face weaker transition pressure. As a result, they have limited scope to improve production efficiency or obtain additional transition-related policy support. Nevertheless, these firms still incur certain adjustment costs associated with enhanced environmental disclosure, ESG compliance, and organizational adaptation. Consequently, the marginal benefits generated by carbon transition may be insufficient to offset the corresponding transition costs, resulting in an economically negative but statistically insignificant coefficient.

4.4.4. Industry Regulation Intensity

Based on the approach of Ke et al. [51], we categorize the sample into regulated industries and competitive industries. Columns (7) and (8) of Table 13 show that rising carbon risk results in a significantly larger increase in the Zscore among competitive firms than among regulated firms, implying a greater reduction in the likelihood of financial distress. In competitive industries, firms face greater market pressure and tighter profit margins. A rise in carbon risks, such as a rise in carbon pricing or a rise in emission costs, requires these firms to address cost increases through a variety of strategies. Investment in green technologies and energy-saving equipment reduces long-term carbon emissions costs by improving production processes and operational management. Enhancements in efficiency and technological advancements mitigate the operational impact of carbon risk, thus decreasing the likelihood of financial distress.

5. Mechanism Analysis

Having established that carbon risk reduces corporate financial distress, the next question is through which channels this effect is realized. We argue that carbon risk does not directly improve firms' financial resilience. Instead, it induces firms to undertake strategic adjustments in response to low-carbon transition pressures. These strategic adjustments constitute the transmission mechanisms linking carbon risk to corporate financial distress.

These strategic adjustments can be classified into three complementary dimensions. First, firms respond through technological adaptation, reflected in greater green innovation, which improves resource efficiency and long-term competitiveness. Second, firms undertake governance adaptation, reflected in enhanced ESG performance, which strengthens stakeholder trust and financing capacity. Third, firms engage in informational adaptation, reflected in greater media attention, which improves information transparency and external monitoring. Together, these three dimensions capture firms' strategic responses to carbon risk and provide the principal channels through which carbon risk affects financial distress.

We examine how carbon risk impacts firms' financial distress. In the model, we include the interaction terms between the mechanism variables and CarbonPost.

$$Zscore_{i,t} = \alpha + \beta_1 Mechanism_{i,t} \times CarbonPost_t + \beta_2 CarbonPost_t + \beta_3 Mechanism_{i,t} + \sigma X_{i,t-1} + \eta_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

In Equation (3), *Mechanism* represents the mechanism variable, and the coefficient of the interaction term, β_1 , is the main focus of interest. Similarly, the meanings of the other variables are consistent with those in the baseline model.

5.1. Corporate Green Innovation Effect

Technological innovation is the fundamental driver of firms' low-carbon transformation, reducing energy costs and overcoming financial difficulties [52]. Likewise, corporate executives' environmental awareness influences how firms leverage their resources and advantages to develop green innovations. We examine the effects of corporate green innovation from two dimensions: executives' green awareness and green technological innovation. Following Duriau et al. [53], we measure executives' green awareness (EGA) by analyzing the occurrence of environment-related terms in the company's annual reports. We classify technological innovation into disruptive innovation (DI) and incremental innovation (II), with the number of green patent applications serving as a measure of the extent of green technological innovation. Based on Mao [54], we consider invention patents to be high-level technological innovations because of their higher technical content and complexity. Thus, the number of invention patent applications is used as an indicator of disruptive technological innovation. The number of utility model patent applications is used to measure incremental technological innovation. All of the aforementioned variables are processed logarithmically.

Table 14 presents the regression results for EGA, DI, and II on CarbonPost. The level of executives' green awareness increased significantly after the Paris Agreement was implemented, whereas disruptive technological innovation did not show a significant increase. Incremental technological innovation has improved significantly. Columns (4)–(6) present the results for the moderating effects. The interaction terms between carbon risk and executives' green awareness, as well as incremental technological innovation, are significantly positive, indicating that these factors further increase the Zscore. This suggests that executives' green awareness and incremental technological innovation positively moderate the effect of carbon risk, leading to a greater reduction in the likelihood of firms' financial distress. In contrast, the interaction term involving disruptive technological innovation is insignificant, suggesting that it does not exert a significant moderating effect.

Table 14. Mechanism analysis: corporate green innovation effect.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	EGA	DI	II	Zscore	Zscore	Zscore
CarbonPost	0.2356 *** (0.0354)	−0.0314 (0.0196)	0.0262 *** (0.0097)	0.0440 (0.0376)	0.2555 *** (0.1041)	0.2124 ** (0.1041)
EGA × CarbonPost				0.1423 ** (0.0674)		
DI × CarbonPost					0.0300 (0.0785)	
II × CarbonPost						0.1663 *** (0.0614)
EGA				0.1385 *** (0.0376)		
DI					0.0023 (0.0477)	
II						0.1393 *** (0.0437)
Constant	0.3726 (0.3211)	−2.4762 *** (0.4147)	−1.2608 *** (0.3222)	1.3468 * (1.0221)	1.9388 *** (0.9438)	1.8435 ** (0.9339)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	22,715	26,130	26,130	22,524	26,130	26,130
Pseudo R ²	0.1756	0.0627	0.0470	0.4933	0.4944	0.4946

