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Beyond Financials: Carbon Emissions and Distance to Default in Indian Firms

Sneha Sarah Alex

fpm22m0009@rajagiri.edu

Rajagiri Business School

Ananya Bhattacharyya

Bank of New York Mellon

Syamraj KP

LEAD College of Management

Jains P Chacko

Mahindra University

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Abstract

This paper investigates the relationship between greenhouse gas (GHG) emissions, environmental performance, and corporate default risk among Indian listed firms. Default risk is proxied by a Merton-based Distance to Default (DD) measure. The sample covers 301 firms listed on the National Stock Exchange of India during 2016–2023, representing 2,408 potential firm-year observations before variable-specific missingness. We use two-step system generalized method of moments (system GMM), supplemented by pooled ordinary least squares (OLS) and fixed- and random-effects estimates. In the principal system-GMM specifications, Scope 1 emissions are negatively associated with DD (reported coefficients of − 0.844 and − 1.170; $p < 0.001$), whereas Scope 2 emissions are not statistically significant. The Scope 1 estimate is not statistically significant in the fixed-effects specification. Environmental-score coverage is sparse, and dynamic specifications including the score retain only 16 observations, preventing reliable inference for that measure. We interpret these findings as associations in the estimation samples, rather than as evidence of causation. Uneven reporting coverage, differences across estimators, and sensitivity to controls limit the generalisability of the results.

1. INTRODUCTION

Climate change is increasingly recognized as a source of financial risk that may affect corporate balance sheets, credit markets, and financial stability (Curcio et al., 2023; Luangaram et al., 2026). Climate-related risks include physical risks, such as extreme weather and supply-chain disruption, and transition risks arising from carbon pricing, regulatory change, and technological substitution. These risks may affect operating costs, cash flows, asset values, and earnings volatility (Nguyen et al., 2023; Umar et al., 2025). The Merton (1974) structural credit-risk framework provides a useful conceptual link: changes in asset value and volatility relative to debt obligations affect a firm's Distance to Default (DD). The relationship between climate-related exposures and DD is nevertheless an empirical question, because sector, firm size, financing structure, and reporting practices may also shape observed differences across firms.

Investors, lenders, regulators, and other stakeholders increasingly consider environmental information when assessing corporate risk. Environmental, Social, and Governance (ESG) frameworks provide broad measures of sustainability performance, while disaggregated greenhouse gas (GHG) emissions provide a more specific view of reported operational emissions. The GHG Protocol distinguishes Scope 1 emissions from owned or controlled sources, Scope 2 emissions from purchased energy, and Scope 3 emissions from other parts of the value chain (WRI and WBCSD, 2020). These measures are not interchangeable: absolute emissions capture the scale of reported emissions, whereas emissions intensity requires a denominator such as revenue, output, or assets. In this study, we use log-transformed absolute Scope 1 and Scope 2 emissions; it therefore examines emissions levels rather than emissions intensity.

Prior research has examined climate exposure and environmental performance in relation to asset prices, financing costs, credit spreads, and credit risk (Choi et al., 2020; Clarkson et al., 2015; Hong et al., 2019; Nguyen et al., 2023). Evidence on firm-level default-risk measures in emerging markets remains less developed. India offers a relevant setting because it combines a large and diverse listed corporate sector with evolving sustainability-disclosure requirements. However, incomplete coverage of environmental scores and emissions makes it important to distinguish the full firm-year panel from the smaller samples available for individual regressions. We therefore treat the data-coverage pattern as a central limitation when interpreting the results.

This paper investigates the relationships among Scope 1 and Scope 2 emissions, environmental performance, and DD for Indian listed firms from 2016 to 2023. DD is constructed from market and accounting information using a Merton-based framework. The second-stage analysis uses a two-step system GMM estimator, supplemented by static pooled OLS and fixed- and random-effects models. The main GMM specifications report a negative and statistically significant association between Scope 1 emissions and DD, whereas the association with Scope 2 emissions is not statistically significant. Yet the fixed-effects estimate for Scope 1 is statistically insignificant, and the Environmental-score specifications have only 16 observations. Accordingly, the paper does not claim that the estimates establish a causal effect or that the Environmental-score hypothesis has been rejected.

This paper makes three contributions. First, it provides firm-level evidence from India on the association between reported direct GHG emissions and a forward-looking structural measure of default risk. Second, it evaluates this association using a dynamic-panel specification and compares the result with alternative estimators. Third, it documents how incomplete environmental-data coverage constrains the joint analysis of emissions and Environmental pillar scores. The results are presented as associations: stronger causal claims would require more persuasive identification and additional robustness analyses. Because the Environmental-score specifications cannot be estimated with adequate precision in the available sample, the paper treats that part of the research question as unresolved.

