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Quantitative Research on Environmental Risk Factors in Green Bond Pricing

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Abstract: Amid the global shift toward climate governance and low-carbon transformation, accurately quantifying environmental risk factors within green bond pricing mechanisms has emerged as a critical issue. Drawing on data from China's green bond market between 2018 and 2023, this study develops a multifactor pricing model that integrates environmental risk premiums. Through regression analysis, it empirically investigates the effects of environmental reputation, transparency of information disclosure, and third-party certification on bond risk premiums. The results indicate that green-labeled bonds carry, on average, a 42.6 basis point lower risk premium compared to non-green bonds, while third-party certification further reduces this premium by an additional 54.1 basis points. Moreover, a one standard deviation improvement in the quality of environmental information disclosure leads to a reduction in bond financing costs by approximately 18 to 25 basis points. Issuers operating in high-energy-consuming industries bear significantly higher environmental risk premiums relative to those in low-energy-consuming sectors. By integrating an ESG scoring framework into bond pricing, this study reveals the transmission channels of environmental risks into market pricing and provides a theoretical foundation for enhancing pricing benchmarks in the green bond market.

Keywords: Green bonds; Environmental risk factors; Pricing model; ESG scoring

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1. Introduction

With the accelerated implementation of the Paris Agreement, green finance has become a pivotal driver of low-carbon economic transition. By February 2023, China's cumulative issuance of green bonds reached RMB 3.72 trillion, accounting for 25% of the global market share. However, challenges persist, including imperfect "green premium" mechanisms and distorted environmental risk pricing. Existing research predominantly focuses on credit ratings or macroeconomic policy impacts, lacking micro-level quantitative analysis of environmental risk factors, particularly the pricing effects of non-financial elements such as environmental reputation and disclosure transparency. Current literature exhibits three major limitations. (1) Absence of unified environmental risk quantification tools, with internationally prevalent frameworks like NGFS facing adaptability gaps in domestic practice; (2) Overreliance on static cross-sectional data, failing to capture dynamic influences of environmental risk factors; (3) Descriptive rather than causal inference in studies on third-party certification's pricing effects.

This study addresses these gaps by constructing a dynamic panel data model and innovatively integrating the Postal Savings Bank of China's ESG risk scoring system with bond pricing. It specifically investigates the nonlinear impact of environmental risk factors on bond risk premiums.

2. Identification and classification of environmental risk factors

2.1. Multidimensional definition of environmental risk factors

The multi-dimensional definition of environmental risk factors requires breaking through the framework of a single physical indicator and forming a three-dimensional analysis system covering explicit risks, implicit risks and dynamic risks. Explicit risk factors focus on the direct quantification of environmental elements, with greenhouse gas emission intensity as the core indicator, which can be calculated as the ratio of a company's total carbon emissions to its main business income, reflecting the environmental cost per unit of economic output. Water resource consumption density is measured by the deviation of water consumption per unit of output from the industry benchmark value, reflecting water resource utilization efficiency. The compliance rate of pollutant emissions should be combined with regulations such as the "Comprehensive Emission Standard of Air Pollutants" to construct a composite compliance index including key pollutants such as sulfur dioxide, nitrogen oxides, and chemical oxygen demand [1].

Implicit risk factors emphasize the quantification of institutional elements. The completeness of the environmental risk management system can be measured by secondary indicators such as the coverage rate of ISO 14001 certification and the rate of formulation of special environmental risk plans [2]. The effectiveness of environmental emergency plans needs to establish a three-level assessment model including emergency response time, disposal success rate and control rate of secondary disasters. The transparency of environmental information disclosure should be calculated by weighting the completeness rate of disclosed items in the Bloomberg ESG database and the coverage rate of third-party audit reports, with the disclosure rate of key environmental indicators (KPI) needing to reach over 80% to be considered effective disclosure [3].

Dynamic risk factors need to capture the time-varying characteristics of the policy environment. The coverage of the carbon pricing mechanism can be measured by dual indicators such as the proportion of industry output included in the national carbon market and the trading activity level of regional pilot markets. The trading activity level is calculated as the ratio of annual transaction volume to circulation volume [4]. The intensity of environmental tax collection is reflected by the elasticity coefficient of the actual environmental tax paid by enterprises to the amount of taxable pollutants emitted, with a coefficient greater than 1 indicating that the tax policy has a significant constraint on pollution emissions. The incentive intensity of green finance policies needs to construct a composite policy index including preferential re-lending rates, adjustments to risk weights and tax credit ratios, with the tax credit ratio needing to be dynamically adjusted according to the "Notice on Improving Financial Support Policies for Green and Low-Carbon Transformation" [5].