Notes: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

The heterogeneous effects of incremental and disruptive green innovation provide further evidence on how carbon risk influences corporate financial resilience. When facing carbon transition pressure, firms are more likely to prioritize incremental green innovation because it requires relatively lower investment, involves less technological uncertainty, and generates economic benefits more quickly through process optimization, improved energy efficiency, and cleaner production. These characteristics enable firms to enhance operational efficiency and strengthen financial resilience within a relatively short period, thereby contributing to a higher Zscore. By contrast, disruptive green innovation typically requires substantial R&D investment, longer development cycles, and entails considerable technological and market uncertainty. Although such innovation has the potential to generate significant environmental and economic benefits over the long term, its contribution to short-term financial resilience is limited. The insignificant moderating effect of disruptive green innovation suggests that firms primarily rely on incremental technological improvements, rather than radical technological breakthroughs, to cope with carbon risk. Overall, these findings indicate that the effectiveness of green innovation in mitigating financial distress depends on both the technological characteristics of innovation and the time horizon over which its benefits are realized.

5.2. ESG Performance

Proactive engagement in ESG practices can help firms build a multidimensional buffer mechanism against financial distress. From the environmental (E) perspective, companies that actively manage their environmental impact, invest in pollution control, and implement energy-saving measures may incur upfront costs, but these actions can effectively prevent large unexpected expenses arising from environmental violations or resource inefficiencies. Moreover, such efforts may qualify firms for government subsidies, tax incentives, and other policy benefits, while also enhancing their ability to adapt to increasingly strin-

gent environmental regulations. From the social (S) dimension, fulfilling corporate social responsibility contributes to building a positive reputation and fostering consumer trust and brand loyalty. This, in turn, mitigates revenue volatility caused by social controversies and enhances employee morale and productivity, providing a stable foundation for ongoing operations. In terms of governance (G), a robust corporate governance framework can constrain managerial opportunism, reduce the risk of financial fraud, self-dealing and market manipulation, and improve the quality of decision-making and resource allocation. This reduces the likelihood of significant strategic errors or regulatory sanctions stemming from governance failures. Therefore, ESG strengthens a firm's financial resilience and risk management capacity through multiple channels. ESG engagement significantly reduces the likelihood of firms falling into financial distress due to either external shocks or internal mismanagement.

We use corporate ESG performance as a mechanism variable, measured by the Huazheng ESG rating. The Huazheng ESG rating is based on international mainstream evaluation frameworks, incorporating multi-dimensional data that aligns with domestic market characteristics. Additionally, the Huazheng ESG rating combines quarterly evaluations with dynamic tracking, ensuring strong timeliness. Thus, Huazheng ESG ratings can be utilized to measure ESG performance. According to the Huazheng index's classification of ESG ratings, companies rated AAA for ESG ratings are assigned a score of "9" with progressively lower scores down to "1" for companies rated C. A higher score indicates better ESG performance. To further understand how ESG affects financial distress, we break it down into three sub-indicators: environmental (E), social responsibility (S), and corporate governance (G).

In Table 15, columns (1)–(4) present the regression results for ESG, E, S, and G on CarbonPost, while columns (5)–(8) display the results of the moderating effect regressions. The findings indicate that following the Paris Agreement, corporate ESG performance, as well as the environmental and social responsibility dimensions, improved significantly, while the corporate governance dimension did not show a significant increase. Moreover, the interaction terms between carbon risk and ESG performance, as well as the environmental and social responsibility dimensions, are significantly positive, indicating a further increase in the Zscore. These results suggest that ESG performance and its environmental and social responsibility dimensions positively moderate the effect of carbon risk, leading to a greater reduction in the likelihood of firms' financial distress. In contrast, the interaction term associated with the corporate governance dimension is statistically insignificant, indicating that it does not exhibit a significant moderating effect.

After the Paris Agreement, high-carbon-emission companies have shown significant improvement in the environmental and social dimensions of ESG, largely due to heightened international and policy emphasis on environmental protection and sustainable social development. By advancing environmental technologies, reducing carbon emissions, and fulfilling social responsibilities toward employees, customers, and local communities, firms enhanced their environmental performance, corporate reputation, and stakeholder relationships. These improvements strengthened investor confidence, reduced financing costs, and ultimately increased the Zscore, indicating a lower likelihood of financial distress.

In contrast, the governance dimension does not exhibit a significant moderating effect. Governance reforms typically involve fundamental adjustments to organizational structures, internal control systems, board effectiveness, and corporate decision-making processes, all of which require considerable time before their economic benefits can be fully realized. Moreover, corporate governance primarily affects firms' long-term strategic decision-making rather than their immediate responses to carbon transition pressure. Compared with the environmental and social dimensions, governance improvements are

therefore less directly associated with firms' short-term efforts to address carbon risk. Consequently, although sound corporate governance remains essential for firms' long-term sustainable development, its moderating effect on the relationship between carbon risk and financial distress is less evident during the sample period.

