The Impact of ESG Scores and Their Interaction with Industry Characteristics on Corporate Bond Financing Costs: An Analysis from the Perspective of Credit Spreads

Xinrong Zhan

Overseas Chinese College, Capital University of Economics and Business, 100070, Beijing, China

32022140004@cueb.edu.cn

Abstract. In today's world, sustainable development is gaining increasing prominence, and the emergence of ESG score is driving the evolution of sustainability. From the perspective of credit spreads, the channels through which ESG score influence bond credit spreads represent an area warranting further research. This study offers investors a fresh perspective on acknowledging the importance of non-financial metrics such as ESG score, while also advocating for Chinese policy to differentiate between enterprises based on their sector-specific characteristics. This study examines the impact pathways from a theoretical standpoint, then employs a fixed-effects model to conduct empirical analysis using corporate bond characteristics issued on the Shenzhen and Shanghai stock exchanges between 2017 and 2023. Heterogeneity analysis is further applied to distinguish between heavily polluting and non-heavily polluting enterprises. Findings confirm that ESG score reduce corporate bond financing costs, with significant differences in main effects between heavily polluting and non-polluting enterprises. Recommendations include: heavily polluting enterprises should prioritise improving their ESG metrics, while policymakers should implement differentiated policies for distinct enterprise types to enhance environmental awareness and advance dual carbon objectives.

Keywords: ESG score, Credit Spread, Financing Cost

1 Introduction

1.1 Research Background

In recent years, ESG has gradually evolved from an additional metric of Corporate Social Responsibility to a critical dimension for measuring a company's long-term value and risks. Globally, amid Global Climate Change and growing resource constraints, regulatory authorities have re-evaluated corporate non-financial performance, while investors have also integrated ESG into their investment assessment frameworks. Strong

X. Pan et al. (eds.), *Proceedings of the 2026 11th International Conference on Financial Innovation and Economic Development (ICFIED 2026)*, Advances in Economics, Business and Management Research 382,
https://doi.org/10.2991/978-94-6239-642-5_46

ESG performance can significantly reduce a company's Compliance Risk, Reputational Risk, and Agency Cost. Similarly, China is in a critical phase of economic restructuring and transitioning toward high-quality development. Promoting ESG principles can facilitate the achievement of the "dual carbon" goals, help prevent major risks, and ensure sustainable resource utilization. Policy-wise, China has established a comprehensive, multi-tiered ESG institutional framework. Currently, the Green Bond Market is gradually expanding, with rapid growth in scale, increasing diversification of issuers, and rising internationalization. These policies have propelled ESG from "concept" to "practice" and rendered the correlation between Chinese enterprises' ESG performance and financing behaviors an urgent practical issue requiring research. Regarding theoretical applicability, the direct applicability of pricing logic theories from mature Western markets to China is questionable. ESG performance among Chinese enterprises is more policy-driven than a market spontaneous choice, suggesting potential differences in its impact mechanism on Financing Cost. heterogeneity differences, Chinese enterprises exhibit significant variations in industry attributes. Consequently, the financing cost effect of ESG scores may display structural differences, necessitating targeted research. In addition, prior to 2019, non-standardized disclosure of ESG information resulted in low data quality. Additionally, certain studies had limited sample sizes, leaving their robustness to be verified. Against this backdrop, ESG's impact on corporate financing and its specific influence on Financing Cost have become focal points of discussion.

1.2 Research Significance

Theoretical Significance. First, this study expands the boundaries of Traditional Credit Risk Theory. It can deepen understanding of the Spread driving mechanism, clarify how non-financial factors influence Spread through direct or indirect pathways, and enhance the application of Signal Transmission Theory. Additionally, it verifies the value of ESG scores in converting implicit non-financial information into explicit signals, providing theoretical support for mitigating bond market Information Asymmetry, strengthening the empirical foundation of Sustainable Finance, and promoting theoretical systematization.

Practical Significance. From a practical standpoint, this research first guides bond issuers to reduce Financing Cost, as higher ESG scores can lower Spread. It helps enterprises identify optimization priorities and avoid ESG risks to reduce financing expenses. For investors, integrating ESG scores into pricing models aids in identifying default risks, constructing robust portfolios, and avoiding pricing biases in "Greenwashing" bonds. Furthermore, it supports regulators by providing empirical basis for policies like mandatory ESG disclosure and unified rating standards, thereby directing capital toward sustainable sectors to serve the "dual carbon" goal. Finally, it enhances bond market efficiency by prompting bond prices to reflect comprehensive risks, reducing pricing distortions, and incentivizing enterprises to improve ESG performance—ultimately optimizing market resource allocation.