The remainder of the paper is organized as follows. Section II reviews the literature and develops the study's hypotheses. Section III describes the data and empirical methodology, including the construction of Distance to Default and the two-step system-GMM specification. Section IV presents descriptive statistics and the main regression and robustness results. Section V discusses the findings, implications, and limitations, and Section VI concludes. The references and variable-definition appendix follow.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Research on climate-related financial risk examines how environmental exposure may affect firm value, financing conditions, and solvency. In the Merton (1974) framework, DD depends on the relationship between the market value of assets, asset volatility, and the default threshold. Carbon-related regulatory costs, technological change, and potential stranded assets could reduce asset values or increase

uncertainty. These mechanisms motivate the examination of emissions and environmental performance alongside conventional firm characteristics. They do not, by themselves, establish that observed differences in emissions cause changes in DD; sector composition, firm scale, and other omitted factors may also influence the relationship.

2.1 Environmental Performance and Solvency

Stronger environmental performance may enhance corporate solvency through regulatory preparedness, improved governance, and reduced information asymmetry. Empirical evidence shows that firms with superior environmental performance benefit from stronger credit ratings and narrower bond spreads (Bauer and Hann, 2010; Dimitropoulos and Koronios, 2023), and environmentally responsible firms face lower loan spreads and improved access to financing (Abdul Razak et al., 2020; Capasso et al., 2020; Y. Liu et al., 2025).

Stakeholder theory suggests that environmental practices may influence a firm's relationships with investors, customers, employees, regulators, and communities, potentially affecting its reputation and cash flow stability (Freeman, 2009). Institutional theory highlights the role of regulatory and normative pressures in shaping environmental disclosure and management (DiMaggio and Powell, 2004). Within the Merton framework, these channels could be reflected in asset value or volatility and therefore in DD. However, an Environmental pillar score is a provider-specific composite indicator and should not be equated with actual environmental impact. Its interpretation is further constrained here by sparse coverage and the absence of validation against an independent provider.

H1: Higher Environmental pillar scores are positively associated with Distance to Default, implying lower model-implied default risk.

2.2 Greenhouse Gas Emissions and Default Risk

Higher absolute GHG emissions may be associated with greater exposure to transition costs, regulation, and technological change. Prior research has documented relationships between carbon risk and the pricing of equity and debt (Bolton and Kacperczyk, 2021, 2023; Ilhan et al., 2021; Seltzer et al., 2022). The expected direction of the association may differ across emissions scopes and sectors. Scope 1 emissions capture direct operational emissions, while Scope 2 emissions are associated with purchased energy. Absolute emissions also reflect firm scale, so a negative association between emissions and DD should not automatically be interpreted as evidence that emissions intensity or emissions increases within a firm raise default risk.

Within the structural credit-risk framework, greater regulatory costs or transition uncertainty may reduce asset value or increase asset volatility, thereby lowering DD. This mechanism motivates the following hypothesis. Its empirical assessment must account for the fact that reported emissions are unevenly available and that between-firm differences may not be equivalent to within-firm changes over time.

H2: Higher reported Scope 1 and Scope 2 GHG emissions are negatively associated with Distance to Default, implying higher model-implied default risk.

Our analysis distinguishes the hypothesized relationships from what the available data can establish. The Environmental-score hypothesis is not reliably testable in the dynamic specifications because the joint sample is too small. The emissions results are interpreted as associations and evaluated in light of differences among GMM, fixed-effects, and random-effects estimates.

3. DATA AND METHODOLOGY

3.1 Data

The estimation frame comprises 301 firms listed on the National Stock Exchange of India over 2016–2023, corresponding to 2,408 possible firm-year cells before variable-level missingness. Stock prices, debt, and financial ratios are sourced from CMIE Prowess; Environmental pillar scores and Scope 1–3 emissions are sourced from Bloomberg/Refinitiv Eikon; and the 91-day Treasury bill yield is sourced from the Reserve Bank of India. The availability of the underlying variables is uneven, so the 2,408 cells should not be interpreted as the sample used in every regression.

Coverage of the key variables is uneven, materially affecting the estimation sample available for each model. Of the 2,408 potential firm-year cells, DD is observed in 1,324, Scope 1 emissions in 728, Scope 2 emissions in 760, and the Environmental score in 243. These marginal counts are not equivalent to the joint sample for any regression. The principal system-GMM specifications report 188 and 186 observations, whereas specifications that include the Environmental score retain only 16 observations. The sample counts must be interpreted as model-specific and reconciled with the final estimation output and the sample construction code.

Composite ESG scores capture environmental, social, and governance dimensions, whereas the Environmental pillar score represents a provider-defined environmental measure. Emissions and Environmental scores therefore capture different constructs: emissions record reported quantities of greenhouse gases, while the score reflects the provider's scoring methodology. The analysis uses log-transformed absolute Scope 1 and Scope 2 emissions rather than emissions intensity. Where reliable denominators are available, future work should assess emissions scaled by revenue, output, or assets to help distinguish firm scale from emissions intensity.