Table 15. Mechanism analysis: ESG performance.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ESG	E	S	G	Zscore	Zscore	Zscore	Zscore
CarbonPost	0.3889 ** (0.1784)	0.3319 *** (0.1229)	1.6299 *** (0.3484)	−0.4011 (0.3646)	0.3097 (0.0068)	0.8438 (0.7263)	0.5753 (0.6103)	−0.0110 (0.7127)
ESG × CarbonPost					0.0591 *** (0.0126)			
E × CarbonPost						0.0161 ** (0.0077)		
S × CarbonPost							0.0059 ** (0.0028)	
G × CarbonPost								0.0017 (0.0094)
Constant	40.5182 *** (1.6353)	28.1562 *** (2.6992)	30.1181 *** (3.3216)	59.7973 *** (1.8852)	7.6689 *** (1.6086)	8.5741 *** (1.5874)	7.3878 *** (1.5575)	6.8394 *** (1.6162)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	26,023	26,022	26,023	26,023	25,800	25,799	25,800	25,800
Pseudo R ²	0.1627	0.2224	0.3394	0.2064	0.4702	0.4719	0.4703	0.4705

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

5.3. Media Attention

Increased media attention helps reduce the likelihood of firms falling into financial distress. On the one hand, media oversight narrows the information gap between management and external stakeholders, thereby promoting more disciplined managerial behavior and improving corporate governance and operational efficiency. This, in turn, mitigates the risk of high costs arising from internal failures or environmental incidents [6,26]. On the other hand, media exposure of environmental violations enhances public scrutiny and increases the pressure on local governments to enforce stricter regulations. Firms that fail to strengthen environmental compliance may face more severe penalties, including production restrictions or shutdowns [55]. Thus, media attention plays a dual role in reducing financial distress by improving internal governance and reinforcing external regulatory pressures.

Following the approach of Fang [56], we measure media attention (MA) using the number of news reports. The media attention data are obtained from the CNRDS database and calculated as the natural logarithm of one plus the total number of news articles mentioning the firm. This includes both online and print media coverage, as long as the firm's name appears in either the headline or the body of the article. Table 16 presents the regression results of MA on CarbonPost, as well as the moderating effect of media attention. Column (1) indicates that an increase in carbon risk significantly heightens media attention. Column (2) indicates that the interaction term between carbon risk and media attention is significantly positive, indicating a further increase in the Zscore. This suggests that media attention strengthens the positive effect of carbon risk on the Zscore, thereby implying a greater reduction in the likelihood of firms' financial distress.

Table 16. Mechanism analysis: media attention.

Variables	(1)	(2)
	MA	Zscore
CarbonPost	0.0635 ** (0.0271)	−0.0175 (0.4535)
MA		0.3216 *** (0.0400)
MA × CarbonPost		0.0610 ** (0.0302)
Constant	−6.3721 *** (0.3780)	4.3960 *** (0.9874)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
N	26,130	26,130
Pseudo R ²	0.3894	0.4979

Notes: *** and ** represent significance at 1% and 5% levels, respectively.

6. Further Analysis

It should be noted that the machine learning analysis is designed to evaluate the predictive importance of explanatory variables rather than establish causal relationships. The causal effect of carbon risk on firms' financial distress is identified through the DID framework, whereas the XGBoost and SHAP analyses provide complementary evidence on predictive performance and variable importance.

6.1. Carbon Risk as Predictive Indicator

The preceding analyses demonstrate that carbon risk is significantly associated with corporate financial distress, with higher carbon risk reducing the likelihood of financial distress among high-carbon firms. This finding raises an important question: Does incorporating carbon risk improve the predictive performance of financial distress models? Existing prediction models largely overlook carbon risk, despite its growing importance under increasingly stringent climate policies. As a result, they may fail to fully capture firms' financial vulnerability during the low-carbon transition. Examining the predictive value of carbon risk is both a natural extension of our earlier analysis and a question of considerable practical relevance. More accurate prediction models can provide earlier warning signals for investors, help managers better assess firms' exposure to transition risk, and assist policymakers in identifying financially vulnerable firms and designing more effective policy interventions. To address this question, we develop an XGBoost-based financial distress prediction model that explicitly incorporates carbon risk and evaluates its incremental predictive value.

Building on the method of Liu et al. [57], we construct a corporate financial distress prediction model incorporating carbon risk using the XGBoost algorithm. It effectively captures nonlinear relationships, which traditional linear models frequently overlook. XGBoost shows outstanding predictive performance and is widely used in financial risk prediction, with the ability to automatically identify the most important predictors. Its feature selection mechanism helps isolate key variables from complex datasets, improving model accuracy. XGBoost demonstrates resilience to noise and overfitting, rendering it appropriate for datasets including missing or outlier values. It is well suited for analyzing how carbon risk affects financial distress because of its computational efficiency and scalability, which also enable it to manage enormous datasets. Previous research has highlighted XGBoost's strong performance in areas like financial distress prediction, mergers and acquisitions,

financial disclosure, and environmental performance [58]. Therefore, we think XGBoost is a great instrument for researching the relationship between corporate financial distress and carbon risk.

