

Carbon risk and corporate creditworthiness: Evidence from a major emerging economy

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ABSTRACT

We examine the relationship between climate-related transition risk and the creditworthiness of non-financial Indian firms. We find that higher emissions are associated with significantly higher market-implied probabilities of default (PD), and that this association becomes stronger after the Paris Agreement. Firms misaligned with Paris-consistent decarbonization pathways and those with greater exposure to prospective carbon pricing exhibit elevated credit risk. The magnitude of the association varies with firm characteristics: stronger financial positions, robust ESG practices, and higher investment capacity attenuate the positive association between emissions and PD. Reputational exposure and the cost of equity emerge as significant channels linking emissions to default risk, whereas no meaningful effect is detected through the cost of debt. These results highlight the growing importance of transition risk in emerging markets and highlight mechanisms through which investors incorporate firm-level environmental exposure into credit risk assessments.

1. Introduction

Climate change has shifted from an environmental concern to a material economic risk. Atmospheric CO₂ concentrations have reached unprecedented levels in human history, unequivocally driven by anthropogenic greenhouse gas emissions. Global temperatures are already about 1.1 °C above pre-industrial levels, increasing the frequency of extreme weather events and disrupting the climate stability on which economic activity depends (IPCC, 2021). In response, the 2015 Paris Agreement committed nearly all nations to limit warming to “well below 2 °C” and to pursue a 1.5 °C cap. Meeting these targets requires a rapid transition to a low-carbon economy through sharp emission reductions and a phase-out of fossil fuels. Governments are implementing stricter climate policies, including carbon pricing, emissions trading, and renewable energy mandates, to align with the goals of the Paris Agreement. While essential to avert long-term climate damage, these policies impose near-term transition risks on fossil-fuel-reliant firms, affecting their profitability, asset values, and creditworthiness.

Investors and regulators increasingly recognize that climate commitments and policies will alter the competitive landscape, effectively pricing in future climate risks (Bolton and Kacperczyk, 2021; Bolton and

Kacperczyk, 2023; Huynh and Xia, 2021). In other words, the expectation of a determined low-carbon transition is changing how capital markets assess firm value and solvency today. Companies with large carbon footprints may face the prospect of stranded assets, higher compliance costs, or demand shifts, all of which can erode creditworthiness. In particular, tighter regulation or carbon costs can raise operating expenses and impair the profitability of high-emitting businesses, potentially weakening their capacity to repay debt (Jung et al., 2025).

Early evidence from developed markets suggests that financial markets have begun penalizing heavy emitters: for example, Capasso et al. (2020) find that firms with larger carbon emissions are viewed by the market as more likely to default on debt, and Ilhan et al. (2021) document that high-emission companies exhibit greater downside risk in equity option markets. Similarly, recent studies of European credit default swap spreads show that companies' CDS-implied credit risk is higher for those with greater CO₂ emissions, especially after the Paris Agreement (Zhang and Zhao, 2022). These findings imply that the transition risk of climate change is increasingly reflected in corporate credit risk in advanced economies. However, much less is known about whether markets price in transition-related credit risk premia in major emerging economies, where energy systems are more carbon intensive

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and institutional settings and developmental priorities differ.

This study examines the relationship between climate-related transition risk and firm credit risk in India, a major emerging economy at the forefront of the climate–development challenge. India is the world's third-largest greenhouse gas emitter, after China and the United States, contributing markedly to global CO₂ levels through its coal-dominated energy sector, heavy industry, and agriculture (e.g. rice paddies and livestock). Unlike advanced economies, however, India's per capita emissions remain relatively low, reflecting the country's still-developing status and pressing energy needs (UNFCCC, 2021; World Bank, 2022). India is increasingly exposed to transition risks as it engages with global climate efforts. The government has committed to ambitious climate goals (including a net-zero emissions target by 2070) and is introducing policies to curb emissions growth (Government of India, 2022). Notably, India plans to launch a national carbon market by 2026 and to penalize industrial facilities that exceed prescribed carbon intensity limits (Ministry of Environment, Forest and Climate Change, 2023). These commitments and prospective policy tightening raise expected transition costs for high-emitting firms, making India a useful setting to test whether investors price carbon exposure into forward-looking default risk.

