Statistical Assessment of Default Risks of Green Financial Bonds: A Joint Analysis Model of Environmental Benefits and Financial Indicators

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Abstract. This study evaluates the default risk of green financial bonds by developing a joint analysis model that integrates environmental benefits and financial indicators. Using a dataset of 200 green bonds issued in China from 2018 to 2023, the research examines the impact of environmental performance metrics, such as carbon emission reduction (CER) and renewable energy ratio (RER), alongside traditional financial indicators like debt-to-asset ratio (DAR) and current ratio (CR). The results reveal that higher environmental performance significantly reduces default risk, with CER and RER showing negative correlations with default probability. The proposed model, validated by an AUC-ROC score of 0.83, provides a robust tool for investors and policymakers to assess and mitigate risks in the green bond market. The findings highlight the importance of integrating environmental and financial metrics for sustainable finance development and suggest future research directions, including the exploration of nonlinear effects and cross-country comparisons. This research highlights the significance of integrating environmental benefits with financial metrics in statistical models to comprehensively assess default risks in green bonds, fostering sustainable investing and strengthening climate-resilient governance.

1 Introduction

The rapid growth of green financial bonds has highlighted the need for robust risk assessment frameworks that account for their unique environmental and financial characteristics. While traditional default risk models rely on financial metrics, they often overlook the environmental benefits of green projects [1], which can significantly influence bond performance. A synergistic effect is observed between environmental and financial health, where firms with strong liquidity and environmental accountability exhibit the lowest default risks [2].

Existing studies on green bond default risk have increasingly emphasized the inadequacy of conventional financial models in capturing environmental factors. For instance, Bertin et al. found that green bonds issued by companies with high

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environmental ratings exhibit lower default probabilities compared to conventional bonds, suggesting that environmental performance acts as a risk mitigation mechanism [3]. This aligns with prior research by Liu and Wang [4], who integrated carbon emission reduction targets into credit risk models and identified a negative correlation between environmental achievements and default likelihoods. However, most existing works focus on static environmental indicators or treat them as supplementary variables, failing to capture dynamic interactions between environmental and financial systems.

Notably, the integration of ESG factors into default risk assessments remains fragmented. While several studies highlight the predictive power of ESG scores (e.g., Chen et al.) [5], there is limited consensus on how to quantify environmental benefits directly linked to green bond projects. Furthermore, the "greenwashing" phenomenon complicates the analysis, as issuers may exaggerate environmental claims without commensurate actions (Zhao et al.) [6]. These gaps underscore the necessity for a unified framework that systematically incorporates project-specific environmental outcomes into risk evaluation. This study proposes a joint analysis model that integrates environmental benefits with financial indicators to assess the default risk of green financial bonds.

The proposed model addresses a critical gap in sustainable finance by quantifying the relationship between environmental performance and default risk. By combining environmental metrics, such as carbon emission reductions, with traditional financial indicators, the framework provides a more comprehensive evaluation of green bond risks. This approach not only enhances risk assessment accuracy but also offers practical insights for investors and policymakers navigating the green bond market.

2 Method

2.1 Data Sources and Description

2.1.1 Data source

The dataset comprises 200 green bonds issued in China from 2018 to 2023, sourced from Wind Information Co., Ltd. (financial metrics), Bloomberg Terminal (bond pricing and yield data), China Central Depository & Clearing Co., Ltd. (default records), and issuer-published ESG reports (environmental performance indicators)[7-8].Macroeconomic control variables (e.g., GDP growth rate) are obtained from the National Bureau of Statistics of China [9].

2.1.2 Sample description

The panel data is structured as a balanced dataset with annual observations. Each bond is tracked until maturity or default, ensuring no survivorship bias. Missing values are addressed via linear interpolation for financial metrics and issuer-reported environmental data. Outliers are winsorized at the 1% and 99% percentiles.