2 Literature Review

2.1 Impact of Traditional Corporate and Bond Characteristics on Financing Costs

Impact of Company Size. Theoretically, Warner noted in the Bankruptcy Cost Theory that,as a key indicator for measuring a firm's Risk Resistance Capability and Information Transparency, the negative correlation between Company Size and bond financing cost[1].

Impact of Profitability (ROA). From a theoretical perspective, Myers and Majiluf proposed the Pecking Order Theory (Pecking Order Theory), which suggests that firms with high ROA can fund their capital needs through internal earnings, reducing reliance on external debt and thereby lowering both their debt ratio and financing cost[2].

The Impact of Issuance Size and Issuance Maturity. Issuance size. From the supply-side perspective, Smith argued that larger issuance size may intensify the "Asset Substitution Effect": Issuance size exhibits a positive correlation with Financing Cost[3]. However, research indicates that bonds with an issuance size exceeding $500 million can reduce Financing Cost by spreading issuance expenses across a larger base, creating an "Economies of Scale Effect".

Issuance Maturity. From a risk pricing perspective, Interest Rate Risk Theory posits that long-term bonds face higher interest rate volatility and Inflation Risk, compelling investors to demand a "Term Risk Premium"[4]. Consequently, Issuance Maturity exhibits a significant positive correlation with bond interest rates. Regarding the unique characteristics of China's bond market, studies have identified an "Ownership Difference" in how Issuance Maturity affects spreads.

2.2 Research Progress on ESG Rating Systems

Fragmentation and Diversification. The global ESG rating industry currently exhibits "diversification and fragmentation". Statistics show there are over 600 influential ESG rating agencies worldwide, primarily categorized into two types: internationally dominant and regionally specialized. These agencies feature significant differences in their rating frameworks and indicator systems. Mainstream international rating agencies all adopt "Environment (E), Social (S), Governance (G)" as their core dimensions, yet they diverge in terms of indicator weighting and evaluation logic. The study from Berg points out that such "Rating Divergence" can cause confusion in investor decision-making, reduce the Bond Demand Elasticity of companies with high ESG ratings, and indirectly increase Financing Cost[5].

Data Quality Issues and Lack of Unified Standards. China's ESG rating still faces three major challenges: first, data quality issues. Huang Zhangkai noted that Chinese enterprises have a low ESG Information Disclosure rate, and the disclosed data contains "vague expressions," leading to high data collection costs for rating agencies; second, lack of unified standards. The correlation of ESG scores among 8 domestic institutions is low, even lower than that among international institutions[6].

Controversies Surrounding the Relationship Between ESG Rating Systems and Financing Costs. In the realm of debt financing, Li Hui empirically demonstrated using 2011-2019 data from China's Shanghai and Shenzhen A-share markets that each one-standard-deviation improvement in ESG performance reduces debt financing costs by 5.17%[7]. Conversely, Wang Ying found that while third-party ESG rankings lower equity financing costs, they actually drive up debt financing costs[8]. This phenomenon arises because upfront ESG investments increase short-term debt repayment risks.

3 Research Content

3.1 Research Content

Drawing upon existing domestic and international research and foundational theories, this paper first synthesizes literature on how corporate ESG ratings impact bond financing cost. It then theoretically analyzes the relationship and underlying mechanism between these two factors before proceeding to empirical investigation. The specific content includes: The first part outlines the research background, theoretical framework, and practical significance; systematically reviews domestic and international literature—encompassing factors influencing bond financing cost and the role of overall ESG performance—and introduces the research methodology, along with its innovations and limitations.The second part defines core concepts and introduces basic theories. The third part, by analyzing these fundamental theories, explores the impact of ESG scores on bond financing cost and the underlying mechanism, while formulating the research hypothesis. The fourth part presents the empirical analysis, including the research design, defining variables ; constructing the model with year fixed effects; and conducting descriptive statistics, correlation analysis, regression analysis, heterogeneity analysis and robustness test. Part 5 summarizes the empirical findings and offers targeted countermeasures and suggestions.

3.2 Theoretical Explanation and Influence Path

This study takes Behavioral Finance as the core theoretical foundation, breaks through the limitations of the "Rational Man Hypothesis" and "Market Perfectly Efficient" in traditional financial research, focuses on the irrational behaviors of market participants, constructs a transmission framework of high ESG ratings on Credit Spread Narrowing, and conducts a systematic analysis from the theoretical basis and action channels[9]:

Core Logic of Behavioral Finance. Behavioral Finance (Behavioral Finance) breaks the assumption of "investors being completely rational and markets automatically achieving efficient pricing" in traditional financial theories, and emphasizes that financial decisions are driven by psychological biases and group behaviors.This study relies on its three branches to explain how ESG ratings amplify the impact on Financing Cost through irrational behaviors[10].