Our study focuses on whether and how transition risk is priced into the credit risk of Indian non-financial companies. We build a panel dataset of Indian listed firms spanning 2005–2023, combining financial information, emissions data, loan-level exposures, and measures of alignment with Paris Agreement targets. We use firms' annual *Scope 1* carbon emissions (direct greenhouse gas emissions) as a proxy for their exposure to transition risk, on the premise that higher emitters are more exposed to future carbon costs, regulatory burdens, or technological disruption in a low-carbon transition. As the outcome of interest, we consider firms' market-implied probability of default (PD), a forward-looking measure of credit risk extracted from financial market data. We empirically investigate the relationship between carbon emissions and default risk, whilst controlling for standard determinants of credit risk and including industry and time fixed effects to absorb unobserved sectoral and time-specific heterogeneity. The core question of our study is whether Indian firms with high carbon footprints exhibit higher perceived default risk.

Our findings show that higher carbon emissions are associated with a significantly higher PD, suggesting that markets are pricing in the transition risk of climate change for Indian firms. Specifically, a one-standard-deviation increase in *Scope 1* emissions is associated with a 22.9% rise in the market-implied PD. Next, we investigate the heterogeneous effects of carbon emissions on credit risk across firms with differing financial conditions, ESG practices, and capital investment levels. We present several novel findings. Firms with weaker financial health experience a larger increase in default risk for a given rise in emissions, consistent with the idea that limited financial buffers make it harder to cope with carbon transition costs. By contrast, firms exhibiting robust ESG practices display a markedly smaller association between emissions and PD. In other words, a firm that ranks well on sustainability metrics tends to be partially insulated from the credit risk consequences of its carbon emissions, perhaps because such a firm is more transparent and proactive about managing climate risks. Similarly, we find that high levels of capital investment moderate the effect of emissions on default risk. Firms in the top tier of CAPEX (relative to assets) show a weaker link between emissions and PD than firms with low investment, suggesting that investors may view capital expenditures as a sign of adaptability or growth that offsets transition vulnerabilities.

We assess whether and how global climate policy signals affect investor perceptions of credit risk. We exploit the 2015 Paris Agreement as a quasi-exogenous shock that redefined transition risk expectations in financial markets. We implement three complementary empirical strategies using Indian firm-level data to evaluate the effects of this global climate accord on market-implied PDs. First, we adopt a difference-in-differences (DiD) approach to test whether the Paris Agreement

triggered a repricing of credit risk for carbon-intensive firms. We find that after 2015, high-emitting firms experienced a significant increase in their PDs relative to low emitters, suggesting a heightened perception of transition risk following the agreement. Second, we examine whether investors penalize firms that are misaligned with the Paris-aligned decarbonization pathway. Our results show that firms exceeding their implied emissions reduction targets exhibit higher PDs. Finally, we estimate the financial vulnerability stemming from unpriced carbon cost exposure by constructing a forward-looking measure that compares firm-level emissions against carbon prices consistent with Paris-aligned scenarios. We find that firms with higher unpriced carbon costs are perceived as significantly riskier.

We explore two channels through which transition risk may be related to default probabilities. First, we examine the “reputational channel”. We show that firms with higher emissions are more likely to be associated with ESG-related incidents and that reputational exposure significantly increases market-based PDs. We next examine whether transition risk is associated with firms' PD through the cost of capital channel. Our results indicate no significant increase in the cost of debt, measured via both effective interest rates and syndicated loan spreads, suggesting that creditors may not fully price in transition risks. In contrast, we find that high emitters face a higher cost of equity, consistent with forward-looking equity markets demanding a premium for climate-related risks. The mediation analysis indicates that both reputational risk and the cost of equity serve as important channels through which emissions are linked to firms' PD.

We conduct a battery of robustness checks to address identification concerns and validate our findings. First, we address potential endogeneity by showing that high- and low-emitting firms exhibit parallel pre-trends in default risk before the Paris Agreement, supporting the validity of the difference-in-differences design. We implement entropy balancing to construct a reweighted control group with covariate distributions closely matching those of high-emitting firms and show that the results remain robust. To isolate unanticipated variation in emissions, we estimate firm-level emission shocks and find that positive shocks are associated with higher default risk. We further demonstrate that the results are consistent across alternative PD maturities, emission scopes, and when using emission intensity instead of absolute emissions. Using quantile regressions, we provide evidence of non-linear effects across the PD distribution, with stronger effects concentrated in the middle range of default risk. We reject the hypothesis that our results are driven primarily by low-emitting firms, whose contribution to greenhouse gas emissions is negligible. Finally, the loan-level analysis confirms that transition risk is not materially reflected in debt pricing in the Indian credit market.