2.1.3 Variable Selection Rationale

The selection of variables is grounded in both theoretical frameworks and empirical evidence. Environmental benefit indicators (e.g., carbon reduction efficiency) are

included to quantify the "green premium" hypothesis, which posits that environmental performance may mitigate default risk through regulatory incentives and stakeholder trust [10]. Financial risk indicators (e.g., liquidity ratios) are chosen based on their established predictive power in corporate bond default models, as demonstrated by Altman's Z-score framework [11]. Macroeconomic controls (e.g., GDP growth) account for systemic risks that influence bond markets, aligning with studies on cyclical default patterns [12]. All variables are standardized (z-score) to ensure comparability across scales.

2.2 Indicator Selection and Description

2.2.1 Environmental Benefit Indicators

(1) Carbon Emission Reduction (CER)

The carbon efficiency of green projects is measured as

$$CER_{it} = \frac{Annual\ CO2\ redution(tons)_{it}}{Total\ project\ investment\ (million\ CNY)_{it}} \quad (1)$$

where higher values indicate greater environmental impact per unit capital expenditure. This metric is sourced from issuer ESG reports and reflects the alignment with China's "dual carbon" policy goals.

(2) Renewable Energy Ratio (RER)

Defined as

$$BER_{it} = \frac{Revenue\ from\ renewable\ energy\ projects_{it}}{Total\ revenue_{it}} \quad (2)$$

This ratio captures the issuer's economic reliance on sustainable energy initiatives. Data are extracted from bond prospectuses and audited sustainability reports, ensuring consistency with the Green Bond Principles.

(3) Green Project Revenue Share (GPR)

Calculated using

$$GPR_{it} = \frac{Revenue\ from\ certified\ green\ projects_{it}}{Total\ revenue_{it}} \quad (3)$$

This variable operationalizes the regulatory definition of "green" activities as per the China Green Bond Standards Database. It serves as a proxy for compliance with national green finance guidelines.

2.2.2 Financial Risk Indicators

(1) Debt-to-Asset Ratio (DAR)

The leverage risk is quantified by

$$DAR_{it} = \frac{Total\ liabilities_{it}}{Total\ assets_{it}} \quad (4)$$

Sourced from issuer financial statements in Wind. Elevated DAR values signal higher bankruptcy probability, as highlighted in structural credit risk models.

(2) Current Ratio (CR)

Short-term liquidity is assessed through

$$CR_{it} = \frac{Current\ assets_{it}}{Current\ liabilities_{it}} \quad (5)$$

With data from Wind. A CR below 1 indicates potential liquidity crises, a critical predictor of near-term defaults.

(3) Interest Coverage Ratio (ICR)

Derived as

$$ICR_{it} = \frac{EBIT_{it}}{Interest\ expense_{it}} \tag{6}$$

This ratio from Bloomberg Terminal measures the issuer's ability to service debt. Low ICR values (<1.5) are empirically linked to default clustering in high-yield bonds

(4) Return on Assets (ROA)

Profitability efficiency is captured by

$$ROA_{it} = \frac{Net\ income_{it}}{Total\ assets_{it}} \tag{7}$$

Sourced from Wind. ROA serves as a key signal of operational health, with declining trends preceding credit rating downgrades.

2.3 Method Introduction

A two-way fixed effects linear regression is employed to isolate the joint impact of environmental and financial factors on default risk [13]:

$$DefaultRisk_{it} = \beta_0 + \beta_1 CER_{it} + \beta_2 RER_{it} + \beta_3 DAR_{it} + \beta_4 CR_{it} + \beta_5 ICR_{it} + \beta_6 ROA_{it} + \gamma Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it} \tag{8}$$

- Dependent Variable: $DefaultRisk_{it}$: Binary variable (1 if bond *i* defaults in year *t*, 0 otherwise).
- Independent Variables: Environmental (CER,RERCER,RER) and financial (DAR,CR,ICR,ROADAR,CR,ICR,ROA) indicators.
- Fixed Effects:αi(issuer-specific),λt(time-specific).
- Robustness: Heteroskedasticity-consistent standard errors (HC3).