Cognitive Bias and ESG Label Heuristics. Investors have a tendency towards "Heuristic Cognition" — when faced with complex information, they simplify the decision-making process and directly equate "high ESG ratings" with a signal label of "low risk and sustainable operation" for enterprises. This cognitive shortcut will irrationally amplify the impact of ESG ratings on investment decisions.

Moral Preference and Irrational Utility. Driven by moral values and the need for social identity, investors develop emotional preferences for enterprises with high ESG performance and are even willing to sacrifice returns for investments that "align with their own values"[11].

Attention Effect and Herding Behavior. High ESG ratings attract market attention through various means, triggering investors' "attention focus". Some investors be driven by the "Herd Effect", will ignore their own judgments and blindly follow the transactions. This behavior spreads the impact of ESG information from "individual decision-making" to "group behavior".

3.3 Impact Channels

Under the foundation of Behavioral Finance, "High ESG Rating" extends three channels of action. The first is the "Risk Mitigation Channel", which relies on Corporate Finance Theory and Merton Model to measure risk indicators . A high ESG rating implies that a company performs better in environmental, social, and governance dimensions, which can effectively reduce potential risks. From the investors' perspective, the lower the risk, the lower the required credit risk premium, which is the path through which ESG affects Financing Cost via the risk dimension.

The second is the "Capital Preference Channel", based on Supply and Demand Theory and Socially Responsible Investment Theory. A high ESG rating will attract qualified groups such as ESG funds and responsible investors. These investors are willing to accept a certain yield concession to support sustainable development enterprises, forming a continuous capital inflow into high ESG bonds and creating demand.

The third channel, "Information Asymmetry Channel", is supported by Information Economics and Signal Transmission Theory. A high ESG rating is essentially the result of enterprises actively or passively disclosing ESG information, which can bridge the information gap between investors and enterprises. When information risk is reduced, the information risk premium required by investors is less, and Financing Cost naturally decreases.

The three channels are not isolated; they ultimately jointly act on "Credit Spread Narrowing".The combined effect of the three has compressed the credit spread and reduced financing costs. The relationship diagram of the three channels is shown in Figure 1.

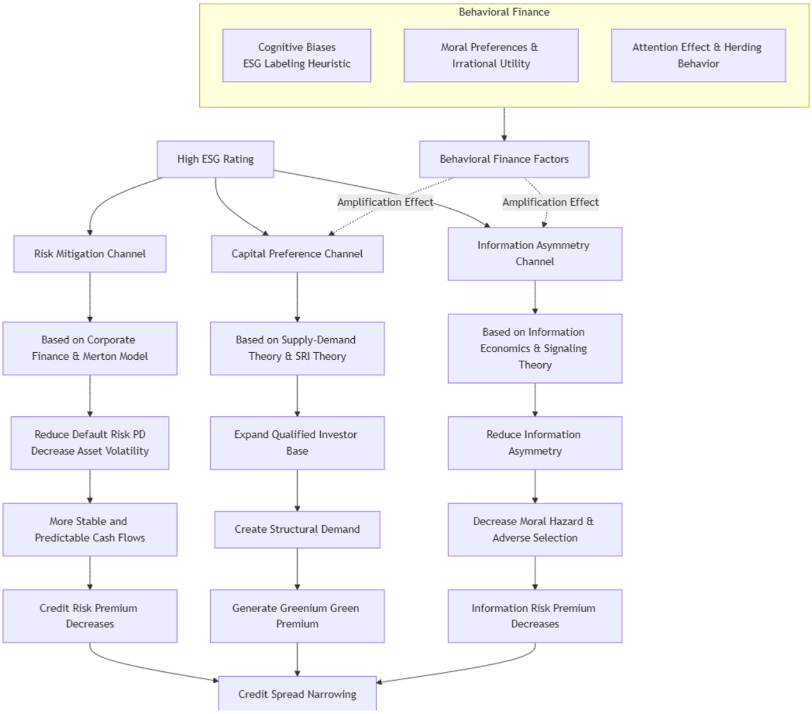

Fig. 1. ESG Score Influence Channel.

3.4 Research Hypothesis

The Relationship between Corporate ESG Ratings and Bond Financing costs. Based on the theoretical analysis above, ESG ratings affect corporate bond financing costs through four aspects.