A growing body of research provides evidence that climate change is increasingly influencing firm performance and financial valuation. Both physical and transition risks have been shown to elevate funding costs and raise the probability of financial distress, particularly for firms that already exhibit underlying financial fragilities (Krueger et al., 2020; Borsuk, 2023). These effects operate through various transmission mechanisms, including reduced operational efficiency (Pankratz and Schiller, 2023), weakened profitability (Ginglinger and Moreau, 2023), disruptions to supply chains (Addoum et al., 2023), and heightened earnings volatility (Huang, 2018). Furthermore, capital markets are progressively incorporating climate risk into asset prices, as evidenced by its effects on equity valuations (Pástor et al., 2022; Bolton and Kacperczyk, 2023; Hsu et al., 2023), the cost of debt (Owolabi et al., 2024), bond yield spreads (Painter, 2020; Huynh and Xia, 2021; Duan et al., 2025), and real estate markets (Bernstein et al., 2019). In terms of credit risk, Capasso et al. (2020) find that firms with higher carbon emissions are perceived as more likely to default. Ilhan et al. (2021) document increased downside risk for high-emission firms in equity option markets. Moreover, recent evidence suggests that CDS spreads are positively associated with firm-level emissions, particularly after the Paris Agreement, indicating greater investor attention to transition risk (Zhang and

Zhao, 2022; Duong et al., 2025).

Our findings extend the evidence on carbon risk and corporate creditworthiness in several ways. First, while prior studies document a positive relationship between emissions and credit risk in advanced economies, we provide evidence from India, where transition exposure is shaped by a coal-intensive energy mix and the prospect of tighter climate policy, implying higher expected adjustment costs and information frictions. Second, we identify two factors that contributed to a post-2015 shift in market pricing of transition risk: misalignment with Paris-consistent decarbonization trajectories and heightened exposure to prospective carbon pricing required to meet Paris targets. Third, we show that firm-level characteristics, including leverage, capital expenditure, and ESG practices, moderate the effect of transition risk on market-implied default probabilities. Finally, we establish and quantify two transmission channels: a cost-of-capital channel, in which higher emissions increase the cost of equity but not debt, and a reputational channel, in which ESG-related incidents amplify the credit risk of high emitters.

The remainder of this paper is organized as follows. Section 2 describes data sources, variable definitions, and estimation methods. Section 3 reports empirical results. Section 4 presents additional results. Section 5 concludes.

2. Data and empirical setting

2.1. Data and sample

Our analysis integrates multiple datasets to construct a panel of 647 non-financial firms from India, spanning the years 2005 through 2023. The objective is to assess the extent to which transition risk is reflected in firms' PDs. To this end, we employ the market-implied PD developed by the Credit Research Initiative (CRI) at the National University of Singapore. This is a forward-looking measure of credit risk derived from the forward intensity model proposed by Duan et al. (2025), which links firm-specific characteristics and macro-financial indicators to multi-horizon default forecasts. We focus on the 5-year PD to reflect the long-term nature of climate risk exposures. Given the delayed realization of transition and physical risks, longer-horizon default measures are better suited to capturing how markets price in climate-related vulnerabilities (e.g., Bolton and Kacperczyk, 2021; Battiston et al., 2017).

To proxy for climate transition risk, we rely on firm-level absolute carbon emissions, in line with the approach adopted by Bolton and Kacperczyk (2023) and Hsu et al. (2023), who assume that firms with higher GHG emissions face elevated transition risk due to their greater exposure to regulatory tightening, investor scrutiny, and reputational costs. Specifically, we use Scope 1 CO₂-equivalent emissions¹—which capture direct emissions from sources owned or controlled by the company, including fuel combustion during production processes. Emissions data are retrieved from S&P Trucost.² Given that both the 5-year PD and Scope 1 emissions are highly positively skewed, we apply a natural logarithmic transformation to each variable. This adjustment reduces the influence of extreme values, addresses heteroscedasticity,

¹ This metric includes both CO₂ and other greenhouse gases.

² Our starting point is S&P Global Sustainable1 Trucost, which covers 34,751 Indian firms over 2005–2023 (unbalanced panel) with Scope 1 emissions data. We merge Trucost to S&P Capital IQ Pro using S&P's CompanyID to obtain annual firm financial controls. Because Capital IQ does not report a complete set of balance-sheet variables for all Trucost firms, the merged Trucost–Capital IQ sample is reduced to 1726 firms with complete coverage of the firm-level controls. We then merge this panel to CRI market-implied default probabilities using ISIN at annual frequency (end-of-year observations). Since CRI covers only publicly listed firms in India, and many of these do not have emissions data in Trucost, the estimation sample contracts to 647 firms with complete information on emissions, financial variables, and PD.

and facilitates interpretation of the estimated coefficients as elasticities (Wooldridge, 2010).

