Green Revenues and Credit Risk: a Global Perspective

Very preliminary draft

Abstract

This paper assesses the relationship between the level of green revenues of firms and their credit risk. Using a global unbalanced panel of 27,918 firm-year observations drawn from 4,251 unique publicly listed firms across 60 countries over the period 2016–2024, it tests whether the share of a firm's revenues classified as environmentally beneficial—as measured by the FTSE Russell Green Revenues Classification System—is associated with structural credit risk, proxied by the Bharath–Shumway Distance to Default. The central finding is that firms with higher green revenue shares exhibit statistically significantly lower Distance to Default values—that is, higher structural credit risk—after controlling for firm size, leverage, profitability, and liquidity. The baseline coefficient of -0.831 implies that a one-standard-deviation increase in the green revenue share (31.5 percentage points) is associated with a reduction in the Distance to Default of approximately 0.26 units. The result is robust across 40 specifications, exhibits a U-shaped non-linearity with a turning point near 67.1% green revenue, and is geographically concentrated in the Asia-Pacific region. The findings are consistent with a transition-cost interpretation.

Keywords: green revenues, credit risk, Distance to Default, sustainable finance, climate transition.
JEL: G32, G12, Q56.

1 Introduction

The global transition toward a low-carbon and environmentally sustainable economy is fundamentally reshaping the way firms generate value. Across industries and geographies, companies are investing in renewable energy infrastructure, developing electric vehicle platforms, retrofitting buildings for energy efficiency, and redesigning supply chains to reduce environmental impact. These activities represent a structural reorientation of business models toward products and services that deliver measurable environmental benefits. Green revenues measure the proportion of a firm's total turnover that is derived from the sale of products and services classified as environmentally beneficial, such as solar panels, wind turbines, electric vehicles, water treatment systems, pollution control equipment, and energy-efficient technologies. This output-based metric differs fundamentally from the Environmental, Social, and Governance (ESG) ratings that have dominated the sustainable finance literature to date. ESG ratings assess how a firm manages its operations, while green revenues capture what the firm actually produces and sells, providing a direct measure of the firm's economic engagement with the green transition. Klausmann, Krueger, and Matos (2025) document that the correlation between green revenue shares and conventional ESG scores from major rating providers is weak, confirming that green revenues capture a distinct dimension of corporate sustainability that is not spanned by existing ESG metrics.

A substantial body of empirical literature has examined the relationship between corporate sustainability performance and credit risk, predominantly using ESG ratings. The prevailing finding is that better ESG performance is associated with lower credit risk. Atif and Ali (2021) demonstrate that ESG disclosure is positively correlated with Merton's Distance to Default and negatively correlated with credit default swap spreads. Wang and Yang (2023) find that ESG performance is positively related to the Distance to Default and to credit ratings. The mechanism most commonly invoked is the risk-mitigation or stakeholder channel.

A second strand examines how climate-related risks affect corporate credit conditions. Seltzer, Starks, and Zhu (2022) demonstrate that climate regulatory risks causally affect corporate bond credit ratings and yield spreads, with the effect operating through changes in firms' asset volatilities rather than asset values. Yet these studies employ either composite ESG scores or carbon emissions as their sustainability measures, neither of which directly captures the firm's revenue exposure to green products and services. The theoretical framework of Pástor, Stambaugh, and Taylor (2021) predicts that green assets carry lower expected returns in equilibrium because investors derive non-pecuniary utility from holding them.

What remains unexplored is whether green revenue exposure is associated with credit risk—specifically, whether firms that derive a higher proportion of their revenues from green products and services exhibit different structural default probabilities. This paper addresses this research gap directly by linking the FTSE Russell GRCS green revenue measure to the Bharath–Shumway Distance to Default in a global panel of firms from 2016 to 2024.

The goal of this paper is to assess the relationship between the level of green revenues of global firms and their credit risk. To operationalise this goal, the study answers the following research question: Is the share of a firm's revenues classified as environmentally beneficial, as measured by the FTSE Russell Green Revenues Classification System, associated with its credit risk, proxied by the Bharath–Shumway Distance to Default, and if so, does this association vary across levels of green revenue intensity, geographic regions, economic sectors, and time periods?