Measurement reliability is also a concern, separate from the limited coverage. The Environmental pillar score is drawn from one provider and is not cross-validated against an independent source in this sample. Prior research documents substantial divergence among ESG ratings providers (Berg et al., 2022), reflecting differences in scope, measurement, and weighting. Given the sparse coverage, findings regarding the Environmental score should be treated as inconclusive rather than definitive.

3.2 Overview of the Empirical Strategy

Our empirical strategy proceeds in two stages. First, firm-year DD is estimated using market and accounting data under a Merton-based structural credit-risk framework. Second, DD is related to reported emissions, Environmental pillar scores where available, and firm-level controls. Two-step system GMM is used for the principal dynamic specifications, with pooled OLS and fixed- and random-effects models reported as supplementary comparisons. The use of internal instruments does not, on its own, establish causal identification; interpretation depends on the instrument assumptions, diagnostic tests, sample composition, and robustness of the estimates.

3.3 Estimating Distance to Default

DD is estimated using the Merton (1974) structural framework, in which equity is modeled as a call option on firm assets and default occurs when asset value falls below a specified debt threshold at maturity. The unobserved market value and volatility of assets are recovered iteratively from observed equity value, equity volatility, and a debt measure, following the approach associated with Bharath and Shumway (2004). The operational definition of the debt threshold must be stated consistently: this manuscript describes it as short-term borrowings plus 50% of long-term borrowings. This differs from a generic reference to total liabilities, so the former should be used consistently wherever it is the actual implementation. The calculations assume a one-year horizon and use annualised equity-return volatility based on the preceding twelve months. DD is interpreted as a model-based indicator; it is not a directly observed default event.

$$DD = [\ln(V_A/X) + (r + \tfrac{1}{2}\sigma_A^2)T] / (\sigma_A\sqrt{T}) \quad \text{..... (Eq. 1)}$$

where V_A is estimated market asset value, X is the operational debt threshold, r is the risk-free rate, σ_A is estimated asset volatility, and T is the one-year horizon. Market capitalisation proxies the market value of equity; the manuscript's stated debt threshold is short-term borrowings plus 50% of long-term borrowings; and equity volatility is calculated from daily returns over the preceding twelve months. V_A and σ_A are recovered iteratively using the stated convergence tolerance. The implementation should be checked for firms with zero debt, negative equity, missing daily prices, and non-convergence, and the resulting DD distribution should be validated against an independent implementation where feasible. A higher DD indicates a larger model-implied buffer above the default threshold.

3.4 Empirical Model and Two-Step System GMM Estimation

The dynamic specifications use two-step system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998), motivated by the lagged dependent variable and possible endogeneity of emissions and firm characteristics. Estimation was performed in Python using pydynpd, with Windmeijer-corrected standard errors and standard overidentification and serial-correlation diagnostics. Instruments were collapsed and lag ranges restricted, following Roodman (2009), to limit instrument proliferation. Nevertheless, system GMM is credible only if the moment conditions and instrument assumptions are defensible. The

small effective sample size and short panel make this a material concern, so the GMM estimates are interpreted with caution and compared with alternative estimators.

For each system-GMM specification, the reported diagnostics include the instrument count, the Hansen J-test, and the Arellano–Bond serial-correlation tests, where available. The principal specifications report 8–9 instruments for approximately 186–188 observations, with Hansen p-values around 0.68 and AR(2) p-values around 0.54–0.61. These results do not reject the relevant null hypotheses, but they do not prove instrument validity. The final empirical record should also document AR(1), difference-in-Hansen tests where applicable, the exact instrument matrix, classifications of regressors as endogenous, predetermined, or exogenous, and sensitivity to alternative lag windows. The small effective sample and negative lagged-DD coefficient make these checks particularly important.

The empirical model is:

$$DD_{i,t} = \beta_0 DD_{i,t-1} + \beta_1 E_{i,t} + \beta_2 SC_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t} \quad \text{(Eq. 2)}$$

where $DD_{i,t}$ is firm i's Distance to Default in year t; $DD_{i,t-1}$ is its one-period lag; $E_{i,t}$ is the provider-reported Environmental pillar score; $SC_{i,t}$ denotes log(1 + x)-transformed absolute Scope 1 and/or Scope 2 emissions; $X_{i,t}$ is the vector of firm-level controls; and $\varepsilon_{i,t}$ is the error term. The use of log(1 + x) accommodates observed zeros but does not resolve missing observations or differences in emissions reporting. Since the regressors and model specifications vary across tables, coefficients should not be compared without considering sample and control-set differences.