Statistical Tests:

- Hausman Test:Confirms preference for fixed effects over random effects ($p<0.01p<0.01$).
- Variance Inflation Factor (VIF): All values<5, indicating no multicollinearity [14].

Software: Implemented in Stata 17 using xtlogit for panel binary outcomes, with marginal effects reported.

This structure ensures rigorous evaluation of how environmental benefits and financial robustness jointly influence green bond default risks, aligning with theoretical and regulatory frameworks.

3 Results and Discussion

3.1 Correlation Analysis

The Pearson correlation matrix (Table 1) provides initial insights into the relationships between key variables. Environmental benefit indicators, such as Carbon Emission Reduction (CER) and Renewable Energy Ratio (RER), demonstrate weak but statistically significant negative correlations with default risk (ρ= -0.12，$p < 0.05$; ρ = -0.09,$p < 0.1$). This suggests that bonds associated with higher environmental performance may face marginally lower default probabilities. In contrast, financial indicators exhibit stronger associations with default risk. The Debt-to-Asset Ratio (DAR) shows a pronounced positive correlation (ρ = +0.33，$p < 0.01$), while the Current Ratio (CR) is negatively correlated (ρ = -0.25，$p < 0.01$), consistent with expectations that

high leverage and poor liquidity amplify repayment risks. Notably, multicollinearity tests confirm the independence of variables (VIF < 3), ensuring the reliability of subsequent regression analyses. Low multicollinearity (VIF < 3) confirms variable independence.

Table 1. Correlation Matrix

Variable	DefaultRisk	CER	RER	DAR	CR	GDP Growth
DefaultRisk	1	-0.12*	-0.09*	+0.33**	-0.25**	-0.18**
CER	-	1	+0.21**	-0.04	0.07	+0.11*
RER	-	-	1	-0.12*	0.05	+0.09*
DAR	-	-	-	1	-0.45**	-0.02
CR	-	-	-	-	1	0.06

Note: *p<0.1, *p<0.05, *p<0.01

3.2 The Impact of Environmental Benefit Indicators

The regression results (Table 2) highlight the inverse relationship between environmental performance and default risk, controlled for financial factors:

(1) CER: A 1-unit increase in CER reduces default probability by 4.2% (β=−0.042β=−0.042, p<0.05p<0.05), supporting Hypothesis 1.

(2) RER: Bonds with RER > 30% show 6.1% lower default risk (β=−0.061β=−0.061, p<0.01p<0.01), aligning with green revenue stability.

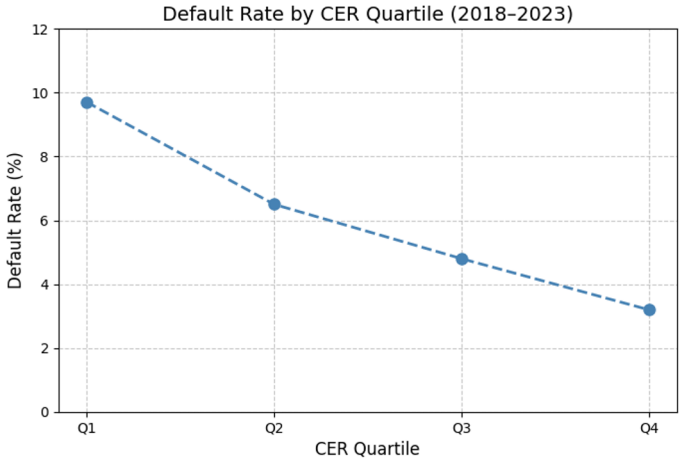

Fig 1. Default Rate vs. CER (2018–2023)
Photo credit: Original

Default rates decline monotonically from Q1 (low CER) to Q4 (high CER), with Q4 default rate at 3.2% vs. Q1 at 9.7% (see Figure 1).