6.2. XGBoost Model

6.2.1. Model

(1) Principles of XGBoost

The core idea of XGBoost is to iteratively refine the residuals of predictions in each round. Specifically, given a training dataset $D = (x_i, y_i)_{i=1}^n$, where x_i represents the input features and y_i denotes the target variable, the objective is to identify a model $f(x)$ that minimizes the loss function $L(y, f(x))$. The XGBoost model can be expressed as:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (4)$$

Here, F represents the space of regression trees and $f_k(x_i)$ denotes the prediction of the k tree for the input samples x_i . XGBoost minimizes the objective function and gradually lowers residual errors by adding new trees. The definition of the loss function is as follows:

$$L = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (5)$$

Here, l represents the loss function, which is typically the squared loss or log loss, while $\Omega(f_k)$ denotes the regularization term. The purpose of the regularization term is to limit overfitting and manage model complexity. The form of the regularization term $\Omega(f_k)$ is expressed as:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T \omega_j^2 \quad (6)$$

Here, T represents the number of leaf nodes in the tree, ω_j denotes the weights of the leaf nodes, and γ and λ are hyperparameters used to control the complexity of the model.

(2) Gradient Boosting Process

In XGBoost, each iteration updates the model by minimizing the objective function. At iteration t , the model's prediction can be expressed as:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (7)$$

XGBoost utilizes a second-order Taylor expansion to approximate the objective function, enabling efficient model updates during each iteration. The expansion is expressed as:

$$L^{(t)} \approx \sum_{i=1}^n \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2 \right] + \Omega(f_t) \quad (8)$$

Here, $g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$ represents the first-order derivative and $h_i = \partial^2_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$ denotes the second-order derivative. The goal of each iteration of a greedy algorithm is to minimize the loss function to efficiently update the model.

6.2.2. Evaluation of Model Performance

A predictive model's accuracy and reliability can be assessed by metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE),

Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). In the model, the following evaluation metrics are used:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (10)$$

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \right]^{\frac{1}{2}} \quad (11)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (12)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\bar{y}_i - y_i)^2} \quad (13)$$

Here, n represents the number of samples, y_i denotes the actual values, $\hat{y}_i$ refers to the predicted values, and $\bar{y}_i$ denotes the mean of the actual values.

6.3. Results Analysis

6.3.1. Optimal Parameters

Using the Zscore as the target variable, the purpose of this research is to forecast company financial distress. The independent variables include carbon risk, firm size (Size), gearing ratio (Lev), return on assets (ROA), market-to-book ratio (MB), cash flow from operations (CFO), liquidity level (Liq), the shareholding of the largest shareholder (Top), dual roles of chairman and managing director (Dual), management shareholding (Mhldn), and firm age (Age). We measure corporate carbon risk using the company's carbon emissions. 70% of the samples are used as the training set and 30% as the test set. We modify the parameters using a Bayesian model to improve the XGBoost model's performance and avoid overfitting. Bayesian optimization is an efficient global optimization method that, by constructing the posterior distribution of the objective function and incorporating prior knowledge, can effectively optimize hyperparameters. Table 17 presents the optimal parameter configuration.

Table 17. XGBoost: optimal parameters.

Parameters	Parameter Value
Booster	gbtree
N_estimators	333
Max_depth	5
Learning_rate	0.078
Reg_alpha	0.573
Reg_lambda	8.438
Colsample_bylevel	0.987
Colsample_bytree	0.999
Colsample_bynode	0.81
Random_state	42

6.3.2. Feature Importance Analysis with SHAP

To reveal the relative importance and mechanisms of various factors affecting corporate financial distress, the study also employs the SHAP value interpretation algorithm. The SHAP value algorithm serves as a tool to open the “black box” of the XGBoost model, providing an intuitive visualization of the relative importance and direction of influence of each factor on financial distress. This study calculates the average SHAP values for each factor across all samples to determine their relative importance, drawing on Zhang et al. [59]. Figure 5 presents the mean SHAP values and their respective proportions for each influencing factor. From the figure, it is clear that the mean SHAP value for financial leverage is the highest, indicating that financial leverage has the greatest impact on corporate financial distress. Carbon risk also ranks high in the SHAP mean values, further highlighting its significance in the prediction of financial distress.