Table 1 presents summary statistics for the key variables in our sample. All variables are winsorized at the 1st and 99th percentiles to limit the influence of outliers. The average 5-year market-implied PD is 8.1%, with a standard deviation of 12.2 percentage points. In log terms, the mean and standard deviation are 0.72 and 1.13, respectively, indicating that a substantial share of Indian public firms is perceived to face non-trivial medium-term credit risk. The average value of the log-transformed Scope 1 emissions (*Scope 1*) is 10.6, with a standard deviation of 3.1, indicating significant variation in carbon intensity across firms.³ The average firm in our sample has total assets (*Assets*) of approximately USD 3.21 billion, indicating a focus on relatively large, publicly listed firms. The average leverage ratio (*Debt-to-equity*) is 48.2%, while the CAPEX-to-revenue ratio (*CAPEX*) averages 10%, reflecting moderate levels of investment intensity. Firms' cash ratios (5.9 on average) (*Cash ratio*) suggest relatively healthy liquidity positions. Profitability is also solid, with an average return on assets (*ROA*) of 7.2%. Tangible assets represent roughly 33% of total assets (*Tangibility*), consistent with the composition of asset-heavy industries such as manufacturing, energy, and infrastructure. The average price-to-book (*P/B*) ratio is 5.8, with a standard deviation of 7.6, indicating considerable dispersion in market valuations and firm-level growth expectations across the sample.

2.2. Empirical strategy

The baseline panel specification quantifies the association between firms' Scope 1 emissions and market-implied default probabilities, controlling for firm-level covariates and including industry and time fixed effects. We estimate the following regression specification:

$$PD_{it} = \beta_1 Scope_{1it-1} + \beta_2 Z_{it-1} + \gamma_t + \alpha_s + \epsilon_{it} \quad (1)$$

In Eq. (1), PD_{it} denotes the natural logarithm of the 5-year market-implied PD for firm i in year t ; $Scope_{1it-1}$ represents the natural

Table 1
Summary statistics.

	N	Mean	SD	p25	Median	p75
PD	3432	0.72	2.1	−0.61	1.13	2.33
Scope 1	3432	10.63	3.08	8.57	10.11	12.29
Assets	3428	6.79	1.3	5.83	6.78	7.86
Scope 1 Intensity	3428	4.05	2.34	2.49	3.46	5.51
Leverage	3428	48.16	20.99	31.69	47.37	63.95
ROA	3426	7.18	6.08	3.43	6.25	10.09
Cash ratio	3428	5.91	8.78	1.03	2.7	6.66
Tangibility	3428	32.95	21.67	14.74	29.61	49.27
CAPEX	3405	10.05	16.81	2.3	4.98	10.86
P/B	2766	5.85	7.65	1.58	3.42	6.92
Revenues	3432	6.56	1.52	5.63	6.45	7.37
Misalignment	2139	−0.29	2.18	−0.08	0.07	0.29
Carbon-at-risk	2342	2.23	1.87	2.44	0.89	3.28
Current RRI	1568	9.76	9.9	0	8.08	18.29
ESG_E	1444	34.89	20.36	21	28	44
Z-score	3426	26.22	23.57	12.52	20.48	31.58
COD	2829	4.27	2.32	2.09	4.63	6.17
COE	2829	13.63	4.18	10.67	13.05	16.03
WACC	2829	11.31	3.32	9.01	11.1	13.32
Loan spread	8497	4.76	0.94	4.09	4.61	5.30

The table provides the summary statistics for the sample from 2005 to 2023. Variable definitions are provided in Appendix A1.

³ In absolute terms, firms in our sample emit an average of approximately 3.5 million metric tons of CO₂ equivalent (tCO₂e) from direct operations, with a standard deviation of 17.6 million tCO₂e, reflecting a highly skewed distribution of emissions levels.

logarithm of the firm's direct absolute emissions, serving as a proxy for transition exposure. We also include a series of control variables. $Z_{i,t-1}$ is a vector of firm-level controls that account for the standard determinants of firms' solvency risk; γ_t represents time-fixed effects that control for time-varying unobservable country characteristics; α_s denotes industry (sector) fixed effects, capturing unobservable, time-invariant firm-specific heterogeneity within economic sectors. Firm-level control variables for default risk include the logarithm of assets (*Assets*), the ratio of tangible assets to total assets (*Tangibility*), return on assets (*ROA*), cash ratio (*Cash ratio*), debt-to-assets (*Leverage*), Capex-to-revenues (*CAPEX*), and price-to-book value (*P/B*). All firm-level controls are lagged by one period to address potential simultaneity between firm characteristics and default risk. Since both the dependent variable and the main explanatory variable are in natural logarithms, β_1 represents an elasticity and captures the percentage change in PD associated with a 1% change in *Scope 1* emissions.