Firstly, enterprises improve Information Transparency by disclosing ESG information, reduce information asymmetry, thereby lowering moral and other risks; secondly, high ESG Rating can convey positive operational signals, enhance investor confidence and influence demand; thirdly, it can improve corporate reputation, obtain high-quality resources, and reduce corporate risks.All these will ultimately contribute to the reduction of claim financing costs.

Therefore, this paper proposes Hypothesis 1: Enterprises improving ESG ratings is beneficial to reducing their Bond Financing Cost.

Industry Characteristics and Bond Financing Cost. Environmental performance is an important component of the ESG concept and also a crucial factor influencing investors' investment decisions.The production and operation activities of Heavy Pollution Industry often have high negative externalities.

Therefore, Hypothesis 2 is proposed: If a company is in the Heavy Pollution Industry, its high ESG rating will more significantly reduce the Bond Financing Cost.

4 Empirical Analysis

4.1 Research Design

This paper employs the Fixed Effects Model with year fixed effects to conduct empirical research and testing on the two hypotheses proposed in this paper. The empirical research in this chapter includes descriptive statistics, correlation analysis, regression result analysis, heterogeneity analysis, and robustness test. The empirical part of this chapter is completed using R Studio and WPS.

Sample Selection and Data Sources. This paper selects general Corporate Bond issued by Shanghai and Shenzhen A-share listed companies from 2017 to 2023 as the research sample to study the impact of corporate ESG ratings on their bond credit spreads. Among them, the financial data of enterprises is derived from the CSMAR database, and ESG ratings as well as bond-related data are obtained from Wind Financial Terminal and Choice Financial Terminal. To enhance the reliability of the research conclusions, this paper processes the samples, and ultimately obtains a total of 469 samples.

Variable Definitions. The Table 1 shows the definition of variables

Table 1. Definition of Variables

Classification	Items	Definition
Dependent variable	Bond Financing Cost (COST)	The difference between the bond's Coupon Rate and the yield to maturity of government bonds with the same term on the issuance date.
Explanatory variable	ESG score	Huazheng ESG score (a third-party rating with comprehensive data and impartial results).
Control variables	Enterprise Size (Size)	The natural logarithm of total Assets
	Return on Assets (ROA)	ROA
	Bond Issuance Term (MAT)	Maturity
	Bond Issuance Size (Scale)	The natural logarithm of the Issuance size
	Leverage Ratio (Lev)	Asset-liability ratio

Model Setting and Data Characteristics. Based on the cleaned panel data, this part adopts the Oneway (individual) effect Within Model (Oneway (individual) effect Within Model) to further explore the impact of Comprehensive Score, corporate pollution attribute (polluting enterprises vs non-polluting enterprises), and their interaction on credit_spread.Compared with the basic model, this model replaces the Profitability Index (adjusted from ROE to ROA) to more accurately measure Enterprise Operating Efficiency, while retaining core independent variable and key control variables. By controlling for time-invariant Individual Heterogeneity (such as corporate industry attributes, core competitiveness, etc.), the net effects between variables are identified.

The model is set as follows:

$$credit\_spreadit = \beta 0 + \cdot\ ESG\ Scoreit + \beta 1 \cdot (ESG\ Score \times Pollution)it + \beta 2 \cdot (ESG\ Score \times Non - Pollution)it + \sum \beta k \cdot Control\ Variablesit + \mu i + \epsilon it \quad (1)$$

Where i represents the enterprise individual and t represents time; μi is the individual fixed effect, which is used to absorb time-invariant individual characteristics; ϵit is the random disturbance term. Core independent variable include: Comprehensive Score (measuring the comprehensive qualification of enterprises), pollution dummy variable (1 = polluting enterprise, 0 = non-polluting enterprise), Non-Pollution Dummy Variable (1 = non-polluting enterprise, 0 = polluting enterprise), and the interaction terms between both and Comprehensive Score (testing the Moderating Effect of pollution attributes). control variables cover Bond Characteristics (Maturity), Enterprise Financial Indicators (Size, Leverage Ratio Leverage, Return on Assets ROA), and Issue Amount (log_issue_amount).

Data characteristics: The sample is Unbalanced Panel Data, including 264 enterprises (n=264), with each enterprise having an observation period of 1-7 years (T=1-7), and a total of 474 observations (N=469). As the GVIF Test is passed, the model is free from severe Multicollinearity, the core conclusions are reliable, and the Coefficient Estimation has statistical reliability, which can provide an empirical basis for subsequent research.

4.2 Empirical Analysis

Descriptive Statistics. This paper uses R Studio to perform descriptive statistics on the main variables, can be seen in Table 2.