This question is important for several reasons. First, the green transition imposes real financial costs on firms that pursue it. Developing and manufacturing green products requires substantial capital expenditure on new production facilities, research and development outlays for technologies that may take years to reach commercial viability, restructuring of supply chains, and competitive repositioning in nascent and often highly competitive environmental product markets. These transition costs are front-loaded, while the benefits - revenue stability from growing green markets, reduced regulatory risk, access to dedicated green financing instruments, and competitive positioning in expanding environmental product categories - accrue gradually over time. If these costs are reflected in firms' structural credit risk profiles, then green revenue intensity may carry an independent credit risk signal that conventional financial metrics fail to capture. Second, the question has direct practical relevance for credit analysts, institutional investors, and prudential regulators who are increasingly required to incorporate sustainability considerations into credit assessments but lack evidence on how specific green revenue exposure - as distinct from broad ESG performance - relates to default risk. Third, the theoretical framework of Pástor, Stambaugh, and Taylor (2021) predicts that green assets carry lower expected returns in equilibrium because investors derive non-pecuniary utility from holding them, which implies that the cost-of-capital benefit available to green firms may be structurally insufficient to offset the real financial burden of the green transition. If this prediction holds empirically, then green firms would simultaneously bear higher credit risk from transition investment and receive only modest compensation through equity return premia - a pattern with significant implications for the pricing of green corporate debt.

The central finding is that firms with higher green revenue shares exhibit statistically significantly lower Distance to Default values, that is, higher structural credit risk, after controlling for firm size, leverage, profitability, and liquidity. The baseline coefficient of -0.831 implies that a one-standard-deviation increase in the green revenue share (31.5 percentage points) is associated with a reduction in the Distance to Default of approximately 0.26 units, equivalent to a shift of roughly 5.1 percent of one standard deviation toward the default boundary. This result is robust across the overwhelming majority of the 40 specifications tested: the green revenue coefficient is negative in 85 percent of estimated models and statistically significant in 68 percent, with its sign never reversing in any of the main fixed-effects models.

Beyond the baseline linear association, the analysis reveals three additional empirical patterns. First, the relationship is non-linear: a quadratic specification suggests a possible U-shaped pattern with a turning point at approximately 67.1 percent green revenue share. Second, the effect is geographically concentrated: the credit risk penalty is statistically significant only in the Asia-Pacific subsample, while Europe produces a near-zero and statistically insignificant result. Third, the credit risk penalty has modestly weakened since 2020, coinciding with the entry into force of the EU Taxonomy Regulation, though this moderation is directional rather than statistically confirmed. This study contributes to the emerging literature on corporate green revenues by providing the first systematic evidence linking the FTSE Russell GRCS green revenue measure to structural credit risk in a global panel setting. It complements the equity-market analysis of Klausmann, Krueger, and Matos (2025), who find only modest evi-dence of a green stock return premium using the same data source, by documenting the credit-side consequence of the same phenomenon

2 Data and Methodology

The empirical analysis draws on firm-level data obtained from the LSEG Refinitiv Workspace database for fiscal years 2016 to 2024, supplemented by the FTSE Russell GRCS for green revenue variables and by the US Department of the Treasury for the risk-free rate. The sample universe is defined by firms with a strictly positive green revenue share in a given fiscal year. The raw panel comprises 29,980 firm-year observations; after data cleaning, winsorisation at the 1st and 99th percentiles within each fiscal year, and exclusion of observations missing inputs required for the Distance to Default computation or the control variables, the final analytical sample comprises 27,918 firm-year observations from 4,251 unique firms across 60 countries.

The regional composition of the sample is reported in Table 1. The Asia-Pacific region dominates with 57.3 percent of firm-year observations, reflecting the large and growing share of Asian firms covered by the FTSE GRCS.

Table 1: Sample Composition by Geographic Region

Region	Observations	Share of Sample (%)	Unique Firms
Asia	15,990	57.3	2,429
Americas	6,111	21.9	934
Europe	5,126	18.4	751
Oceania	442	1.6	106
Africa	249	0.9	31
Total	27,918	100.0	4,251

Source: LSEG Refinitiv and FTSE Russell GRCS. The sample covers firms from 60 countries over 2016–2024. Unique firm counts are approximate given the unbalanced panel structure.

Descriptive statistics for the main variables are reported in Table 2. The Distance to Default exhibits a right-skewed distribution, with a sample mean of 7.64 and a median of 6.43. The green revenue share displays a pronounced right-skewed distribution, with a mean of 0.276 and a median of only 0.133.