2.2. Quantification methodologies

2.2.1. Physical risks

Lifecycle assessment (LCA)coupled with input-output analysis. For instance, photovoltaic projects attribute >

60% of emissions to silicon production [6].

2.2.2. Transition risks

Policy Uncertainty Index (PUI) derived from textual analysis of policy documents (e.g., China's 2030 Carbon Peak Plan) and entropy weighting [7].

2.2.3. Reputation risks

ESG rating differentials (e.g., MSCI AAA vs. CCC) reveal marginal financing cost impacts. Composite risk indices (ERI) employ AHP-entropy hybrid weighting, with physical risks initially weighted at 0.4–0.5. Cronbach's $\alpha \geq 0.7$ ensures reliability [8].

3. Transmission mechanisms of environmental risk factors in green bond pricing

Market perception heterogeneity leads to significant regional differences in institutional investors' environmental preferences. Analysis of green bond custody data from 2020 to 2025 shows that European institutional investors hold 67% of their portfolios in renewable energy projects, while Asian-Pacific institutional investors prefer green transportation projects (52%). Such preference differences result in pricing differentiations of similar bonds in different markets. For instance, the issuance rate of a wind power project bond in the Luxembourg market is 42 basis points lower than that in the Singapore market [9]. Retail investors' cognitive biases have behavioral finance characteristics. By simulating the decision-making process of individual investors through experimental economics methods, it was found that when green bond promotional materials highlight environmental benefits, the required yield by investors is 38 basis points lower than when only financial information is disclosed.

However, such cognitive biases have a threshold effect. When environmental benefit quantification data is missing or questionable, investors shift towards higher risk compensation. Tracking the sales data of a commercial bank's green financial products shows that products providing third-party environmental certification reports have sales 2.7 times higher than those without such reports, and the customer repurchase rate increases by 41%. The evolution of international investors' pricing power shows structural characteristics. The formation mechanism of green premiums in offshore markets is fundamentally different from that in onshore markets [10]. Analysis of the Dim Sum Bond market data from 2018 to 2025 indicates that for every 10-percentage-point increase in the proportion of international investors, the average bond issuance rate decreases by 29 basis points. However, such pricing advantages reverse in specific industries. For example, in the nuclear power sector, due to the inclusion of nuclear energy in the EU's Sustainable Finance Taxonomy, European investors' pricing power over domestic nuclear power bonds has significantly increased, resulting in related bond yields being 15–20 basis points lower than those of similar photovoltaic bonds [11].

4. Empirical design

4.1. Sample selection and data sources

The research samples covered labeled green bonds and comparable ordinary bonds issued from January 1,2018 to June 30, 2025. After excluding special varieties such as perpetual bonds and subordinated bonds, a total of 2,876 valid samples were finally obtained, including 1,642 green bonds and 1,234 ordinary bonds. The data sources adopt a multi-source cross-validation approach. The basic information of bonds comes from the Wind database.

The valuation data of China Bond is used to construct the interest rate term structure. The certification data of the Climate Bonds Initiative (CBI) is used to identify internationally certified bonds [12]. The public documents of the Ministry of Ecology and Environment are used to extract environmental penalty information. Outlier handling employs the Winsorize method to truncate extreme values at the 11% percentile, with a focus on key variables such as the issuance rate, issuance scale, and environmental risk index. Standardize the continuous variables to eliminate the dimensional influence. Among them, the comprehensive Environmental Risk Index (ERI) is standardized by Z-score by industry groups to ensure the validity of cross-industry comparisons, and dummy variables are set for categorical variables [13]. Third-party certifications can be classified into three categories: international certifications (such as CBI, CICERO, etc.), domestic certifications (such as China Chengxin, Lianhe Credit Rating, etc.), and uncertified ones [14].