4. RESULTS

4.1 Descriptive Statistics

Table 1
Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
Annualized SD	1,923	0.450	0.752	0.112	0.380	21.325
Long-term borrowings	2,128	47,311.3	234,678.1	0.0	373.8	3,808,364.3
Short-term borrowings	2,090	12,561.3	48,993.4	0.0	1,010.6	802,620.0
Market capitalisation	2,143	408,041.5	1,017,952.8	527.3	142,093.2	17,826,702.0
Default point	2,090	31,945.2	124,740.0	0.0	2,145.7	1,571,000.0
ln(V/D)	1,497	3.403	2.562	−3.498	2.904	15.064
DD	1,324	9.888	9.629	−10.528	7.501	73.607
E score (ES)	243	39.948	24.517	1.111	37.854	93.175
Total assets	2,182	211,586.9	646,765.8	0.0	47,947.0	9,716,990.0
Firm age	2,408	40.533	26.339	−3	33	126
Debt/Equity (times)	2,120	0.471	1.506	−4.784	0.131	35.336
EPS	2,099	26.631	53.909	−190.780	13.827	626.481
Net profit before tax	2,068	16,092.5	48,906.5	−291,595.0	4,512.7	541,180.0
SC1 (Scope 1, metric tons)	728	1,127.68	3,492.14	0.0	10.10	20,306.43
SC2 (Scope 2, metric tons)	760	85.30	233.60	0.0	18.84	2,623.41
SC3 (Scope 3, metric tons)□	316	3,277.24	13,724.79	0.0	82.55	152,475.34
Operating profit margin (%)	2,154	−44.77	1,496.32	−56,721.62	12.84	99.25
Current ratio	2,165	3.567	23.772	0.013	1.471	594.132

Notes: 301 NSE-listed Indian firms, 2,408 firm-year cells (2016–2023), prior to winsorization and the log/signed-log transformations described in Appendix Table A1. Statistics are computed directly from the underlying firm-level dataset. □ Scope 3 emissions are reported for context but are not used in the regression models given their very sparse coverage (13% of cells). A field labeled “SCLOC2” in the original data extract was confirmed, by direct comparison, to duplicate SC2 exactly (732/732 matched cells identical) and has been dropped. Source: compiled by authors from CMIE Prowess, Bloomberg, and Refinitiv Eikon.

Table 1 summarises the available variables. DD has a reported mean of 9.89 (SD = 9.63), and its negative minimum indicates that some model-based estimates fall below the specified default threshold. Environmental scores are observed in only 243 firm-year cells, approximately 10% of the 2,408-cell frame. Scope 1 and Scope 2 emissions are highly dispersed. Because these statistics are calculated from available observations, they may not represent all listed firms. The reported minimum firm age of −3 years is not interpretable if age is defined as years since incorporation; this data-quality issue must be resolved by reconciling it with the underlying incorporation-year and financial-year fields before submission.

4.2 Cross-Sectional Climate Profile by Firm Size

Firms are grouped into terciles based on average total assets to compare their Environmental scores, absolute Scope 1 emissions, and DD. This descriptive comparison helps illustrate how environmental variables and credit-risk measures vary across firm-size groups; it does not identify causal effects.

Table 2
Environmental Score, Absolute Emissions, and DD by Firm-Size Tercile

Size tercile	ES (mean)	ES (median)	SC1 (mean)	DD (mean)	DD (median)
Small	34.15	33.58	854.67	10.47	8.28
Mid	37.25	37.32	331.76	10.95	8.42
Large	46.53	42.89	1,924.19	8.60	6.08
ANOVA	F = 5.98, p = 0.003		F = 36.93, p < 0.001	—	

Notes: Terciles formed on each firm's average total assets across 2016–2023 (N = 301 firms). ANOVA tests the null of equal group means (ES: N = 239 firm-years with non-missing ES and SizeTercile; SC1: N = 728). Source: authors' calculations from the underlying dataset.

In the reported tercile comparison, large firms have higher average Environmental scores and higher absolute Scope 1 emissions than small and medium firms, while their mean DD is lower. This pattern illustrates why absolute emissions should not be described as emissions intensity: larger firms may emit more because of their scale. A higher provider score does not necessarily imply lower absolute emissions. The differences are descriptive and may also reflect industry composition and data coverage.

The following figures provide additional descriptive context on the annual distribution and coverage of environmental scores and Scope 1–3 emissions.

The annual score distributions should be interpreted cautiously because provider coverage changes over time. An increase in the number of observed scores in later years may reflect expanded coverage rather than a population-wide change in environmental performance.

Increases in the number of observed scores in later years may reflect expanded provider coverage rather than changes in the underlying population's environmental performance. The figures are therefore

descriptive and should not be interpreted as evidence of a population-wide trend without a balanced-sample analysis.

Notes: Firms grouped into four score categories — Poor (< 25), Average (25–49), Good (50–74), Excellent (75+) — by year. Source: authors' construction from Bloomberg/Refinitiv Eikon data.

The number of firms with observed scores increases in some later years. This may reflect changes in provider coverage and should not be interpreted as evidence of a population-wide shift in environmental performance without a balanced-sample analysis.

Notes: Box plots of firm-level Scope 1, 2, and 3 emissions (metric tons CO_2e) by year. Source: authors' construction from Bloomberg/Refinitiv Eikon data.