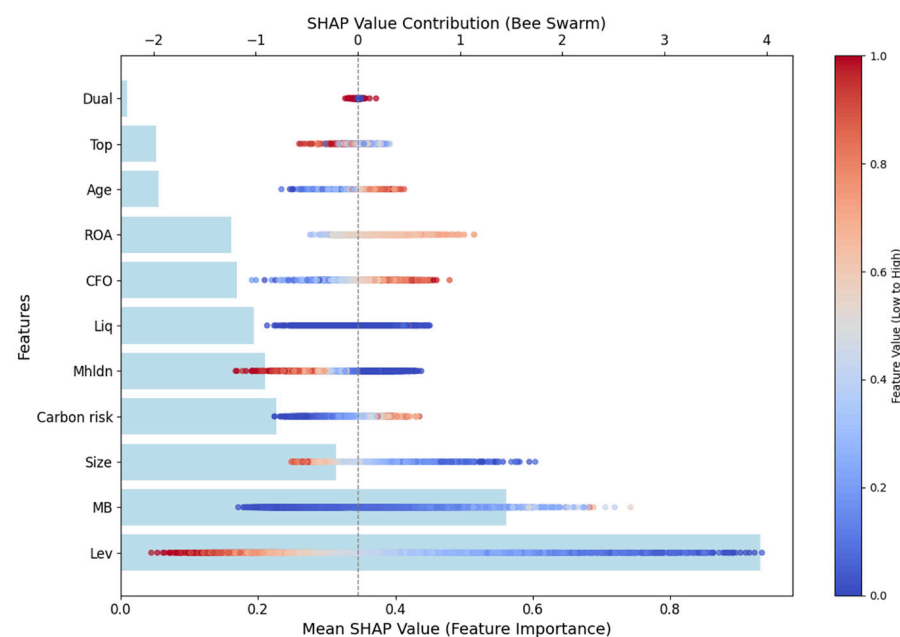


Figure 5. SHAP value analysis. The bar chart reflects the mean SHAP value, which is used to represent feature importance. The bee swarm plot illustrates the contribution of SHAP values. In the plot, each point represents a sample, with red points indicating higher values of the influencing factor and blue points indicating lower values. The SHAP value of 0 serves as a dividing line. If a sample is located in the right-hand area (SHAP value > 0), it indicates a positive impact on corporate financial distress; conversely, if the sample is in the left-hand area (SHAP value < 0), it indicates a negative impact.

Although the SHAP mean values measure the relative importance of each variable, they do not provide an intuitive indication of the specific direction of their influence. Therefore, this study further presents SHAP value bee swarm plots to reveal the direction of impact of each factor on corporate financial distress, as shown in Figure 5. In the plot, each point represents a sample, with red points indicating higher values of the influencing factor and blue points indicating lower values. The SHAP value of 0 serves as a dividing line. If a sample is located in the right-hand area (SHAP value > 0), it indicates a positive impact on corporate financial distress; conversely, if the sample is in the left-hand area (SHAP value < 0), it represents a negative impact. It can be observed that both red and blue points for carbon risk are distributed on either side of the dividing line, with a greater concentration in the right-hand area. This indicates that carbon risk plays a more significant role in increasing corporate financial distress.

6.3.3. Comparison of Results

By contrasting the predictive effectiveness of the XGBoost model with and without carbon risk, this study assesses the contribution of carbon risk to the prediction of corporate financial distress. We thoroughly examine both models using some criteria and determine the percentage differences between them. Figure 6 compares the actual and predicted values of the Zscore. A comparison of Model 1 (Results 1), which includes carbon risk factors, and Model 2 (Results 2), which excludes carbon risk factors, is presented in Table 18.

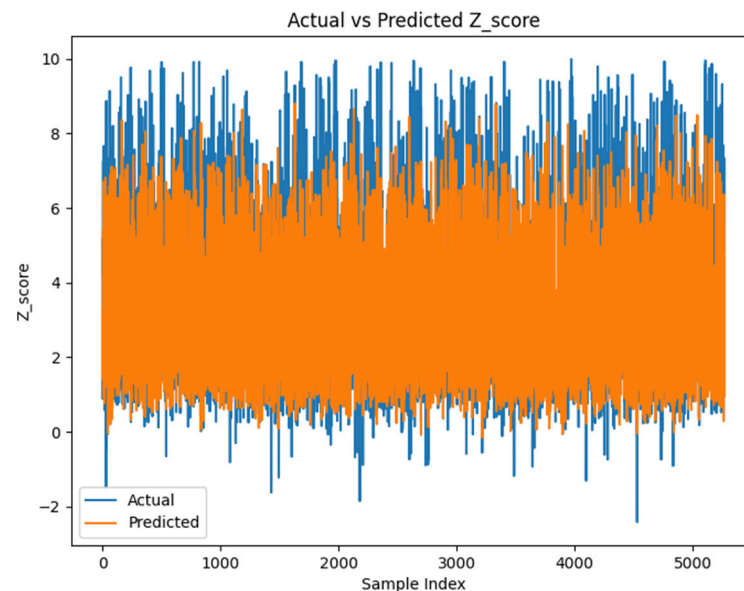


Figure 6. Actual vs. predicted Zscore.

Table 18. Comparative analysis with and without carbon risk factors.

	Training Set			Test Set		
	Result 1	Result 2	Change (%)	Result 1	Result 2	Change (%)
MAE	0.748	0.802	−6.75	0.900	0.932	−3.43
MSE	1.138	1.273	−10.6	1.717	1.778	−3.43
RMSE	1.067	1.128	−5.41	1.310	1.333	−1.73
MAPE	49.32%	55.05%	−10.41	46.08%	51.45%	−10.44
R2	0.755	0.726	3.99	0.631	0.618	2.10

The data comparison indicates that Model 1 surpasses Model 2 in all performance indicators for both the training and testing datasets. A further analysis of the performance on the testing set shows that, compared to Model 2, Model 1 reduces MSE by 3.43%, RMSE by 1.73%, MAE by 3.43%, and MAPE by 10.44%, indicating higher prediction accuracy. Additionally, R2 increases by 2.1%, demonstrating stronger explanatory power. Carbon risk factors greatly increase the model's prediction accuracy, explanatory power, and generalizability.

7. Conclusions and Implications

7.1. Conclusions

This study investigates the impact of carbon risk on corporate financial distress by exploiting China's accession to the Paris Agreement as a quasi-natural experiment. The results show that high-carbon firms are significantly less likely to experience financial distress than low-carbon firms following the policy shock, providing empirical support for the regulatory benefit perspective. To further validate the baseline results, we employ

a double machine learning approach that addresses potential limitations of conventional regression models, including model misspecification, estimator instability, and the curse of dimensionality. The findings remain robust across these alternative specifications.