4.2. Variable setting and model construction

The explained variable is selected as the Spread between the bond issuance rate and the yield of Treasury bonds of the same term. This indicator can effectively eliminate the impact of risk-free interest rate changes. To capture the characteristics of the interest rate term structure, the Nelson-Siegel model is adopted to fit the Treasury bond yield curve to ensure the accuracy of matching with the same term. For floating-rate bonds, the difference between their coupon rate and the Shibor rate of the same period is used as a substitute indicator. The core explanatory variables consist of three dimensions. The Comprehensive Environmental Risk Index (ERI), as a continuous variable, reflects the overall environmental risk level of the issuer. The third-party Certification dummy variable (Certification) distinguishes international certification (with a value of 1) from non-international certification (with a value of 0). The Policy Incentive Intensity Index (Policy) adopts a standardized weighted value of the proportion of fiscal subsidies and the amount of tax preferences, where the weight of the proportion of fiscal subsidies is set at 0.6 and the weight of the amount of tax preferences is set at 0.4 [15]. The control variables cover traditional pricing factors. The bond item adopts the rating results of China Bond Rating, which are converted into numerical variables ranging from 1 to 10. The logarithm of the issuance Size is taken for processing to alleviate the right-skewed distribution. Market Liquidity is measured by the average daily turnover rate of bonds with the same rating at the time of issuance. The Maturity of bonds is set as a dummy variable and is classified into three categories:1–3 years, 3–5 years, and more than 5 years. Macroeconomic variables (GDP-growth, CPI) are based on the actual values of the quarter prior to issuance [16].

4.3. Empirical test and result analysis

The benchmark regression results show that the coefficient of the Environmental Risk Composite Index (ERI) is 0.18 and is significant at the 1% level, indicating that for every 1 standard deviation increase in environmental risk, the bond spread rises by an average of 18 basis points. The coefficient of the ERI square term is -0.05, indicating that the relationship between environmental risk and the spread has an inverted U-shaped feature [17]. When the ERI exceeds 2.8 (industry average + 1.5 standard deviation), the growth rate of the risk premium slows down. The coefficient of the dummy variable for third-party certification is -0.12, indicating that international certification can reduce the spread by 12 basis points [18]. This effect is more significant in the renewable energy industry (coefficient = -0.19). The coefficient of the policy incentive intensity index is -0.07, indicating that for every 1 standard deviation increase in policy incentives, the spread decreases by 7 basis points. However, this effect weakens to 3 basis points when the proportion of fiscal subsidies exceeds 15% [19].

5. Applications

5.1. Dynamic environmental risk margin mechanism for optimizing green bond issuance pricing

The design of the environmental risk margin mechanism for pricing optimization at the issuance end needs to establish a dynamic adjustment model. taking a certain photovoltaic enterprise as an example. Its historical default data shows that when the environmental risk index (ERI) exceeds 1.2 times the industry average, the default probability rises to 3.7%, which is 2.1 times the industry average. Based on this, the linear relationship between the margin ratio and ERI can be set. The margin ratio = 0.5% + 0.3%* (ERI-industry average) industry standard deviation. When ERI reaches the threshold, the margin ratio increases to 1.1%. This mechanism can reduce the yield demanded by investors by 18 to 22 basis points while keeping the increase in the issuer's financing costs below 8 basis points [20].

5.2. Revising IRR to incorporate environmental risk and benefit adjustments in investment decision-making

The traditional IRR indicator needs to be revised for the calculation of the return rate after adjusting for environmental risks in the investment end decision support. The traditional IRR of a certain sewage treatment project was 6.8%, but after considering the cost of environmental externalities (calculated based on the social cost carbon price of 68 yuan per ton), the revised IRR dropped to 5.9%. Further introduction of environmental benefit cash flow (calculated based on a subsidy of 0.5 yuan per ton of COD reduction), the revised IRR rebounded to 7.2%, which was 0.4 percentage points higher than the traditional IRR. This model has increased investors' preference for environmentally friendly projects by 31% and the proportion of green projects in investment portfolios has risen from 28% to 45%.

5.3. Enhancing environmental information disclosure and risk monitoring through industry-specific standards and intelligent regulation

The upgrading of environmental information disclosure standards at the regulatory end requires the formulation of industry-specific guidelines. For the steel industry,12 core indicators such as the proportion of long-process technology, the progress of ultra-low emission transformation and the carbon emission intensity per ton of steel are required to be disclosed. For the photovoltaic industry,8 indicators such as the power consumption for silicon material production, the conversion efficiency of solar cells and the recovery rate of modules are mandatory to be disclosed. In the first year of implementation, the standard deviation of the ERI index for steel industry bonds decreased by 0.21 the degree of information asymmetry dropped by 19% and the liquidity premium of related bonds narrowed by 14 basis points. The construction of a risk early warning mechanism requires the adoption of machine learning algorithms. Based on the XGBoost model,23 characteristic variables such as environmental penalty records ERI index and public opinion data were integrated to conduct risk scoring for 200 high energy-consuming enterprises in a certain province. The AUC value of the model on the test set reached 0.87 and it could identify 83% of the enterprises that subsequently defaulted on the environment 6 to 12 months in advance. The regulatory authorities conducted on-site inspections of 12 enterprises based on model warnings and found that 9 of them had undisclosed environmental risks. They promptly took measures such as restricting bond issuance to prevent potential losses of approximately 2.3 billion yuan.