Table 2. Definition of Vaiables

Variables	Mean	Median	sd	Min	Max	IQR	N
credit_spread_	1.640	1.270	1.110	0.060	5.160	1.348	474
ESG Score	76.377	76.110	5.342	55.900	90.150	7.905	474
Maturity_	4.171	5.000	1.440	1.000	10.000	2.000	474
Size_	10.677	10.632	0.610	9.167	12.380	0.828	474
Leverage	1.911	1.340	2.398	0.812	24.261	0.570	474
ROE	0.020	0.016	0.021	-0.046	0.192	0.018	474
log_issue_amount	2.078	2.303	0.828	-0.693	4.094	1.099	474

The samples were divided into heavily polluting enterprises and non-heavily polluting enterprises, and descriptive statistics were performed on the main variables. The results are as Table 3 and Table 4:

Table 3. Definition of Vaiables

Heavy pollution	_mean	median	spread_sd	_min	_max	IQR	N
credit_spread_	1.058	0.980	0.510	0.190	2.790	0.690	89
ESG Score	76.810	77.430	4.518	69.030	90.150	6.890	89
Maturity_	4.517	5.000	1.943	1.000	10.000	2.000	89
Size_	10.793	10.762	0.494	9.786	11.642	0.840	89
Leverage	1.790	1.492	0.943	0.971	5.962	0.611	89
ROE	0.026	0.017	0.030	0.001	0.192	0.016	89
log_issue_amount	2.424	2.303	0.637	0.693	4.094	0.865	89

Table 4. Definition of Vaiables

Non-heavy pollution	_mean	median	spread_sd	_min	_max	_IQR	N
credit_spread_	1.775	1.370	1.167	0.060	5.160	1.650	385
ESG Score	76.277	76.010	5.515	55.900	88.480	8.240	385
Maturity_	4.091	5.000	1.286	1.000	10.000	2.000	385
Size_	10.650	10.610	0.631	9.167	12.380	0.810	385
Leverage	1.939	1.305	2.622	0.812	24.261	0.493	385
ROE	0.018	0.016	0.018	-0.046	0.135	0.018	385
log_issue_amount	1.998	2.079	0.847	-0.693	3.689	0.956	385

Correlation Analysis. This section analyses the linear association strength and direction between the dependent variable (credit spread, credit_spread) and the core explanatory variables (ESG composite score, ESG composite score × pollution interaction term), as well as the control variables (bond maturity, company size, leverage ratio, return on assets, and logarithm of bond issue amount), based on the Pearson correlation coefficient matrix. The Table 5 shows the core function of correlation analysis is to preliminarily identify patterns of association among variables, providing a foundational basis for subsequent regression model specification, while also identifying potential multicollinearity risks (typically, correlation coefficients with absolute values > 0.7 indicate severe multicollinearity).

Table 5. Correlation Matrics

Variables	credit_spread	ESG score	ESG score_Pollution	Maturity	Size	Leverage	ROA	log_issue_amount
credit_spread	1							
ESG score	-0.283***	1						
ESG score_Pollution	-0.248***	0.062***	1					
Maturity	-0.161***	0.096***	0.121***	1				
Size	-0.331***	0.362***	0.094***	0.080***	1			
Leverage	0.157***	-0.103***	-0.023***	-0.029***	-0.005***	1		
ROA	-0.095***	0.029***	0.164***	-0.058***	-0.092***	-0.263***	1	
log_issue_amount	-0.429***	0.255***	0.206***	0.143***	0.5917***	0.087***	0.062***	1

Correlation between Credit Spreads and Various Variables.

Core Explanatory Variables: Preliminary Indicators of ESG Effects. The ESG composite score exhibits a moderate negative correlation with credit spreads (-0.2837), indicating that superior ESG performance correlates with lower overall credit spreads. This preliminarily validates the expectation that 'ESG mitigates costs through risk reduction' and provides justification for including ESG main effects in regression models. The ESG composite score × pollution interaction term also exhibits a negative correlation (-0.2486), though with weaker intensity than the main effect. This arises because the positive correlation between ESG and spreads in polluting industries is diluted by the overall sample, indicating the need to define industry boundaries through grouping or interaction terms to avoid obscuring internal sectoral variations.

Screening for Multicollinearity Among Explanatory Variables. The absolute values of correlation coefficients among all explanatory variables are <0.7, indicating no significant multicollinearity risk. Weaker correlations among certain variables suggest subsequent regression analyses should employ 'robust standard errors' or 'fixed effects' to control for weak multicollinearity interference, without necessitating variable exclusion.