Mechanism analyses reveal that carbon risk reduces the likelihood of financial distress through three complementary channels. First, it promotes technological adaptation by strengthening executives' environmental awareness and encouraging incremental green innovation. By contrast, disruptive green innovation does not exhibit a significant effect because of its high investment requirements, long development cycles, and considerable technological uncertainty. Second, carbon risk facilitates governance adaptation through improved ESG performance. Among the three ESG dimensions, environmental and social performance significantly mitigate financial distress, whereas the effect of corporate governance is not statistically significant in the short run. Third, carbon risk promotes informational adaptation by increasing media attention, which enhances information transparency, reduces managerial opportunism and information asymmetry, and ultimately strengthens firms' abilities to withstand financial distress.

The heterogeneity analysis further shows that the mitigating effect of carbon risk on financial distress is more pronounced for firms operating in high-tech industries, high-pollution industries and highly competitive markets, as well as for firms located in regions with stronger environmental governance. Finally, incorporating carbon risk into an XGBoost-based financial distress prediction model significantly improves predictive performance, demonstrating that carbon risk provides valuable incremental information for identifying firms' financial vulnerability during the low-carbon transition.

7.2. Implications

The government should improve governance assistance and boost green innovation subsidies, with a particular emphasis on helping high-carbon-emission businesses implement green technologies. This can be achieved by establishing dedicated green innovation funds and offering R&D subsidies, which would alleviate the financial burden of high costs and long payback periods linked to technological innovation. The government should enforce carbon emission regulations more effectively by setting clear emission standards and implementing strong accountability measures, reinforcing its commitment to both governance and sustainable development. We should also urge local governments to promote carbon trading markets and green finance tools to enable more enterprises to reduce the financial distress caused by carbon risk.

Companies should improve green innovation and governance. They must incorporate low-carbon development into their long-term strategy, increase green technology R&D, prioritize incremental improvements to comply with regulations, and explore disruptive ideas to obtain a sustainable competitive edge. Executives should learn about green concerns and the necessity of low-carbon transformation for the company's future. They should incorporate green concepts into decision-making and promote sustainable practices. Company ESG performance must be improved by raising environmental responsibility awareness and governance systems. This will build investor trust, cut financing expenses, and stabilize company finances while controlling carbon risk.

People ought to be more involved in environmental awareness and social supervision. The public can put pressure on high-carbon-emission enterprises to enhance their environmental management by concentrating on their environmental performance and media disclosures. Enhancing environmental education will also promote greater participation in the low-carbon development process, which will further the transition to a green economy.

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References

- Cheng, T.; Dong, L.; Dong, Y.; Lam, K. How does climate risk affect corporate financialization? *Res. Int. Bus. Financ.* **2025**, *78*, 102954. [\[CrossRef\]](#)
- Xu, P.; Dai, H.; Li, S.; Huang, R. How low-carbon transition enables corporate sustainability: A corporate risk-taking perspective. *Sust. Cities Soc.* **2024**, *115*, 105816. [\[CrossRef\]](#)
- Domon, S.; Hirota, M.; Kono, T.; Managi, S.; Matsuki, Y. The long-run effects of congestion tolls, carbon tax, and land use regulations on urban CO₂ emissions. *Reg. Sci. Urban Econ.* **2022**, *92*, 103750. [\[CrossRef\]](#)
- Liu, T.; Zhao, W. Climate Shocks, Stock Price Crash Risk, and Corporate Sustainability: Evidence from China’s Financial System. *Systems* **2026**, *14*, 18.
- Shen, J.; Zheng, H.; Zhu, L. Quantifying firm-level carbon risk: A novel emission reduction stress factor. *Econ. Model.* **2025**, *151*, 107210. [\[CrossRef\]](#)
- Shu, H.; Tan, W.; Wei, P. Carbon policy risk and corporate capital structure decision. *Int. Rev. Financ. Anal.* **2023**, *86*, 102523. [\[CrossRef\]](#)
- Bolton, P.; Kacperczyk, M. Global Pricing of Carbon-Transition Risk. *J. Financ.* **2023**, *78*, 3677–3754. [\[CrossRef\]](#)
- Bolton, P.; Kacperczyk, M. Do investors care about carbon risk? *J. Financ. Econ.* **2021**, *142*, 517–549. [\[CrossRef\]](#)
- García, C.; Herrero, B. Female directors, capital structure, and financial distress. *J. Bus. Res.* **2021**, *136*, 592–601. [\[CrossRef\]](#)
- He, Y.; Xu, L.; Yang, M. The impact of tunneling on financial distress and resolution: Evidence from listed firms in China. *Int. J. Financ. Econ.* **2020**, *26*, 1773–1792. [\[CrossRef\]](#)
- Bhamra, H.; Fisher, A.; Kuehn, L. Monetary policy and corporate default. *J. Monet. Econ.* **2011**, *58*, 480–494. [\[CrossRef\]](#)
- Zhou, F.; Fu, L.; Li, Z.; Xu, J. The recurrence of financial distress: A survival analysis. *Int. J. Forecast.* **2022**, *38*, 1100–1115. [\[CrossRef\]](#)
- Boubaker, S.; Cellier, A.; Manita, R.; Saeed, A. Does corporate social responsibility reduce financial distress risk? *Econ. Model.* **2020**, *91*, 835–851. [\[CrossRef\]](#)
- Nguyen, D.; Pham, T.; Tran, N.; Zurbrugg, R. The dynamic effects of debtor bankruptcy on unsecured creditors’ stock liquidity. *J. Financ. Stab.* **2024**, *74*, 101322. [\[CrossRef\]](#)
- Dang, V.; Nguyen, D.; Pham, T.; Zurbrugg, R. The dynamics of informed trading around corporate bankruptcies. *Financ. Res. Lett.* **2024**, *63*, 105385. [\[CrossRef\]](#)
- Liu, Y.; Yang, J.; Pham, T. The hidden cost of firm-level political risk: Impairing liquidity in corporate bond markets. *Financ. Res. Lett.* **2025**, *85*, 108058. [\[CrossRef\]](#)
- Wasi, M.; Pham, T.; Zurbrugg, R. Bank systemic risk: An analysis of the sovereign rating ceiling policy and rating downgrades. *J. Bus. Financ. Account.* **2023**, *50*, 411–440.
- Fard, A.; Javadi, S.; Kim, I. Environmental regulation and the cost of bank loans: International evidence. *J. Financ. Stab.* **2020**, *51*, 100797. [\[CrossRef\]](#)
- Ehlers, T.; Packer, F.; de Greiff, K. The pricing of carbon risk in syndicated loans: Which risks are priced and why? *J. Bank. Financ.* **2022**, *136*, 106180. [\[CrossRef\]](#)
- Wang, C.; Hu, M.; Lu, J.; Liu, X. Carbon exposure of credit assets and banking systemic risk caused by climate transition. *Res. Int. Bus. Financ.* **2025**, *77*, 102980. [\[CrossRef\]](#)
- Luo, C.; Wei, D.; He, F. Corporate ESG performance and trade credit financing: Evidence from China. *Int. Rev. Econ. Financ.* **2023**, *85*, 337–351. [\[CrossRef\]](#)
- Karydas, C.; Xepapadeas, A. Climate change financial risks: Implications for asset pricing and interest rates. *J. Financ. Stab.* **2022**, *63*, 101061. [\[CrossRef\]](#)
- Brown, J.; Martinsson, G.; Petersen, B. Law, stock markets, and innovation. *J. Financ.* **2013**, *68*, 1517–1549. [\[CrossRef\]](#)