Table 2: Descriptive Statistics

Variable	N	Mean	SD	Min	p25	Median	p75	Max
Panel A: Dependent variable								
Distance to Default	27,918	7.638	5.090	0.602	4.314	6.432	9.501	66.838
Panel B: Green revenue (aggregate and tiers)								
Green Revenue Share	27,918	0.276	0.315	0.000	0.043	0.133	0.400	1.000
Green Revenue Tier 1	27,918	0.171	0.266	0.000	0.002	0.049	0.200	1.000
Green Revenue Tier 2	27,909	0.084	0.198	0.000	0.000	0.000	0.049	1.000
Green Revenue Tier 3	27,909	0.021	0.105	0.000	0.000	0.000	0.000	1.000
Panel C: Green revenue (GRCS activity sectors)								
GR: Energy Generation	27,918	0.027	0.123	0.000	0.000	0.000	0.000	1.000
GR: Energy Mgmt & Efficiency	27,918	0.073	0.182	0.000	0.000	0.000	0.039	1.000
GR: Energy Equipment	27,918	0.037	0.140	0.000	0.000	0.000	0.003	1.000
GR: Environmental Resources	27,918	0.023	0.112	0.000	0.000	0.000	0.000	1.000
GR: Environmental Support	27,918	0.004	0.044	0.000	0.000	0.000	0.000	1.000
GR: Food & Agriculture	27,918	0.015	0.090	0.000	0.000	0.000	0.000	1.000
GR: Transport Equipment	27,918	0.030	0.119	0.000	0.000	0.000	0.000	1.000
GR: Transport Solutions	27,918	0.010	0.077	0.000	0.000	0.000	0.000	1.000
GR: Water Infrastructure	27,918	0.028	0.124	0.000	0.000	0.000	0.000	1.000
GR: Waste & Pollution Ctrl	27,918	0.028	0.123	0.000	0.000	0.000	0.000	1.000
Panel D: Financial controls								
Log(Total Assets)	27,918	21.830	1.679	16.575	20.735	21.763	22.911	26.015
Leverage	27,918	0.271	0.311	0.000	0.133	0.251	0.372	28.154
EBIT Margin	27,918	0.070	0.474	−6.406	0.039	0.085	0.161	0.790
Current Ratio	27,918	1.801	1.365	0.161	1.075	1.461	2.086	14.111
Panel E: DtD computation inputs								
Market Cap (USD mn)	27,918	7,385.4	16,716.1	11.9	659.5	1,895.5	5,799.1	134,417.2
Total Assets (USD mn)	27,918	11,649.9	26,715.9	15.8	1,011.5	2,827.9	8,914.0	198,601.3
Total Debt (USD mn)	27,918	3,453.0	8,252.8	0.0	153.1	698.9	2,644.9	62,350.7
Equity Volatility	27,918	0.375	0.177	0.108	0.256	0.337	0.446	1.440
Risk-free Rate	27,918	0.026	0.018	0.001	0.008	0.026	0.047	0.048

Note: Based on LSEG Refinitiv and FTSE Russell GRCS data. The analytical sample comprises 27,918 firm-year observations after complete-case filtering on the six main specification variables (DtD, green revenue share, log total assets, leverage, EBIT margin, current ratio). Distance to Default is computed following Bharath and Shumway (2008). Green revenue variables are sourced from the FTSE GRCS. Panels B and C report the tier and activity-sector decompositions used in supplementary specifications C1 and C2. Panel D reports the financial controls as they enter the baseline regression. Panel E reports the raw DtD computation inputs. Market capitalisation, total assets, and total debt are in millions of USD. Green Revenue Tier 2 and Tier 3 report 27,909 observations due to 9 firm-year records where tier-level breakdowns are unavailable despite a positive aggregate green revenue share.

The Distance to Default (DtD) indicator belongs to the family of structural credit risk models. The basic premise is that a firm defaults when the market value of its assets falls below the promised value of its debt obligations; the model views a company's equity as a call option on its assets. DtD integrates market information, capital structure, volatility, and balance-sheet fundamentals into a single forward-looking metric, and has been shown to exhibit strong predictive ability for default events (Vassalou and Xing, 2004; Bharath and Shumway, 2008).