Core Findings and Regression Insights. Bond issuance volume, firm size, and composite ESG score emerged as the variables most strongly correlated with credit spreads. Their negative relationships provided preliminary expectations for regression coefficient signs. The weak correlation between interaction terms and credit spreads confirms that ESG's impact on spreads exhibits industry boundaries, necessitating the inclusion of industry interaction terms in subsequent regressions. No severe multicollinearity exists among variables, thus requiring no variable exclusion in model specification. Robust standard errors enhance model robustness. Overall, credit spreads are influenced by multiple factors including ESG performance, firm size, and issuance scale, exhibiting industry heterogeneity. Regression models incorporating interaction terms are necessary to further validate causal and heterogeneity mechanisms.

Model Estimation Results and Interpretation. The Table 6 reports the estimation results for the individual fixed effects model. The overall F-statistic for the model is 5.5533 ($p = 7.465 \times 10^{-6}$), significant at the 1% level, indicating the model specification is broadly valid. The adjusted R^2 is -0.9757, a characteristic feature of fixed-effects models. Individual fixed effects absorb substantial variation that does not change over time, reducing the proportion of explainable variation attributable to time-dependent factors. Consequently, the adjusted R^2 is negative, though this does not compromise the statistical validity of coefficient estimates.

Table 6. Estimation Results for the Individual Fixed-Effects Model

Variable	Estimate	Std. Error	t-value	Pr(>|t|)	Significance
ESG Score	0.0318	0.0102	-3.1067	0.002170	**
Maturity	0.0181	0.0276	-0.6542	0.513716	
Size	0.5315	0.1216	-4.3705	2.000e-05	***
Leverage	0.0137	0.0192	0.7148	0.475600	
ROA_B	9.0332	4.9862	-1.8116	0.071556	.
log_issue_amount	0.0976	0.0630	-1.5490	0.122983	
ESG Score：Pollution	0.0585	0.0218	2.6787	0.008013	**

Note: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

Core variable: Interaction effect between overall rating and pollution attributes.

*Main effect of composite score. Coefficient of -0.*0318 ($p < 0.01$), indicating that among non-polluting enterprises (as the 'composite score × non-polluting' interaction term was excluded, the main effect actually reflects the baseline effect for non-polluting firms), a one-unit increase in composite score significantly reduces the credit spread by 0.0318 units. This result aligns with prior analyses, validating the conclusion that 'improved composite scores reduce credit risk premiums for non-polluting enterprises' optimising the overall qualifications of non-polluting enterprises directly lowers their default risk, thereby diminishing the spread compensation demanded by investors.

*Interaction effect between composite score and pollution. The coefficient is 0.*0585 ($p < 0.01$), significantly positive, indicating that the impact of composite scores on credit spreads exhibits significant heterogeneity among polluting enterprises. The marginal effect of comprehensive score on credit spreads for polluting firms is: main effect + interaction coefficient =(-0.0318 + 0.0585 = 0.0267). This implies that for polluting firms, a one-unit increase in the composite score leads to a marginal increase of 0.0267 units in the credit spread (though this marginal effect was not individually tested for significance, the positive significance of the interaction term clearly distinguishes it from non-polluting firms).

This result further corroborates the 'risk discount effect of pollution attributes'. environmental policy risks (such as production restrictions and fines) and reputational risks faced by polluting enterprises may offset the positive effect of improved composite scores, causing the 'reducing effect' of composite scores on credit spreads to be entirely reversed for polluting enterprises. Market credit pricing for polluting enterprises focuses more on their environmental risks than on their overall qualifications alone.

*Enterprise Size. The coefficient is -0.*5315 ($p < 0.001$), significantly negative at the 1% level. This indicates that for every one-unit increase in enterprise size, the credit spread decreases significantly by 0.5315 units. This result reinforces the robustness of the 'scale effect' larger enterprises possess stronger risk resilience, more stable financing channels, and lower default risk, hence exhibiting narrower credit spreads. The effects of other control variables were not significant.

Heterogeneity Test. To test whether the impact of ESG composite scores on credit spreads is subject to industry boundaries, this section groups the sample based on a 'polluting industry' dummy variable (polluting = 1 for polluting industries, polluting = 0 for non-polluting industries) and constructs separate one-way individual fixed effects Within Models. This model controls for firm-level heterogeneity that does not change over time (e.g., environmental risk endowments in polluting industries, business model differences in non-polluting industries) to precisely identify the net effects of core variables and control variables on credit spreads across different industries.