24. Hsu, P.; Tian, X.; Xu, Y. Financial development and innovation: Cross-country evidence. *J. Financ. Econ.* **2014**, *112*, 116–135. [\[CrossRef\]](#)
25. Wang, J.; Qiang, H.; Liang, Y.; Huang, X.; Zhong, W. How carbon risk affects corporate debt defaults: Evidence from Paris agreement. *Energy Econ.* **2024**, *129*, 107275. [\[CrossRef\]](#)
26. Nguyen, J.; Phan, H. Carbon risk and corporate capital structure. *J. Corp. Financ.* **2020**, *64*, 101713. [\[CrossRef\]](#)
27. Ding, X.; Li, J.; Song, T.; Ding, C.; Tan, W. Does carbon emission of firms aggravate the risk of financial distress? Evidence from China. *Financ. Res. Lett.* **2023**, *56*, 104034. [\[CrossRef\]](#)
28. Bebbington, J.; Unerman, J. Achieving the United Nations sustainable development goals. *Account. Audit. Account.* **2018**, *31*, 2–24. [\[CrossRef\]](#)
29. De Beule, F.; Dewaelheyns, N.; Schoubben, F.; Struyfs, K.; Van Hulle, C. The influence of environmental regulation on the FDI location choice of EU ETS-covered MNEs. *J. Environ. Manag.* **2022**, *321*, 115839. [\[CrossRef\]](#)
30. Huang, X.; Tian, P. How does heterogeneous environmental regulation affect net carbon emissions: Spatial and threshold analysis for China. *J. Environ. Manag.* **2023**, *330*, 117161. [\[CrossRef\]](#)
31. Meng, L.; Liu, K.; He, J.; Han, C.; Liu, P. Carbon emission reduction behavior strategies in the shipping industry under government regulation: A tripartite evolutionary game analysis. *J. Clean. Prod.* **2022**, *378*, 134556. [\[CrossRef\]](#)
32. Hasan, M.; Du, F. Nexus between green financial development, green technological innovation, and environmental regulation in China. *Renew. Energy* **2023**, *204*, 218–228. [\[CrossRef\]](#)
33. Lyu, H.; Ma, C.; Arash, F. Government innovation subsidies, green technology innovation and carbon intensity of industrial firms. *J. Environ. Manag.* **2024**, *369*, 122274. [\[CrossRef\]](#)
34. Myers, S. The capital structure puzzle. *J. Financ.* **2012**, *39*, 574–592.
35. Balachandran, B.; Nguyen, J. Does carbon risk matter in firm dividend policy? Evidence from a quasi-natural experiment in an imputation environment. *J. Bank. Financ.* **2018**, *96*, 249–267. [\[CrossRef\]](#)
36. Rennings, K. Redefining innovation—Eco-innovation research and the contribution from ecological economics. *Ecol. Econ.* **2000**, *32*, 319–332. [\[CrossRef\]](#)
37. Horbach, J.; Rammer, C.; Rennings, K. Determinants of eco-innovations by type of environmental impact—The role of regulatory push/pull, technology push and market pull. *Ecol. Econ.* **2012**, *78*, 112–122. [\[CrossRef\]](#)
38. Hossain, M.; Yoshino, N.; Taghizadeh-Hesary, F. Default risks, moral hazard and market-based solution: Evidence from renewable energy market in Bangladesh. *Econ. Model.* **2021**, *95*, 489–499. [\[CrossRef\]](#)
39. Altman, E. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *J. Financ.* **1968**, *23*, 589–609. [\[CrossRef\]](#)
40. Ji, Y.; Shi, L.; Zhang, S. Digital finance and corporate bankruptcy risk: Evidence from China. *Pac.-Basin Financ. J.* **2022**, *72*, 101731. [\[CrossRef\]](#)
41. Jacobson, L.; LaLonde, R.; Sullivan, D. Earnings losses of displaced workers. *Am. Econ. Rev.* **1993**, *83*, 685–709.
42. Roth, J.; Sant’Anna, P.; Bilinski, A.; Poe, J. What’s trending in difference-in-differences? A synthesis of the recent econometrics literature. *J. Econom.* **2023**, *235*, 2218–2244. [\[CrossRef\]](#)
43. Rambachan, A.; Roth, J. A more credible approach to parallel trends. *Rev. Econ. Stud.* **2023**, *90*, 2555–2591. [\[CrossRef\]](#)
44. Biasi, B.; Sarsons, H. Flexible wages, bargaining, and the gender gap. *Q. J. Econ.* **2022**, *137*, 215–266.
45. Rahat, B.; Nguyen, P. Risk-adjusted investment performance of green and black portfolios and impact of toxic divestments in emerging markets. *Energy Econ.* **2022**, *116*, 106423. [\[CrossRef\]](#)
46. Chernozhukov, V.; Chetverikov, D.; Demirer, M.; Duflo, E.; Hansen, C.; Newey, W.; Robins, J. Double/debiased machine learning for treatment and structural parameters. *Econom. J.* **2018**, *21*, C1–C68. [\[CrossRef\]](#)
47. Bodory, H.; Huber, M.; Laffers, L. Evaluating (weighted) dynamic treatment effects by double machine learning. *Econom. J.* **2022**, *25*, 628–648. [\[CrossRef\]](#)
48. Chen, Z.; Kahn, M.; Liu, Y.; Wang, Z. The consequences of spatially differentiated water pollution regulation in China. *J. Environ. Econ. Manag.* **2018**, *88*, 468–485. [\[CrossRef\]](#)
49. De Chaisemartin, C.; D’Haultfoeulle, X. Two-Way fixed effects estimators with heterogeneous treatment effects. *Am. Econ. Rev.* **2020**, *110*, 2964–2996. [\[CrossRef\]](#)
50. Bharath, S.; Shumway, T. Forecasting default with the Merton distance to default model. *Rev. Financ. Stud.* **2008**, *21*, 1339–1369. [\[CrossRef\]](#)
51. Ke, B.; Liu, N.; Tang, S. Does Anti-Corruption Regulation Improve the Performance of State-Controlled Firms? Evidence from China. *Soc. Sci. Res. Netw.* **2018**. [\[CrossRef\]](#)
52. Wen, H.; Shi, J.; Lu, P. Can Green Technology Innovation Reduce the Operational Risks of Energy-Intensive Enterprises? *Systems* **2023**, *11*, 194. [\[CrossRef\]](#)
53. Duriau, V.; Reger, R.; Pfarrer, M. A content analysis of the content analysis literature in organization studies: Research themes, data sources, and methodological refinements. *Organ. Res. Methods* **2007**, *10*, 5–34. [\[CrossRef\]](#)