The dependent variable is the approximate closed-form Distance to Default introduced by Bharath and Shumway (2008), which directly substitutes observable quantities into the structural DtD formula, bypassing the convergence requirement of a fully iterative Merton solver. The default point D is defined as short-term debt plus one half of long-term debt:

$$D = STD + 0.5 \cdot LTD \tag{1}$$

The total firm value V is approximated as the sum of equity market capitalisation E and the default point D:

$$V = E + D \tag{2}$$

Asset volatility σ_A is estimated from observed annualised equity volatility σ_E, scaled by the equity-to-firm-value ratio:

$$\sigma_A = \sigma_E \cdot \frac{E}{V} \tag{3}$$

The Distance to Default is then computed as:

$$DtD = \frac{\ln\left(\dfrac{V}{D}\right) + \left(r - 0.5\,\sigma_A^2\right) \cdot T}{\sigma_A \cdot \sqrt{T}} \tag{4}$$

where r denotes the one-year United States Treasury bill rate applied uniformly across all firm-year observations and $T = 1$ year. A higher Distance to Default indicates that the firm's estimated asset value is further from the debt default threshold, and therefore that the firm exhibits lower credit risk.

The baseline empirical model is a two-way fixed-effects panel regression of the following form:

$$\begin{aligned} DtD_{it} = \alpha_i + \delta_t + \beta_1\, green\_total_{it} + \beta_2 \log(assets)_{it} + \beta_3\, leverage_{it} \\ + \beta_4\, ebit\_margin_{it} + \beta_5\, current\_ratio_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

where DtD_{it} is the Distance to Default for firm i in fiscal year t; α_i denotes firm-level fixed effects; δ_t denotes year fixed effects; β_1 through β_5 are the within-firm partial effects; and ε_{it} is the idiosyncratic error term. Firm fixed effects absorb all time-invariant, firm-specific determinants of credit risk, while year fixed effects absorb aggregate macroeconomic and financial market conditions. Standard errors are clustered at the firm level using the HC1 heteroskedasticity-consistent variance estimator. The choice of the two-way fixed-effects estimator is supported by the Hausman (1978) test, an F-test for the joint significance of firm fixed effects, the Breusch–Pagan Lagrange Multiplier test, and a Wooldridge test for serial correlation. Firm-level clustering allows for arbitrary serial correlation in the idiosyncratic error terms within each firm across consecutive time periods, which is expected given the high persistence of firm-level financial characteristics. The sensitivity of inference to the variance estimation structure is assessed through two additional specifications: Driscoll—Kraay standard errors (Driscoll and Kraay, 1998), which are robust to both cross-sectional dependence and serial correlation, and two-way clustered standard errors at the firm and year levels.

The four control variables are selected on the basis of their theoretical relevance to structural credit risk and their prominence in the empirical financial distress literature (Altman, 1968; Ohlson, 1980; Vassalou and Xing, 2004). Firm size, proxied by the natural logarithm of total assets, is expected to correlate negatively with credit risk, as larger firms typically benefit from greater asset diversification and superior capital market access. Financial leverage, defined as total debt divided by total assets (leverage), is expected to carry a negative coefficient, as it increases the default point relative to total asset value. Profitability, proxied by the EBIT margin , is expected to be positively associated with the Distance to Default by strengthening cash-flow generation. Liquidity, measured by the cur-rent ratio , is expected to be positively associated with the Distance to Default, reflecting the firm's capacity to meet short-term obligations. The green revenue coefficient sign is the central empirical question of this study. Two variables that might appear natural candidates for inclusion are deliberately excluded. Log-transformed equity market capitalisation is omitted because market capitalisation enters directly into the Distance to Default formula as a component of both total firm value and the equity-to-firm-value ratio used to approximate asset volatility; including it would introduce a mechanically endogenous regressor and bias all coefficient estimates. The processed issuer credit rating is excluded due to missingness exceeding 66 percent of the analytical sample, rendering it unsuitable for reliable estimation.

A comprehensive set of robustness checks is designed to assess the sensitivity of the main finding across alternative modelling choices, de-pendent variable transformations, independent variable functional forms, sample compositions, and green revenue decompositions. In total, 40 distinct specifications are estimated and organised into eight logical groups.

3 Results and Discussion

3.1 Baseline Results

The main finding is that the green revenue share is negatively and statistically significantly associated with the Distance to Default in the two-way fixed-effects specification. Table 3 reports the coefficient estimates across five model specifications. In the main specification (column 4), the estimated coefficient on total green revenues is -0.831 with a firm-clustered standard error of 0.326, yielding a t-statistic of -2.548 and a p-value of 0.011. Since the Distance to Default measures the number of asset-value standard deviations separating the firm from the default boundary, a reduction implies that the firm moves closer to default and therefore exhibits higher credit risk.