The results of the two regression analyses are as Table 7 and Table 8:

Table 7. Regression analyses of heavily polluting enterprises

	Estimate	Std. Error	t-value	Pr(>|t|)	Significance
ESG Score	0.05624770	0.01807455	3.1120	0.003895	**
Maturity	0.09779447	0.05209670	1.8772	0.069637	.
Size	-0.12469722	0.10670416	-1.1686	0.251187	
Leverage	0.00039137	0.08030159	0.0049	0.996142	
ROA_B	1.67896694	7.82399616	0.2146	0.831447	
log_issue_amount	-0.15869029	0.15715549	-1.0098	0.320182	

Note: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Regression analyses of Non-heavily polluting enterprises

	Estimate	Std. Error	t-value	Pr(>|t|)	Significance
ESG Score	-0.013787	0.017584	-0.7840	0.434197	
Maturity	-0.124072	0.066672	-1.8609	0.064622	.
Size	-0.134339	0.088116	-1.5246	0.129378	
Leverage	0.035911	0.028204	1.2732	0.204811	
ROA_B	-26.011019	8.605992	-3.0224	0.002929	**

Note: *, **, and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel Data and Model Validation.

Heavily polluting industries. 51 enterprises (years 1–4, 89 observations), model F-value 3.637 (p=0.0073, 1% significance), R^2=0.405, adjusted R^2=-0.635 (individual fixed effects explain within-industry variance);

Non-heavily polluting industries. 217 enterprises (years 1–7, 380 observations), model F-statistic 6.217 (p=7.08×10^{-6}, 1% significance), R^2=0.192, adjusted R^2=-0.951 (significant firm heterogeneity, fixed effects absorb greater variance). Both models exhibit *no extreme outliers in residuals and stable distributions, satisfying panel regression assumptions.*

*Core Variable. Industry Heterogeneity in ESG Composite Scores. The high-pollution industries' ESG score improvements significantly widen credit spreads (coefficient 0.0562, p=0.0039, 1% significance). Each 1-unit increase in ESG score expands spreads by 0.0562 units. This stems from ESG improvements often arising from compliance expenditures (rather than substantive reductions in environmental risk), coupled with investor vigilance against "greenwashing" practices, leading to elevated risk premiums. But the non-high-pollution industries' ESG scores exert no significant impact on credit spreads, indicating weaker influence on risk perception*s.

Control Variables. Differentiated Effects Under Industry Risk Dominance. Regarding bond maturities, extended maturities in high-pollution industries correlate positively with widening spreads; conversely, non-high-pollution industries exhibit a negative correlation with narrowing spreads . Return on assets (ROA) exhibits a significant negative correlation with spreads only in non-high-pollution industries, with no significant effect observed in high-pollution industries.The logarithm of bond issuance size exhibited a negative correlation in both industry categories, with a more pronounced effect in non-high-pollution industries. The effect was insignificant in high-pollution industries. Meanwhile, firm size and leverage ratio had no significant impact on spreads for either industry category.

Robustness Testing. Robust standard e*rrors are an estimation method that can address heteroscedasticity (non-constant variance of error terms) that may exist in a model. Their core function is to provide m*ore reliable coefficient standard error estimates even when the classical assumption of 'homoscedasticity' is violated, thereby making t-tests and p-values more st*atistically valid.*

Robust standard error analysis provides a more reliable statistical inference foundation for the credit spread regression model. The results can be seen in Table 9.

Table 9. Robustness Testing Result

Variable	Robust Standard Error
Comprehensive Score	0.01050071
Pollution Industry	1.25663031
Maturity	0.02835406
Size	0.03767717
Leverage	0.02056809
ROA (Return on Assets)	3.79430009
log_issue_amount	0.06967481
Comprehensive Score:Pollution Industry	0.01626786

The core conclusions of the model (such as industry heterogeneity in ESG impacts and the significant negative effect of bond issuance size) remain valid under robust standard errors, demonstrating high reliability;

The coefficient estimates for asset return rates and industry pollution attributes exhibit significant uncertainty, necessitating further examination of their sample distribution characteristics in subsequent studies;

Overall, the model's estimation results exhibit a certain degree of robustness to heteroskedasticity, providing a reliable basis for understanding the factors influencing credit spreads in 2019.

5 Conclusion

5.1 Research Findings

This study innovatively analyses the impact of ESG ratings on bond financing costs through three distinct channels, offering a relatively comprehensive perspective. Building upon robust model stability and correlation analysis that validates the reliability of our conclusions, we draw the following findings:

Non-polluting Industries. Enhanced ESG ratings reduce credit spreads, primarily through 'risk mitigation + information optimisation'

In non-polluting industries (e.g., information technology, modern services), a one-unit increase in the composite ESG score significantly reduces the credit spread. High ESG performance mitigates default risk through enhanced corporate governance and supply chain stability, while high-quality ESG disclosure reduces information asymmetry. Combined with ESG fund allocation preferences, this creates a positive feedback loop: 'ESG improvement → spread reduction'.