We do not include firm fixed effects due to the limited within-firm variation in *Scope 1* emissions over the sample period. This approach aligns with the empirical design in Bolton and Kacperczyk (2021, 2023), Zhang and Zhao (2022), and Aswani et al. (2024), who study the link between carbon emissions and financial risk premia using primarily cross-sectional variation.⁴

To mitigate endogeneity concerns, we exploit the 2015 Paris Agreement as a plausibly exogenous global policy signal that shifted investors' expectations about the stringency and timing of climate transition policy. Importantly, the likelihood and scope of a binding international agreement remained uncertain until late in the negotiations, so the Agreement plausibly changed beliefs about the expected policy path. This shift should matter disproportionately for high-emitting firms, whose business models are more exposed to prospective carbon pricing, tighter emissions standards, and higher expected adjustment costs required to align with a Paris-consistent trajectory.⁵

We introduce a dummy variable, *Paris*, which equals one for all firm-year observations after 2015—the year in which the Agreement was formally adopted. To facilitate interpretation and align with the DiD framework, we construct a binary variable, *High Emitter*, which equals one if a firm's absolute *Scope 1* emissions exceed the median value of the sample distribution.⁶ Our primary variable of interest is the interaction term *High Emitters* \times *Paris* which captures whether the credit risk of more carbon-intensive firms increased (relative to low emitting firms) following the global climate policy shift (see Eq. (2)).

⁴ Following Berger et al. (2017) and Martynova and Vogel (2021), we report two diagnostics. First, between-firm variation in *Scope 1* emissions substantially exceeds within-firm variation: the average within-firm standard deviation equals 0.70, while the cross-sectional standard deviation within year equals 3.17, a ratio of 4.55. Second, emissions are persistent, with a within-demeaned AR(1) correlation of 0.55 (0.97 in levels). Together, these results imply that firm fixed effects would rely on limited within-firm variation and reduce statistical power.

⁵ We do not characterize the Paris Agreement as a quasi-natural experiment and refrain from making causal claims, since both high- and low-emitting firms were exposed to the policy shock. Nonetheless, DiD framework remains informative in this context. By comparing changes in default risk across treatment and control groups over time, the DiD specification helps control for unobserved, time-invariant heterogeneity. Formally, our approach belongs to a class of methods that estimate the effect of a variable of interest by exploiting an exogenous shift in the dependent variable and examining heterogeneous responses based on pre-existing variation in the covariate of interest (e.g., high-versus low-emitting firms). See, for example, Campello (2003), Frésard (2010), Gilje and Taillard (2016), and Altunbas et al. (2022).

⁶ This median-based classification follows standard empirical practice and ensures balanced group sizes while limiting sensitivity to extreme values in the emissions distribution.

$$PD_{i,t} = \beta_1 High\ Emitter_i + \beta_2 Paris_t + \beta_3 High\ Emitter_i \times Paris_t + \beta_2 Z_{i,t-1} + \gamma_t + \alpha_s + \epsilon_{i,t} \quad (2)$$

We estimate Eqs. (1) and (2) using ordinary least squares (OLS) on a panel of firm-year observations spanning 2005–2023. Standard errors are clustered at the firm level to account for serial correlation within firms.⁷ Variable definitions and data sources are documented in Appendix A1.

3. Results

This section presents the results of our regression analysis. We first report the main findings from the baseline specification, followed by the effects of the Paris Agreement, heterogeneous firm responses, and evidence on transmission channels.

3.1. Main results

Table 2 presents the estimation results for Eq. (1). We begin with a parsimonious specification and gradually enrich the model by including various fixed effects and firm-level control variables. Across all specifications in Columns (1) through (3), we consistently find a positive and statistically significant relationship between GHG emissions and firms' PD, with coefficients significant at the 1% level.

The effects are also economically meaningful. In Column (3), a one-standard-deviation increase in *Scope 1* emissions is associated with a $e^{0.067 \times 3.08} - 1 = 22.9\%$ increase in the implied PD. At the sample mean PD of 8.1%, this corresponds to an increase of about 1.9 percentage

Table 2
Scope 1 emissions and firms' probability of default.

	PD (1)	PD (2)	PD (3)
Scope 1	0.166*** (0.009)	0.206*** (0.015)	0.067*** (0.014)
Assets			0.016 (0.029)
Leverage			0.050*** (0.001)
ROA			-0.069*** (0.009)
Cash ratio			-0.020*** (0.003)
Tangibility			-0.004*** (0.001)
CAPEX			0.005*** (0.001)
P/B			-0.071*** (0.005)
Observations	4307	4237	3432
Firms	695	690	647
R-squared	0.058	0.332	0.667
Industry FE	No	Yes	Yes
Time FE	No	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

⁷ Results are robust to alternative clustering schemes, including two-way clustering by firm and year and clustering at the industry level. Alternative estimates are available upon request.

points (from 8.1% to 10.0%) This suggests that firms with higher emissions are perceived as closer to default. The findings are consistent with the interpretation that markets incorporate transition risk into credit assessments, potentially reflecting expected regulatory costs, compliance burdens, and reputational liabilities. Overall, the carbon risk profile appears to influence how investors and creditors price solvency risk, with high-emitting firms in India facing adverse credit market consequences.