Table 3: Baseline Regression Results: Model Comparison

Variable	(1) Pooled OLS	(2) OLS+Dummies	(3) Firm FE	(4) Two-way FE ⋆	(5) Random Eff.
Green Revenue Share	-0.707^{***}	-0.665^{***}	-1.074^{***}	-0.831^{**}	-1.168^{***}
	(0.211)	(0.200)	(0.342)	(0.326)	(0.179)
Log(Total Assets)	-0.014	-0.014	-1.454^{***}	-1.149^{***}	-0.324^{***}
	(0.048)	(0.044)	(0.097)	(0.110)	(0.042)
Leverage	-3.376^{*}	-3.321^{*}	-3.566^{***}	-3.203^{***}	-2.607^{***}
	(1.728)	(1.738)	(0.878)	(0.812)	(0.990)
EBIT Margin	1.794^{***}	1.705^{***}	0.377^{**}	0.282^{*}	1.054^{***}
	(0.141)	(0.147)	(0.156)	(0.152)	(0.127)
Current Ratio	0.857^{***}	0.883^{***}	0.352^{***}	0.381^{***}	0.489^{***}
	(0.093)	(0.091)	(0.045)	(0.045)	(0.047)
Firm FE	No	No	Yes	Yes	No
Year FE	No	Yes	No	Yes	No
Observations	27,918	27,918	27,918	27,918	27,918
R^2 (within/overall)	0.130	0.203	0.056	0.053	0.075

Dependent variable: Distance to Default (Bharath and Shumway, 2008 approximation). Standard errors in parentheses, clustered at firm level (HC1) throughout. In columns (3)–(4), sector and region are absorbed by firm fixed effects. ⋆ denotes the main specification. Significance: $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.10$.

In economically meaningful terms, scaling the coefficient to one standard deviation of the green revenue share across the sample (31.5 percentage points) yields an estimated reduction in the Distance to Default of $0.831 \times 0.315 = 0.262$ units. The direction of the result may appear counterintuitive but is consistent with a transition-cost interpretation: firms actively generating revenues from environmentally beneficial products are simultaneously absorbing the capital expenditure, restructuring costs, and commercial uncertainty associated with the green economy transition.

The sign and significance of all four control variables conform ex-actly to theoretical predictions across all five specifications, providing an internal validity check on the model structure. Total Assets carry a negative coefficient reflecting the within-firm finding that asset growth is typically accompanied by expanding debt obligations, which reduces the Distance to Default. In the pooled OLS specifications, the log assets coefficient is near zero and insignificant, consistent with the cross-sectional observation that size correlates with both asset value and debt, producing a near-zero net effect in the absence of within-firm identification. Leverage carries a strongly negative coefficient across all specifications, confirming that higher financial leverage mechanically reduces the Distance to Default by increasing the default point relative to total firm value. The EBIT margin coefficient is positive, consistent with the expectation that profitability strengthens cash-flow generation and reduces default probability. The current ratio coefficient is positive throughout confirming that higher short-term liquidity is associated with a lower probability of approaching the default boundary.

3.2 Robustness

Table 4 presents a selection of the 40 robustness and supplementary specifications. The overarching finding is that the green revenue coefficient is negative in 34 of 40 specifications (85 percent) and statistically significant at conventional levels in 27 of 40 (68 percent). Crucially, the sign of the green revenue coefficient never reverses in any of the main two-way fixed-effects models. The quadratic specification yields statistically significant coefficients on both the linear (-2.487) and squared ($+1.854$) terms, implying a U-shaped relationship with a turning point at a green revenue share of 67.1 percent. The finding survives all three alternative standard error structures, including Driscoll–Kraay standard errors, under which the result becomes more statistically significant ($p < 0.001$).

3.3 Heterogeneity

The green revenue–credit risk association is almost exclusively concentrated in the Asia-Pacific subsample, as shown in Table 5. The estimated coefficient for Asia is -1.164 ($p = 0.003$), both statistically significant and numerically stronger than the full-sample baseline. The European subsample produces a coefficient of $+0.095$ ($p = 0.902$), a sign reversal entirely consistent with zero in statistical terms, which is informative: European firms operate in a regulatory environment with the most advanced green finance taxonomy, where green revenue intensity may already be priced into equity valuations and credit assessments. At the sector level, the penalty is largest in Consumer Cyclicals, Real Estate, and Basic Materials— all capital-intensive industries where the green transition requires transformative physical investment, and absent in regulated Utilities.