Differences in the annual emissions distributions may reflect reporting coverage, sample composition, or actual emissions. These figures alone cannot tell us which of these explanations' accounts for the observed differences.

4.3 Association Between Reported Emissions and Distance to Default

Table 3
Two-Step System GMM Estimates for Distance to Default

Variable	M1 (Base)	M2 (+ SC2)	M3 (+ ES)□	M4 (+ SC2,ES,Age)□	M5 (Full)□
lag(DD, 1)	−0.320*	−0.345*	−0.647***	−0.609***	−0.635***
	(0.033)	(0.034)	(< 0.001)	(< 0.001)	(< 0.001)
log SC1	−0.844***	−1.170***	−0.760	−0.329	−0.495
	(< 0.001)	(< 0.001)	(0.259)	(0.735)	(0.527)
log SC2	—	0.263	—	−2.670	−1.669
		(0.539)		(0.175)	(0.275)
ES	—	—	0.047	−0.029	0.0001
			(0.203)	(0.576)	(0.999)
Firm age	0.121**	—	—	0.418**	0.412**
	(0.008)			(0.004)	(0.004)
log(Debt/Equity)	−10.149**	—	−15.061	—	—
	(0.009)		(0.096)		
log(Asset)	—	—	—	—	−3.279*
					(0.024)
log net profit	0.260*	0.492***	0.310	—	—
	(0.010)	(< 0.001)	(0.463)		
N (firm-years)	188	186	16	16	16
Instruments	9	8	9	9	10
Hansen J (p)	0.683	0.685	0.690	0.829	0.804
AR(2) (p)	0.605	0.543	—	—	—

Notes: Two-step system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998), Windmeijer (2005)-corrected standard errors, estimated in Python via pydynpd (Wu et al., 2023). p-values in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001. □ M3–M5 require the Environmental score jointly with the dynamic specification; usable N collapses to 16 firm-years, close to the number of instruments — these columns are reported for completeness per reviewer request but should not be treated as reliable estimates (see Section III.D and IV.C). Hansen tests in near-saturated specifications (N close to instrument count) lose power and should not be read as confirming correct specification. AR(2) test could not be computed at N = 16 (insufficient residual variation across the required lag structure).

Table 3 reports two-step system-GMM estimates of Eq. (2). The principal specifications (M1 and M2) contain 188 and 186 firm-year observations, respectively, substantially fewer than the 2,408 potential firm-year cells. These estimates are based on the subset of firm-years with complete data for DD, lagged DD, emissions, and the relevant controls. In these specifications, Scope 1 emissions are negatively associated with DD (reported coefficients − 0.844 and − 1.170; $p < 0.001$), while Scope 2 is not statistically significant in M2. The negative coefficient on lagged DD is unusual for a measure often expected to be persistent and should be treated as an unresolved diagnostic issue pending sensitivity analysis.

The system-GMM specifications that include the Environmental score retain only 16 observations, with approximately 9–10 instruments. These estimates are too sparse to support reliable inference about the Environmental-score hypothesis. The small sample also limits the usefulness of overidentification diagnostics. The estimates are retained only to document the coverage constraint and should not be interpreted as evidence either for or against a relationship between environmental performance and DD.

A descriptive rescaling of the reported M1 coefficient suggests that a one-standard-deviation increase in log Scope 1 emissions is associated with a 2.39-unit lower DD, equivalent to approximately 24.8% of the reported standard deviation of DD. This calculation is not an estimate of a percentage change in default probability and should not be interpreted causally. Its validity depends on the coefficient and standard deviations being drawn from the same estimation sample.

4.4 Validity Check: Pooled OLS and Fixed-Effects Bounds on the Dynamic Coefficient

A common diagnostic in dynamic-panel analysis compares the lagged-dependent-variable coefficient from pooled OLS, fixed effects, and system GMM. In standard settings, pooled OLS and fixed-effects estimates can provide rough upper and lower benchmarks, respectively, although the interpretation depends on model assumptions and sample comparability. This comparison is informative but is not a formal test of instrument validity or proof that the GMM estimate is consistent.

Table 4
Dynamic-Coefficient Bias-Bounds Check

Estimator	N (firm-years)	lag(DD) coefficient	p-value	Role
Pooled OLS (dynamic)	319	0.531	< 0.001	Upper bound
System GMM (M1, Table 3)	188	−0.320	0.033	Estimate under test
Fixed Effects (dynamic)	319	−0.350	0.035	Lower bound

Notes: The reported pooled OLS and fixed-effects estimates use 319 observations, whereas the system-GMM estimate in Table 3 uses 188 observations. Because the estimation samples differ, this comparison is only indicative and should not be treated as a strict bias-bounds test. Standard errors are firm-clustered where reported.

The reported GMM coefficient falls between the pooled OLS and fixed-effects coefficients shown in Table 4. However, because the reported sample sizes differ, this comparison cannot be interpreted as a formal bias-bounds diagnostic. It also does not establish that the system-GMM model is correctly identified. The negative lagged-DD coefficient remains unusual and should be examined across alternative instrument sets, lag windows, and specifications before drawing a substantive interpretation.