These findings are in line with prior research documenting the financial materiality of carbon risk (Pástor et al., 2022; Bolton and Kacperczyk, 2023; Hsu et al., 2023), particularly with respect to equity markets. Interestingly, the magnitude of our estimates exceeds those reported by Capasso et al. (2020), who study the link between climate exposure and firm credit risk using an international sample. This discrepancy may reflect India-specific factors—most notably, the country's continued dependence on coal, which makes high-emission firms particularly vulnerable to future policy tightening.

In our baseline specification (Column 3), the coefficients on control variables are broadly consistent with prior literature (e.g., Blume et al., 1998; Alp, 2013; Baghai et al., 2014) and economic intuition. Firms with higher return on assets, greater cash holdings, a larger share of tangible assets, and higher price-to-book ratios tend to have lower PDs, reflecting lower perceived credit risk. In contrast, firms with higher leverage and those with greater capital expenditures relative to revenue are perceived as riskier. Firm size shows no significant effect on default risk.

3.2. The effects of Paris agreement

In this subsection we examine how the Paris Agreement influenced market pricing of transition risk by analyzing how investors responded to the policy shock, whether firms were aligned with Paris-consistent decarbonization trajectories, and the extent to which they were exposed to future increases in carbon pricing under transition-aligned scenarios.

3.2.1. Difference-in-differences results

Signed by 194 parties in December 2015, the Agreement established a global commitment to limit the rise in average temperature to well below 2 °C above pre-industrial levels, with efforts to pursue a 1.5 °C threshold. While the event was scheduled in advance, the breadth of participation and the level of ambition were uncertain up until the final stages of negotiation (Seltzer et al., 2022). The scope and strength of the Agreement—both in symbolic and substantive terms—surprised many observers, making it a credible external shock from the perspective of financial markets (Bolton and Kacperczyk, 2021; Degryse et al., 2023; Seltzer et al., 2022).

India formally ratified the Paris Agreement on October 2, 2016, reinforcing its support for global climate action. Given India's high reliance on fossil fuels, particularly coal, for electricity generation, the Agreement signaled a potential shift in policy direction with implications for firms in carbon-intensive sectors. We conjecture that this announcement meaningfully altered how investors perceived the long-term regulatory and economic risks faced by high-emission (“brown”) firms relative to their low-emission (“green”) counterparts. In particular, it may have triggered a reassessment of transition risk exposure, increasing the perceived probability of future carbon-related regulation and its financial implications. To empirically test this hypothesis, we implement a DiD framework that compares changes in firm-level outcomes before and after the Paris Agreement across firms with varying levels of carbon emissions.

Table 3 presents the regression results based on the Eq. (2). For brevity, we report only the coefficients of primary interest. The estimated coefficient for the interaction term is positive and statistically significant at the 1% level. According to our estimates, the market-implied PD for high-emission firms increased by $e^{0.385} - 1 = 46.9\%$ relative to low-emission firms. This suggests that the Paris Agreement

Table 3
Paris agreement and firms' probability of default.

	PD (1)
High Emitter	−0.162*** (0.115)
High Emitter × Paris	0.385*** (0.118)
Observations	3432
Firms	647
R-squared	0.666
Controls	Yes
Industry FE	Yes
Time FE	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. *Paris* equals one for all firm-year observations after 2015—the year in which the Agreement was formally adopted. *High Emitter* equals one if a firm's absolute *Scope 1* GHG emissions exceed the median value of the sample distribution. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

marked a substantial shift in how financial markets perceive the credit risk of carbon-intensive firms. This finding is consistent with the notion that, after 2015, investors began to price in greater transition risks for carbon-intensive firms, likely reflecting expectations of stricter future regulation, increased compliance costs, and heightened climate awareness among market participants. In the Indian context, where the energy sector is predominantly fossil fuel-based, the Agreement may have heightened perceived vulnerability among high-emitting firms, reinforcing the market's response to global climate policy signals.