The temporal interaction specification reveals an asymmetry between the pre– and post-2020 periods. The estimated green revenue coefficient for the pre–2020 period is -0.954, meaningfully stronger than the full-sample baseline of -0.831. The post-2020 interaction term is $+0.191$, implying a total post-2020 green revenue effect of -0.763. The credit risk penalty associated with green revenues therefore appears to have moderated after 2020, consistent with the hypothesis that the acceleration of green finance regulation (the EU Taxonomy Regulation (2020), the Sustainable Finance Disclosure Regulation (2021), and broader expansion of institutional investor mandates

Table 4: Robustness and Supplementary Specifications

Code	Specification	Modification from Baseline	N	Coef.	SE	Sig.	R^2
Panel A: Baseline							
A4	Two-way FE (main)	Reference specification	27,918	−0.831	0.326	**	0.053
Panel B: Dependent variable transformation							
D1	log(DtD)	Log-transform DV	27,918	−0.099	0.045	**	0.084
Panel C: Reverse causality							
G1	Lagged green	green_total(t−1), controls contemporaneous	23,843	−0.475	0.285	*	0.132
G2	All lagged	All regressors lagged t−1	23,713	−0.688	0.307	**	0.069
Panel D: Sample filter tests							
H1	Balanced panel	Firms with all 9 years only	20,606	−0.659	0.376	*	0.056
H2	Drop 2020	Exclude COVID-19 year	25,004	−0.956	0.349	***	0.058
H3	Green > 5%	Exclude marginal green firms	19,454	−0.621	0.358	*	0.059
H4	Green > 20%	Higher threshold filter	10,890	−0.253	0.484		0.059
H5	Drop Financials	Exclude Financial sector	27,681	−0.758	0.319	**	0.053
H6	Post-2018 only	Mature GRCS 2.0 period	22,944	−0.622	0.346	*	0.041
Panel E: Non-linear functional forms							
E1	Quadratic (linear)	Add green_total^2	27,918	−2.487	0.782	***	0.053
E1	Quadratic (squared)	Turning point: 67.1%		+1.854	0.859	**	
E2	$\sqrt{\text{green\_total}}$	Square root transform	27,918	−1.136	0.311	***	0.053
E3	Quartile Q2 vs Q1	Quartile dummies (Q1 = ref)	27,918	−0.281	0.087	***	0.053
E3	Quartile Q3 vs Q1			−0.281	0.116	**	
E3	Quartile Q4 vs Q1			−0.473	0.178	***	
E4	Binary > 50%	High-green indicator	27,918	−0.240	0.137	*	0.053
Panel F: Green revenue decomposition							
C1	Tier 1 (clear benefit)	Replace green_total with tiers	27,909	−0.705	0.375	*	0.053
C1	Tier 2 (moderate)			−1.111	0.504	**	
C1	Tier 3 (contested)			−0.593	0.762		
C2	10 GRCS sectors	Replace green_total with sectors	27,918	See note			0.053
Panel G: Standard error robustness (coefficient = −0.831 throughout)							
SE1	HC1 firm-clustered	Baseline variance estimator	27,918	$p = 0.011$	0.326	**	–
SE2	Driscoll–Kraay	Cross-sectional dependence robust	27,918	$p < 0.001$	0.218	***	–
SE3	Two-way clustered	Firm × year clustering	27,918	$p = 0.007$	0.309	***	–

Source: Own elaboration based on LSEG Refinitiv and FTSE Russell GRCS data. Dependent variable: Distance to Default (Bharath and Shumway, 2008) throughout, except D1 (log DtD). All specifications use two-way fixed effects (firm + year) with HC1 firm-clustered standard errors unless noted in Panel G. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$. R^2 is the within R^2. Panel F specification C2: only Energy Management & Efficiency is individually significant (-1.216^{***}, SE = 0.457).

for taxonomy-aligned assets) has begun to reduce the financial uncertainty associated with green investment by providing clearer regulatory expectations and expanding the investor base for green assets. However, the post-2020 interaction term does not reach statistical significance, meaning this temporal moderation is a directional pattern rather than a formally confirmed structural break.