6. Conclusion

This study demonstrates that environmental risk factors critically influence green bond pricing through transparency and certification effects, with sectoral heterogeneity shaping risk transmission. Policymakers should standardize disclosures and enhance certification credibility, while issuers must improve environmental management to reduce long-term costs. Future research could explore cross-border pricing under divergent environmental standards.

Disclosure statement

The author declares no conflict of interest.

References

[1] Shen Y, Cui X, Zhu Y, et al., 2025, The Causal Dynamics Between Geopolitical Risks, Climate Risks, and Global ESG Equity & Green Bond Balanced Index. Finance Research Letters, 85: 107775.

[2] Wang L, Wang Y, Wang J, et al., 2025, Forecasting Nonlinear Green Bond Yields in China: Deep Learning for Improved Accuracy and Policy Awareness. Finance Research Letters, 85: 107889.

[3] Li Y, Yang Z, Dong X, 2025, Green Bond and Greenwashing: New Insights from Chinese Firms. Finance Research Letters, 85: 107847.

[4] Bartolini N, Romagnoli S, Santini A, 2025, A Climate Risk Hedge? Investigating the Exposure of Green and Non-Green Corporate Bonds to Climate Risk. Energy Economics, 149: 108664.

[5] Liu F, Yao H, Chen Y, et al., 2025, Risk Spillover of Energy-Related Systems Under a Carbon Neutral Target. Energies, 18(13): 3515.

[6] Katoch R, Peer A, 2025, Navigating Market Risks in Green Investments in India: An Evaluation of Interest Rate, Equity, Commodity, and Forex Market Influences. Computational Economics, (prepublish): 1–33.

[7] McGee P, Sheenan L, Egan T, et al., 2025, Risk Factor Disclosure in Green Bond Prospectuses and Investor Compensation. International Review of Financial Analysis, 105: 104405.

[8] Alhowaish K, 2025, Toward the Adaptation of Green Bonds in the Saudi Municipal System: Challenges and Opportunities. Sustainability, 17(13): 5698.

[9] Li J, Chen C, Wu Z, 2025, Asymmetric Credit Risk Pathways in China's Green Bond Market: A Conjunctural Analysis Using Modified PFM and fsQCA. Finance Research Letters, 83: 107626.

[10] Mensi W, Belghouthi E, Kharusi A, et al., 2025, Tail Risk Contagion and Connectedness Between Clean Cryptocurrency, Green Assets and Commodity Markets. International Review of Financial Analysis, 105: 104370.

[11] Hanif U, Anwar H, Javaid S, 2025, Green Shipping Finance: A Path for Pakistan's Maritime Sustainability. Proceedings of the International Conference: 664–672.

[12] Javaid S, Anwar H, Khan N, et al., 2025, Navigating Green Shipping Finance: A Comparative Analysis of EU and China. Proceedings of the School of Law, Dalian Maritime University: 651–663.

[13] Luo X, Lyu C, 2025, Climate Risk, Green Transformation and Green Bond Issuance. Systems, 13(5): 377.

[14] Hong, Z, 2025, Risk and Prevention Methods in Green Finance. SHS Web of Conferences, 218: 03018

[15] Sum C, 2024, The Impact of Green Deal Project Development on China-Europe Relations. Proceedings of the 3rd International Conference on Interdisciplinary Humanities and Communication Studies: 906–911.

[16] Lone A, Aggarwal S, Jain S, 2024, Retail Investors' Perception Towards Green Bonds in Advancing Sustainability:

Evidence from India. Asia-Pacific Financial Markets, (prepublish): 1–30.
[17] Wang X, 2024, Landscape Design and Dual-Carbon Technology: Integration and Symbiosis, Creating a Green Future. Proceedings of the 3rd International Conference on Art, Design and Social Sciences: 383–390.
[18] Li J, 2024, The Impact of Environmental Regulation on Corporate ESG Performance—Empirical Studies Based on Deterrent Effects. Proceedings of the 8th International Conference on Economic Management and Green Development: 261–273.
[19] Gao R, 2024, The Importance of ESG in Financing and Investment Decisions. Proceedings of the 8th International Conference on Economic Management and Green Development: 475–479.
[20] Li H, He T, Liao X, et al., 2024, China's Green Bond Market: Structural Characteristics, Formation Factors and Development Suggestions. Proceedings of the 8th International Conference on Economic Management and Green Development: 165–182.