3.2.2. Misalignment with Paris agreement targets and exposure to underpriced carbon risk

Our baseline specification proxies transition risk using firms' *Scope 1* emissions, based on the premise that carbon-intensive firms are more exposed to regulatory tightening and will likely face higher adjustment costs as economies move toward decarbonization. However, absolute emission levels alone do not indicate how effectively a firm's current practices align with future global climate targets. Carbon emissions thus capture the extent of exposure but do not fully reflect the direction or credibility of a firm's decarbonization strategy. An alternative and potentially more informative proxy incorporates a firm's alignment with the Paris Agreement, integrating both current emissions and forward-looking emissions pathways. Firms aligned with Paris-consistent trajectories are less likely to face abrupt transition costs, while misaligned firms may be viewed by investors as carrying elevated long-term regulatory and reputational risks, leading to increased perceived credit risk.

To empirically examine this hypothesis, we construct two complementary measures explicitly capturing these forward-looking dimensions. First, following Borsuk et al. (2026a), we develop a firm-level misalignment measure defined as the percentage deviation between a firm's actual emissions and the required emissions reduction trajectory consistent with the Paris Agreement's “well below 2°C” target. Positive deviations indicate non-compliance with this emissions target, signaling greater future regulatory and financial risks. Based on this, we generate a binary indicator (*Misalignment*) equal to one if a firm exceeds its emissions target.

Second, we consider that carbon pricing schemes remain either absent or substantially below the Paris-aligned trajectories in many jurisdictions, including India. According to the International Energy Agency (IEA, 2023), carbon prices in advanced economies will need to reach approximately USD 140 per ton by 2030 to remain consistent with Paris

Agreement objectives. Currently, many jurisdictions have implemented relatively low carbon taxes or no pricing mechanisms at all, which significantly underprices carbon emissions. Consequently, many firms, particularly those in jurisdictions with minimal carbon pricing, face latent risks due to anticipated regulatory tightening and potential increases in carbon-related costs.

To capture this latent exposure, we employ a forward-looking measure based on the Carbon Price Risk Premium (CPRP). The CPRP is calculated as the difference between the current carbon price faced by firms (determined by geographic and sectoral contexts) and the projected future carbon price aligned with Paris-consistent policy scenarios. The projected future carbon price is based on the IEA World Energy Outlook scenario framework and relies on the High (Net Zero 2050-consistent) pathway with a 2030 forecast horizon. By applying the CPRP to firms' emissions, we estimate the unpriced carbon cost, reflecting the additional financial burden firms would incur under stringent global climate policy alignment. To facilitate meaningful comparison across firms, we normalize this unpriced carbon cost by each firm's EBITDA and take the natural logarithm of the ratio to account for skewness in the distribution.⁸ This yields our main variable of interest: unpriced carbon cost as a share of EBITDA (*Carbon-at-risk*). A higher *Carbon-at-risk* ratio indicates greater vulnerability to future increases in carbon pricing and thus greater exposure to transition risk. The construction of the two indicators draws on data provided by Trucost.⁹ Note that data availability is limited prior to 2016, which prevents us from implementing the DiD analysis around the Paris Agreement.

We empirically test the relationship between these forward-looking measures and market-implied default probabilities. Table 4 presents the regression results. Column (1) shows a positive and statistically significant association between *Misalignment* and firms' PD. Specifically, misaligned firms exhibit $e^{0.13} - 1 = 13.9\%$ higher PDs relative to aligned firms, suggesting investors perceive these firms as bearing substantial

transition risks due to anticipated regulatory adjustments and compliance costs. Column (2) tests the relationship between *Carbon-at-risk* and PD, finding a similarly positive and statistically significant association. A one standard deviation increase in *Carbon-at-risk* corresponds to $e^{0.166 \times 1.87} - 1 = 36.3\%$ increase in the PD. These findings highlight investors' recognition of latent carbon pricing risks even in jurisdictions with currently limited regulatory frameworks, demonstrating that forward-looking measures of emissions misalignment and future carbon pricing significantly inform market assessments of firms' credit risk.

3.3. Cross-sectional analysis

The effect of transition risk on firms' PD is unlikely to be uniform and may depend on firm-specific financial and non-financial characteristics. In this section, we conduct a cross-sectional analysis to examine the mechanisms through which transition risk is related to default risk across different firm-level dimensions, including financial constraints, ESG performance, and investment activity.

3.3.1. Financial constraints

We begin by investigating how a firm's financial condition shapes its capacity to manage climate-related risks and influences how investors perceive its creditworthiness. Firms with strong financial flexibility are better positioned to allocate capital toward climate mitigation and adaptation strategies, thereby reducing their exposure to transition and physical risks (Borsuk et al., 2026b). In contrast, financially constrained firms face structural limitations that hinder their ability to respond effectively to climate challenges. As a result, such firms are more likely to be viewed by investors as carrying elevated credit risk in the face of growing environmental pressures (Nguyen and Phan, 2020; Fabisik et al., 2023).