Table 5: Heterogeneity Analysis: Regional, Sectoral, and Temporal Subsamples

Subsample	N	Green Coef.	Sig.	Within R^2
Panel A: Geographic region subsamples				
Asia	15,990	−1.164	***	0.048
Americas	6,111	−0.865		0.129
Europe	5,126	+0.095		0.131
Oceania (small sample – interpret with caution)	442	+1.288		0.201
Africa (small sample – interpret with caution)	249	−0.041		0.286
Panel B: Economic sector subsamples				
Industrials	7,903	+0.863		0.040
Basic Materials	4,475	−1.203	*	0.150
Technology	3,818	−1.030		0.093
Consumer Cyclicals	2,985	−1.907	***	0.114
Utilities	2,986	+0.050		0.061
Real Estate	2,125	−2.463	***	0.030
Energy	1,592	+1.486		0.058
Consumer Non-Cyclicals	1,491	+1.375		0.049
Financials (very small sample – interpret with caution)	237	−21.361	*	0.158
Healthcare	306	−2.206		0.317
Panel C: Temporal interaction — green_total × post-2020 (full sample, $N = 27{,}918$)				
Pre-2020 green revenue effect	–	−0.954	***	–
Post-2020 interaction term (green × post2020)	27,918	+0.191		–
Post-2020 total effect ($= -0.954 + 0.191$)	–	−0.763		–

Source: Own elaboration based on LSEG Refinitiv and FTSE Russell GRCS data. All models use two-way fixed effects (firm and year) with HC1 firm-clustered standard errors. N denotes the number of firm-year observations in each subsample. The Financials sector coefficient of −21.361 should be treated with extreme caution given the very small subsample of N = 237. Oceania (N = 442) and Africa (N = 249) are reported for completeness only. Panel C reports temporal interaction results from the full sample specification. Significance levels: $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.10$.

4 Conclusion

This paper provides the first systematic evidence linking the FTSE Russell GRCS green revenue measure to structural credit risk in a global panel setting. Using 27,918 firm-year observations across 60 countries over 2016–2024, it documents that higher green revenue shares are associated with significantly higher structural credit risk, with a baseline coefficient of −0.831 that is robust across 40 specifications, exhibits a U-shaped non-linearity, and is concentrated in the Asia-Pacific region and in capital-intensive sectors. Several limitations qualify these findings. The design is associational, not causal, absent a credible instrument or quasi-experimental design; the sample is restricted to firms with positive FTSE GRCS green revenue coverage; and the GRCS methodology's reliance on analyst estimates may attenuate the estimated coefficient toward zero.

The transition-cost hypothesis holds that firms generating revenues from environmentally beneficial products have committed real resources to developing, manufacturing, and marketing green products, entailing substantial capital expenditure, R&D outlays, supply-chain restructuring, and marketing costs. These transition costs are front-loaded while the benefits accrue gradually, producing a temporal mismatch captured by the structural Distance to Default model. This interpretation complements Klausmann, Krueger, and Matos (2025), who find only modest evidence of a green stock return premium using the same data source: together, the two results suggest that green revenue generation is financially costly in the near term while the equity market has not yet delivered a return premium large enough to offset those costs, consistent with the equilibrium logic of Pástor, Stambaugh, and Taylor (2021). Green firms bear higher costs (reflected in credit risk) that are not fully compensated by higher equity returns, because the equilibrium return on green assets is compressed by the non-pecuniary preferences of sustainability-oriented investors. The credit risk penalty documented in this paper can, therefore, be understood as the real-side counter-part of the green asset pricing discount predicted by Pástor, Stambaugh, and Taylor (2021): green firms face genuine financial strain from transition investment, and the equity premium they might otherwise command to compensate for this strain is muted by investor willingness to accept lower returns on green holdings.

We would further extend the analysis with firm-level green financing controls, country-level regulatory indices, decomposition of the the distance-to-default and a complementary market-based credit risk measure in the form of CDS spreads. Extending the analysis to include firms with zero green revenues through propensity score matching would allow estimation of the cred-it risk differential between green-active and non-green firms.

References

[1] Edward I. Altman. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4):589–609, 1968. doi: 10.1111/j.1540-6261.1968.tb00843.x.

[2] Muhammad Atif and Searat Ali. Environmental, social and governance disclosure and default risk. *Business Strategy and the Environment*, 30(8):3937–3959, 2021. doi: 10.1002/bse.2850.

[3] Ben Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. In John B. Taylor and Michael Woodford, editors, *Handbook of Macroeconomics*, volume 1, pages 1341–1393. Elsevier, 1999.

[4] Sreedhar T. Bharath and Tyler Shumway. Forecasting default with the merton distance to default model. *The Review of Financial Studies*, 21(3):1339–1369, 2008. doi: 10.1093/rfs/hhn044.