Polluting Industries. ESG Enhancement Increases Credit Spreads, Primarily Due to 'Cost Perception + Greenwashing Concerns'

In polluting industries (e.g., chemicals, steel).The credit spreads increase with the ESG score. Markets interpret ESG improvements as increased environmental compliance costs (crowding out debt servicing cash flows). Given past 'greenwashing' issues, investors question the authenticity of such information, necessitating higher spreads to hedge risks.

Industry Interaction Validation. Polluting Attributes Offset ESG's 'Cost Reduction Effect'

The industry interaction term indicates that pollution attributes fully offset ESG's spread-reducing effect. In non-polluting industries, ESG value focuses on 'governance and disclosure,' directly reducing risk. Polluting industries must first convert ESG investments into 'reduced environmental risk + green returns'; otherwise, ESG enhancements may actually increase financing costs, highlighting the core moderating role of industry pollution attributes.

However, limitations remain. Firstly, this study utilises general corporate bonds issued by Shanghai and Shenzhen A-share listed companies from 2017 to 2023 as research samples. Yet, due to missing ESG data from earlier years, the selected sample may suffer from representativeness issues, potentially introducing bias into empirical findings. Secondly, as current ESG ratings in China primarily target listed companies, existing ESG rating data only covers listed entities, with no access to relevant data for unlisted companies. Consequently, issues concerning unlisted firms cannot be examined. Finally,

China's ESG rating market currently lacks unified standards and a regulated rating system. Different agencies employ varying data sources, rating metrics, and methodologies when conducting ESG assessments. This leads to potential biases in third-party rating outcomes, which may compromise the accuracy of research findings.

5.2 Policy Recommendations

Enterprises: Focus on ESG Materiality by Industry. Polluting industries must set carbon reduction targets, enhance environmental internal controls, quantify and disclose carbon emissions/environmental investment returns, and introduce third-party verification to avoid mere score-chasing. Non-polluting industries should optimise board independence, manage supply chain responsibilities, and consider issuing sustainability-linked bonds that tie ESG targets to coupon rates to attract ESG funds and reduce costs.

Regulators: Refine Differentiated ESG Governance Systems. Establish sector-specific disclosure standards: mandate environmental liability disclosure and environmental investment return metrics for polluting industries; clarify 'governance-financial risk' guidance for non-polluting sectors. Strictly combat greenwashing and promote standardised ESG verification. Additionally, publish sector-specific ESG-credit spread reference coefficients and offer preferential terms for ESG bond pledges. Channel capital towards enterprises implementing substantive improvements, fostering a virtuous cycle in polluting industries: From ESG enhancement to risk reduction so cost reduction could be the result.

References

1. Dimitrios, N., Orestes, V.: Exploring the predictive ability of cost asymmetry on bankruptcy.The European Journal of Finance,31(5),553-593.(2025).
2. Myers, S. C., Majluf, N. S.: Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics, 13(2), 187–221. (1984).
3. Smith, C. W., Warner, J. B.: On financial contracting: An analysis of bond covenants. Journal of Financial Economics, 7(2), 117–161. (1979).
4. Ahmet, K., Neslihan, O., Junyang, Y.: Uncertainty and loan pricing for public and private firms: evidence from the Brexit referendum.The European Journal of Finance,31(8),1018-1041.(2025).
5. Berg, F., Fabisik, K., Sautner, Z.: ESG, material credit events, and credit risk. Journal of Applied Corporate Finance, 32(2), 22–37. (2020).

6. Huang, Z., Huang, J., Chen, H.: ESG information disclosure, vague rhetoric and cost of debt financing. Journal of Financial Research, (11), 130–149. (2020).
7. Li, H., Wang, C., Wang, S.: Can ESG performance reduce the cost of debt financing?——A dual perspective based on information disclosure and third-party rating. Securities Market Herald, (02), 36–47. (2023).
8. Wang, Y., Feng, J., Zhang, G.: Can a social responsibility “model” play a financing role? Policy experiments from the ESG star list. China Economic Quarterly, 23(3), 1121–1140. (2023).
9. Cai, Q.: Research on the impact of ESG rating on the cost of corporate bond financing [Master’s thesis, Anhui University of Finance and Economics]. (2024).
10. Liu, M., Tian, Y., Zhou, Y.: Corporate ESG performance, credit rating, and bond financing cost. Commercial Accounting, (24), 73–78. (2024).
11. Niu, B. Y.: "Corporate ESG Performance and Bond Financing Costs: From the Perspective of Credit Spreads," Engineering Economy, vol. 32, no. 06, pp. 4-27. (2022).