4.5 Static Pooled OLS Cross-Check for Environmental-Score Specifications

Because the dynamic specifications that include the Environmental score are estimated on only 16 observations, a static pooled-OLS cross-check is reported without the lagged-DD requirement. This produces a larger but still limited sample of 53 firm-years from 34 firms. It is a supplementary check only and cannot replace a properly identified dynamic model or overcome the underlying coverage limitation.

Table 5
Static Pooled OLS Cross-Check, Environmental-Score Specifications

Variable	**M3 (SC1 + ES)**	**M4 (+ SC2, Age)**	**M5 (Full, +Asset)**
log SC1	−0.345 (0.616)	0.044 (0.953)	−0.102 (0.870)
log SC2	—	−2.069 (0.130)	−1.068 (0.393)
ES	−0.048 (0.519)	−0.017 (0.803)	−0.004 (0.954)
Firm age	0.264 (0.130)	0.275 (0.117)	0.280 (0.092)
log(Asset)	—	—	−2.367 (0.140)
log(Debt/Equity)	−5.574 (0.410)	−7.999 (0.189)	−4.561 (0.469)
log net profit	0.482* (0.023)	0.310 (0.178)	0.296 (0.158)
N (firm-years)	53	53	53
Firms	34	34	34
R^2	0.360	0.385	0.414
Overall F-test (p)	0.155	0.085	0.028*

Notes: Static pooled OLS (no lagged DD), cluster-robust (firm-level) standard errors; p-values in parentheses. * p < 0.05. Sample does not require a non-missing lagged DD, so N is larger than the dynamic GMM columns in Table 3 (N = 53 vs. N = 16) but still small.

No individual coefficient on Scope 1, Scope 2, or the Environmental score is statistically significant in the static pooled-OLS cross-check. Because this model contains only 53 firm-years from 34 firms, estimates are imprecise and should not be interpreted as evidence that the underlying associations are zero. This analysis does not resolve the Environmental-score hypothesis.

4.6 Additional Robustness: Fixed- and Random-Effects Panel Models

Table 6
Panel Fixed- and Random-Effects Estimates (Robustness Check, SC1 specification)

Variable	Fixed Effects	Random Effects
log SC1	−0.355 (0.544)	−0.622** (0.003)
Firm age	−0.143 (0.517)	0.084† (0.081)
log(Debt/Equity)	−3.956† (0.083)	−9.724*** (0.001)
log net profit	0.171** (0.005)	0.252*** (0.001)
Constant	17.419† (0.085)	9.676*** (< 0.001)
N (firm-years)	362	362
Entities (firms)	133	133

Table A1
Variable Description

#	Variable	Description
1	Company / ISIN	Firm identifier (301 unique NSE-listed firms).
2	Year	Financial year of the data record (2016–2023).
	Merton model (Stage 1)	
3	Annualized SD	Annualized standard deviation of daily equity returns, used as a proxy for equity volatility.
4	Long-term borrowings	Long-term debt held by the company.
5	Short-term borrowings	Short-term debt liabilities.
6	Market capitalisation	Market value of the company's equity.
7	Default point (calc.)	Book value of liabilities, used as the default threshold in the Merton model.
8	ln(V/D) (calc.)	Natural log of the ratio of firm value to the default point.
9	DD (calc.)	Distance to Default, estimated using the Merton model. Observed in 55% of firm-year cells.
	Two-step system GMM (Stage 2)	
10	ES	Environmental score. Observed in only 10% of firm-year cells — the binding data constraint in this paper.
11	Asset size	Natural log of total assets.
12	Incorporation year	Year the company was incorporated.
13	Firm age	Year minus incorporation year.
14	Debt/Equity (times)	Total debt / shareholders' equity; winsorized at the 1st/99th percentiles and signed-log transformed.
15	EPS	Earnings per share.
16	Net profit before tax	Winsorized at the 1st/99th percentiles; signed-log transformed.
17	SC1	Scope 1 GHG emissions (metric tons); log(1 + x) transformed. Observed in 30% of cells.
18	SC2	Scope 2 GHG emissions; log(1 + x) transformed. Observed in 32% of cells.

* Considered as a candidate variable but excluded from the final models due to very sparse coverage. Note: an original field "SCLOC2" was confirmed to be an exact duplicate of SC2 and was removed. Source: compiled by authors from CMIE Prowess, Bloomberg, and Refinitiv Eikon.

#	Variable	Description
19	SC3*	Scope 3 GHG emissions; not used in the final models (13% coverage).
20	Operating profit margin (%)	Winsorized at the 1st/99th percentiles; signed-log transformed.
21	Current ratio	Current assets / current liabilities; winsorized and log-transformed.