54. Mao, C.; Zhang, C. Managerial risk-taking incentive and firm innovation: Evidence from FAS 123R. *J. Financ. Quant. Anal.* **2018**, *53*, 867–898. [[CrossRef](#)]
55. Li, X.; Hu, Z.; Cao, J.; Xu, X. The impact of environmental accountability on air pollution: A public attention perspective. *Energy Policy* **2022**, *161*, 112733. [[CrossRef](#)]
56. Fang, L.; Peress, J. Media Coverage and the Cross-section of Stock Returns. *J. Financ.* **2009**, *64*, 2023–2052. [[CrossRef](#)]
57. Liu, F.; Wang, R.; Fang, M. Mapping green innovation with machine learning: Evidence from China. *Technol. Forecast. Soc. Change* **2024**, *200*, 123107. [[CrossRef](#)]
58. Meng, Q.; Zheng, X.; Wang, S. Corporate governance and financial distress in China a multi-dimensional nonlinear study based on machine learning. *Pac.-Basin Financ. J.* **2024**, *88*, 102549. [[CrossRef](#)]
59. Zhang, J.; Ma, X.; Zhang, J.; Sun, D.; Zhou, X.; Mi, C.; Wen, H. Insights into geospatial heterogeneity of landslide susceptibility based on the SHAP-XGBoost model. *J. Environ. Manag.* **2023**, *332*, 117357. [[CrossRef](#)]

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