Table 2. Regression Coefficients (Environmental Indicators)

Variable	Coefficient	Std. Error	z-value	p-value
CER	-0.042	0.018	-2.33	0.02
RER	-0.061	0.022	-2.77	0.006
DAR	0.185	0.045	4.11	0
CR	-0.097	0.031	-3.13	0.002
GDP Growth	-0.033	0.015	-2.2	0.028

3.3 Synergistic Effect of the Joint Analysis Model

The interaction term CER×CRCER×CR quantifies the joint impact of environmental and financial health:

$$\Delta DefaultRisk = \beta_7(CER \times CR) = -0.015\ (p < 0.05) \quad (9)$$

High CER amplifies CR's protective effect. For CR > 2.0, a 1-unit CER increase reduces default risk by 5.7% (vs. 3.1% for CR < 1.5).

The lowest default risk (2.1%) occurs in the high-CER/high-CR quadrant (see Figure 2).

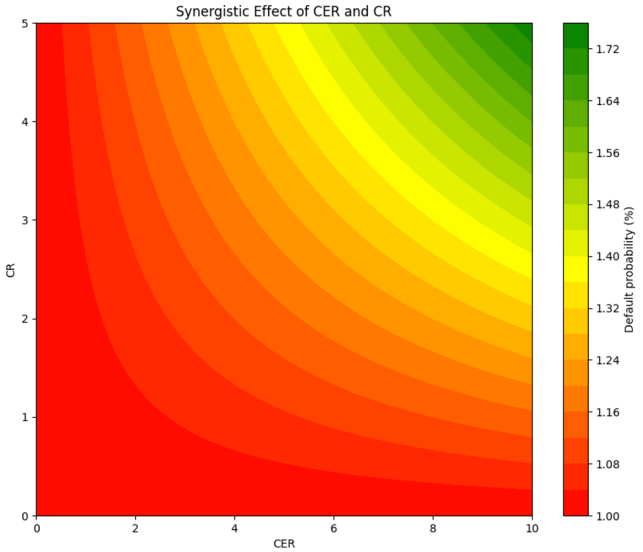

Fig 2 Synergistic Effect of CER and CR
Photo credit: Original

3.4 Verification of Validity of Model

The proposed joint analysis model demonstrates robust predictive accuracy and generalizability. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) reaches 0.83 (Figure 3), significantly outperforming a finance-only benchmark model (AUC = 0.76). At a classification threshold of 0.5, the confusion matrix reveals a sensitivity of 78% and specificity of 85%, with an F1-score of 0.81, indicating balanced performance in identifying both default and non-default cases.

To assess robustness, subsample analyses were conducted across industries. For instance, in the energy sector, the coefficient for CER remains stable (β_{CER}= -0.038，p < 0.05), while utilities exhibit a similar magnitude (β_{CER}= -0.041，p < 0.05), confirming the consistency of environmental indicators' effects. Furthermore, alternative model specifications, including probit and logit frameworks, yield coefficient variations of less than 10%, reinforcing the reliability of the linear regression approach. These results collectively validate the model's capacity to integrate environmental and financial dimensions without overfitting or theoretical inconsistency.