* Considered as a candidate variable but excluded from the final models due to very sparse coverage. Note: an original field “SCLOC2” was confirmed to be an exact duplicate of SC2 and was removed. Source: compiled by authors from CMIE Prowess, Bloomberg, and Refinitiv Eikon.

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Cluster-robust (firm-level) standard errors. Sample: all firm-years with non-missing DD, SC1, firm age, Debt/Equity and net profit (a larger, static sample than the dynamic GMM specifications above). A formal Hausman test could not be computed reliably (the FE–RE variance-difference matrix was not positive definite, a known artifact in short, unbalanced panels), so we do not report a single test statistic; we instead compare the two estimators directly below.

The fixed-effects (FE) estimate uses within-firm variation over time, whereas random effects (RE) combine within- and between-firm variation under stronger assumptions. The RE coefficient on Scope 1 is negative and statistically significant, whereas the FE coefficient is negative but not statistically significant. This divergence indicates that the evidence does not demonstrate a stable within-firm association and is consistent with persistent firm-level differences contributing to the pooled relationship. It does not, by itself, identify the precise source of those differences.

5. DISCUSSION AND POLICY IMPLICATIONS

Taken together, the reported estimates show a negative association between Scope 1 emissions and DD in the principal system-GMM specifications and the random-effects model. The fixed-effects estimate is directionally negative but not statistically significant, and the reported robustness checks indicate attenuation when firm size, sector, and year effects are included. These patterns are consistent with absolute emissions partly capturing persistent differences in scale, industry, capital intensity, or business model. They do not establish that emissions cause a deterioration in creditworthiness. The negative lagged-DD coefficient and the dependence on a much smaller estimation sample also require additional validation.

The Environmental-score hypothesis cannot be tested reliably in the dynamic-panel setting because only 16 observations remain when the score and other required variables are jointly included. The static cross-check is also small and yields imprecise estimates. The evidence is inconclusive; it does not show that environmental performance is unrelated to DD. Future analysis should compare firms with and without score coverage and assess whether missingness is related to firm size, industry, leverage, or credit risk.

6. CONCLUSION

This paper investigates the relationships among Scope 1 and Scope 2 emissions, Environmental pillar scores, and a Merton-based Distance to Default measure for Indian listed firms over 2016–2023. In the principal system-GMM specifications, Scope 1 emissions are negatively associated with DD, whereas Scope 2 emissions are not statistically significant. The Scope 1 coefficient is statistically insignificant in the fixed-effects model and attenuates in the reported robustness specifications with additional size, sector, and year controls. Environmental score results are inconclusive due to sparse coverage. Overall, the evidence suggests that absolute Scope 1 emissions may be associated with firm characteristics related to credit risk, but it does not establish a causal effect of emissions on default risk.

Several limitations qualify these findings. The joint sample for the regressions is substantially smaller than the initial firm-year frame and may be non-random. Environmental-score coverage is sparse and comes from one provider. The emissions measures are absolute quantities rather than intensity measures and may proxy for firm size and sector. System-GMM estimates rely on internal-instrument assumptions, and the negative lagged-DD coefficient requires further investigation. Future research should validate DD construction, improve emissions and ESG coverage, estimate emissions-intensity and within-between specifications where feasible, and use credible regulatory or other quasi-experimental designs to strengthen causal identification.

Declarations

Author Contribution

S.S.A. contributed to the conceptualisation, research design, data collection, data analysis, and drafting of the original manuscript. A.B. contributed to the methodology, interpretation of results, and critical review of the manuscript. S.K.P. contributed to the theoretical framework and editing of the manuscript. J.P.C. contributed to supervision, critical review, and refinement of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Data Availability Statement

The data supporting the findings of this study are obtained from CMIE Prowess and LSEG Eikon and Bloomberg. These datasets are proprietary and available under license; therefore, they are not publicly available.

Disclosure Statement

I declare that I have no financial, commercial, or business interests in any organization that could be affected by the research reported in this paper. The study was conducted independently, and there are no potential conflicts of interest to disclose. All data analyses and interpretations are the authors' own, and all relevant affiliations have been fully disclosed to Taylor & Francis.

Declaration of Generative AI Use

During the preparation of this work, the authors used OpenAI's ChatGPT to improve the manuscript's language and readability. After using this tool, the authors carefully reviewed and edited the content and take full responsibility for the final version of the manuscript.