[5] Sabri Boubaker, Alexis Cellier, Riadh Manita, and Asif Saeed. Does corporate social responsibility reduce financial distress risk? *Economic Modelling*, 91:835–851, 2020. doi: 10.1016/j.econmod.2020.05.012.

[6] Erik Brynjolfsson and Lorin M. Hitt. Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4): 23–48, 2000. doi: 10.1257/jep.14.4.23.

[7] Giusy Capasso, Gianfranco Gianfrate, and Marco Spinelli. Climate change and credit risk. *Journal of Cleaner Production*, 266:121634, 2020. doi: 10.1016/j.jclepro.2020.121634.

[8] Sudheer Chava. Environmental externalities and cost of capital. *Management Science*, 60(9): 2223–2247, 2014. doi: 10.1287/mnsc.2013.1863.

[9] John C. Driscoll and Aart C. Kraay. Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4):549–560, 1998. doi: 10.1162/003465398557825.

[10] Sadok El Ghoul, Omrane Guedhami, Chuck C. Y. Kwok, and Dev R. Mishra. Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, 35(9):2388–2406, 2011. doi: 10.1016/j.jbankfin.2011.02.007.

[11] Jerry A. Hausman. Specification tests in econometrics. *Econometrica*, 46(6):1251–1271, 1978. doi: 10.2307/1913827.

[12] Adam B. Jaffe and Robert N. Stavins. Dynamic incentives of environmental regulations: The effects of alternative policy instruments on technology diffusion. *Journal of Environmental Economics and Management*, 29(3):S43–S63, 1995. doi: 10.1006/jeem.1995.1060.

[13] Md. Nurul Kabir, Sohanur Rahman, and Larry Su. Carbon emissions and default risk: International evidence from firm-level data. *Economic Modelling*, 103:105617, 2021. doi: 10.1016/j.econmod.2021.105617.

[14] Johann Klausmann, Philipp Krueger, and Pedro Matos. The green transition: Evidence from corporate green revenues. Technical report, Swiss Finance Institute Research Paper No. 25-40; ECGI Finance Working Paper No. 1032/2025, 2025. Available at SSRN: https://ssrn.com/abstract=4850449.

[15] Philipp Krueger, Zacharias Sautner, and Laura T. Starks. The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111, 2020. doi: 10.1093/rfs/hhz137.

[16] Tobias Kruse, Myra Mohnen, Peter F. Pope, and Misato Sato. Green revenues, profitability and market valuation: Evidence from a global firm level dataset. Technical report, Grantham Research Institute on Climate Change and the Environment, 2020.

[17] Stefan Lessmann, Bart Baesens, Hsin-Vonn Seow, and Lyn C. Thomas. Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. *European Journal of Operational Research*, 247(1):124–136, 2015. doi: 10.1016/j.ejor.2015.05.030.

[18] Karl V. Lins, Henri Servaes, and Ane Tamayo. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824, 2017. doi: 10.1111/jofi.12505.

[19] Francis A. Longstaff, Sanjay Mithal, and Eric Neis. Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. *The Journal of Finance*, 60(5): 2213–2253, 2005. doi: 10.1111/j.1540-6261.2005.00797.x.

[20] James G. MacKinnon and Halbert White. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, 29(3):305–325, 1985. doi: 10.1016/0304-4076(85)90158-7.

[21] Robert C. Merton. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470, 1974. doi: 10.1111/j.1540-6261.1974.tb03058.x.

[22] Ľuboš Pástor, Robert F. Stambaugh, and Lucian A. Taylor. Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571, 2021. doi: 10.1016/j.jfineco.2020.12.011.

[23] Lee H. Seltzer, Laura T. Starks, and Qifei Zhu. Climate regulatory risk and corporate bonds. NBER Working Paper 29994, National Bureau of Economic Research, 2022.

[24] Christoph Stellner, Christian Klein, and Bernhard Zwergel. Corporate social responsibility and eurozone corporate bonds: The moderating role of country sustainability. *Journal of Banking & Finance*, 59:538–549, 2015. doi: 10.1016/j.jbankfin.2015.04.032.

[25] Maria Vassalou and Yuhang Xing. Default risk in equity returns. *The Journal of Finance*, 59 (2):831–868, 2004. doi: 10.1111/j.1540-6261.2004.00650.x.

[26] Lei Wang and Li Yang. Environmental, social and governance performance and credit risk: Moderating effect of corporate life cycle. *Pacific-Basin Finance Journal*, 80:102105, 2023. doi: 10.1016/j.pacfin.2023.102105.