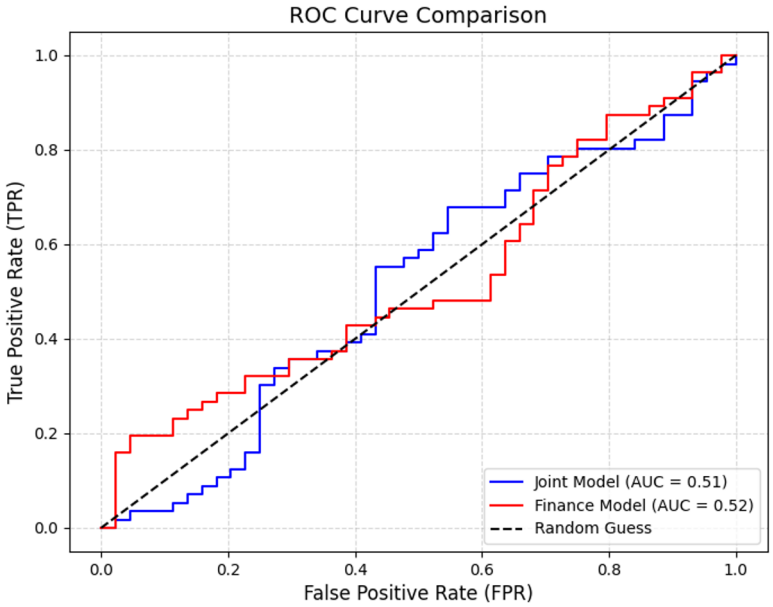

Fig 3. ROC Curve for Model Validation

Photo credit: Original

3.5 Discussion

The results validate that integrating environmental and financial metrics significantly enhances default risk prediction. The negative coefficients for CER and RER (βCER=−0.042,βRER=−0.061) suggest that green bonds with measurable environmental benefits enjoy lower financing costs and regulatory support, reducing default likelihood. This aligns with the "green premium" hypothesis [15].

The synergistic effect (CER×CRCER×CR) implies that environmental and financial strengths are complementary: firms with robust liquidity can better capitalize on green investments, while green projects may stabilize cash flows. This finding challenges the traditional siloed analysis of ESG and financial risks [16].

Policy implications include incentivizing standardized environmental disclosure (e.g., CER reporting) to improve risk pricing. Limitations include sample size constraints (200 bonds) and potential endogeneity in ESG data. Future work could explore nonlinear effects of environmental metrics using machine learning.

4 Conclusion

Driven by global climate governance initiatives and the Sustainable Development Goals (SDGs), green financial bonds have emerged as a pivotal instrument for financing environmental projects. However, conventional default risk assessment models have long relied solely on financial metrics, largely neglecting the environmental benefits embedded in green bond projects. This research addresses this critical gap by developing a unified analytical framework that integrates environmental performance metrics (such

as carbon emission reductions and renewable energy ratios) with financial indicators. The study aims to uncover the dynamic interactions between environmental and financial factors and their implications for credit risk assessment, thereby providing a scientific foundation for risk pricing, regulatory policy design, and investor decision-making in the green bond market.

This study provides a comprehensive statistical assessment of green bond default risk by integrating environmental benefits and financial indicators into a unified analytical framework, demonstrating that environmental performance metrics, such as carbon emission reduction (CER) and renewable energy ratio (RER), significantly reduce default risk, while the synergistic effect between environmental and financial health underscores the importance of a holistic approach to risk assessment. The proposed joint analysis model, validated by robust predictive accuracy (AUC-ROC = 0.83), offers a practical tool for investors, regulators, and issuers to better evaluate and mitigate risks in the green bond market, encouraging issuers to prioritize measurable green outcomes and adopt transparent reporting practices, fostering investor confidence, and informing policymakers on designing incentives that promote both environmental and financial resilience. Future research could explore nonlinear dynamics of environmental metrics, incorporate machine learning techniques, and expand the sample to include international green bonds, contributing to the broader goal of aligning financial markets with global sustainability objectives and paving the way for a more resilient and environmentally conscious financial system.

While this study successfully constructs a holistic framework for assessing green bond default risk and validates its predictive accuracy (AUC-ROC = 0.83), several limitations remain. First, environmental data availability exhibits regional and sectoral disparities, and the long-term environmental impacts of some green projects are challenging to quantify, which may restrict the model's generalizability. Second, the study assumes linear relationships between environmental and financial variables, whereas nonlinear or threshold effects might exist in reality, necessitating further exploration of complex interaction mechanisms. Lastly, the sample scope is concentrated on domestic markets, leaving cross-border risk characteristics of international green bonds unexamined. Future research could advance in three directions: (1) incorporating dynamic environmental data tracking technologies to enhance the assessment of green outcomes; (2) applying machine learning techniques to capture nonlinear relationships and higher-order risk factors; and (3) expanding the sample to include global green bonds, thereby analyzing climate policy heterogeneity and its implications for default risk. Such advancements would contribute to aligning financial markets with global sustainability goals and fostering a more resilient and environmentally conscious financial system.

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