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Figures

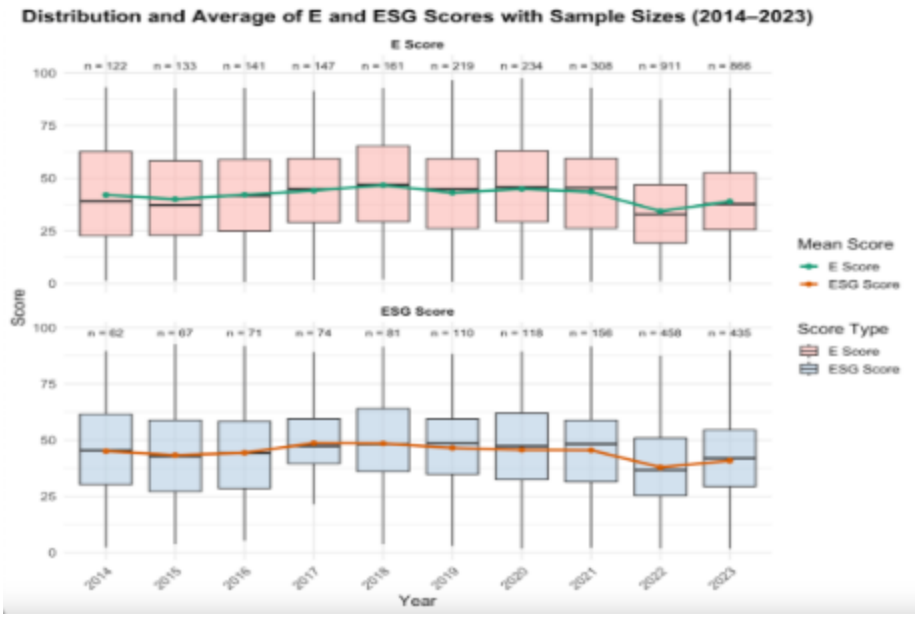


Figure 1

Distribution of Environmental (E) Score and ESG Score, 2014–2023

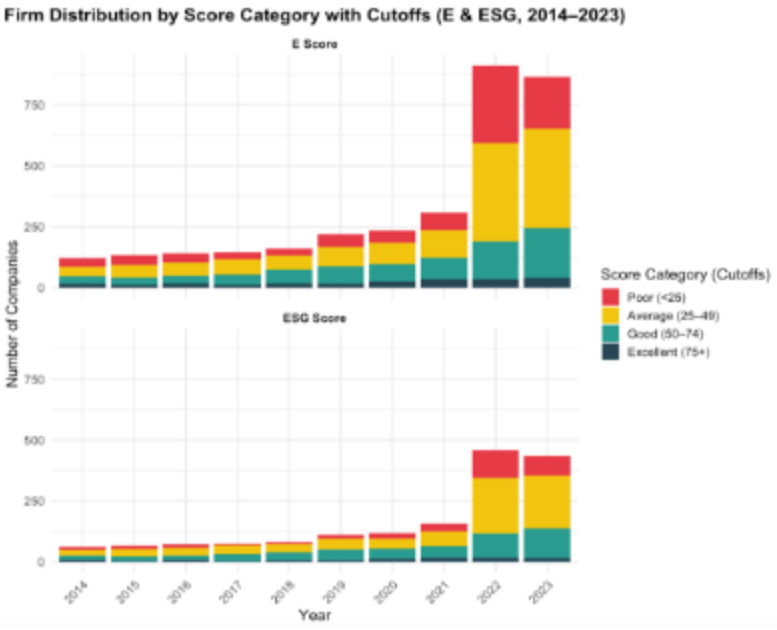


Figure 2

Firm-wise ESG Performance by Score Category, 2014–2023

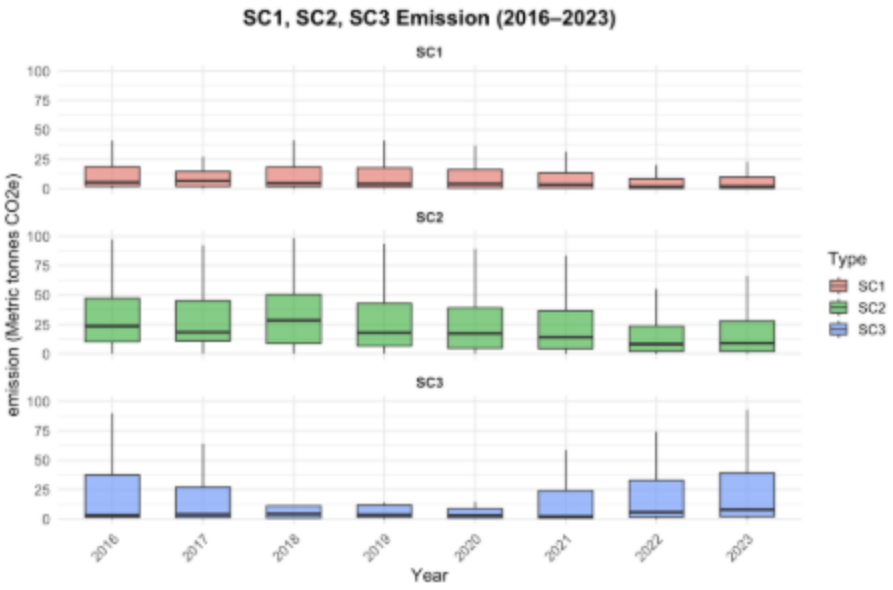


Figure 3

Annual Distribution of Scope 1, 2, and 3 Emissions, 2016–2023