We examine whether investors penalize financially fragile firms more heavily for their exposure to climate-related risks. Measuring financial constraints poses empirical challenges, given the absence of a standard definition. We rely on balance sheet data to construct firm-level estimates commonly used in the literature. Firms with high leverage respond more strongly to external shocks, which raises borrowing costs and tightens financing terms. Low profitability compounds these constraints by limiting internal cash flow and reducing access to external capital. To proxy for financial constraint, we use the *Z-score* (*Z-score*), a widely adopted measure of firm stability and distance to default. The *Z-score* is constructed using three firm-level indicators: the average return on assets, the equity-to-asset ratio, and the standard deviation of return on assets (see Boyd and Graham, 1986; Laeven and Levine, 2009). Specifically, we compute the *Z-score* using a three-year rolling window of ROA. For each firm-year, we estimate the rolling mean and standard deviation of ROA (minimum three observations) and scale equity-to-assets plus the rolling mean ROA by the rolling ROA volatility. A higher *Z-score* reflects greater financial resilience and a lower PD.

Under this framework, firms with higher *Z-scores* are interpreted as financially unconstrained, given their stronger balance sheets and more stable earnings. These firms are more likely to possess the capacity to finance climate mitigation and adaptation measures. Consequently, investors may perceive them as less vulnerable to transition risk, which should be reflected in a lower market-implied PD. To test this hypothesis, we interact our transition risk proxy *Scope 1* with the *Z-score*. For ease of interpretation and to align with our empirical framework, we construct a binary indicator, *Z-score High*, which equals one for firms with a *Z-score* above the sample median. This allows us to examine whether the credit risk associated with climate transition exposure is more pronounced among firms with weaker financial positions.

Table 5 presents the results of the cross-sectional analysis examining how financial strength moderates the relationship between climate transition risk and credit risk. In Column (1), we first test the direct association between the *PD* and the *Z-score*. In line with expectations, we

Table 4

The role of alignment with Paris agreement goals.

	PD (1)	PD (2)
Misalignment	0.127** (0.062)	
Carbon-at-risk		0.166*** (0.023)
Observations	2648	2013
Firms	634	597
R-squared	0.665	0.664
Controls	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. *Misalignment* equals to one if a firm exceeds its emissions target. *Carbon-at-risk* is the natural logarithm of unpriced carbon cost as a share of EBITDA. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

⁸ The results are robust to using either the raw ratio or its log transformation.

⁹ Future carbon prices are derived from the latest transition scenarios published by the IEA. Current carbon pricing levels are compiled from the World Bank, OECD, and the International Carbon Action Partnership (ICAP), allowing for country- and sector-specific precision. Financial variables, including EBITDA, are sourced from S&P Capital IQ and computed as three-year trailing averages to smooth out short-term volatility. Company-level emission data, along with the geographic distribution of emissions, are obtained from Trucost's Environmental Database and supplemented where necessary with public disclosures to the Carbon Disclosure Project (CDP).

Table 5
The role of financial constrains.

	PD (1)	PD (2)
Scope 1	0.062*** (0.014)	0.078*** (0.015)
Z-score	-0.006*** (0.001)	
Z-score High		0.518*** (0.175)
Scope 1 × Z-score High		-0.033** (0.014)
Observations	3426	3432
Firms	646	647
R-squared	0.669	0.668
Controls	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. *Z-score* is the sum of a firm's average return on assets and equity-to-asset ratio, divided by the standard deviation of its return on asset. *Z-score High* equals one for firms with a *Z-score* above the sample median. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

observe a positive and statistically significant relationship, indicating that firms with higher *Z-score* i.e., greater financial buffers and more stable earnings, are perceived as less risky by investors. Notably, *Scope 1* emissions continue to exert a positive and significant effect on firms' PD.

In Column (2), we examine the interaction between transition risk and financial resilience. Specifically, we interact our key transition risk proxy (*Scope 1*) with a dummy variable equal to one for firms with *Z-score High*. The coefficient on the interaction term is negative and statistically significant at the 5% level, suggesting that financially stronger firms are better positioned to absorb the impact of transition risk. In terms of economic magnitude, the estimated effect of *Scope 1* on the PD is approximately half as large among financially resilient firms compared to their more constrained peers. This finding is consistent with the interpretation that high-emission firms face rising costs associated with transitioning to lower-carbon operations, which can strain their financial position, particularly during the adjustment phase. For already financially constrained firms, these pressures may result in elevated borrowing costs and a heightened perception of credit risk. A firm's ability to maintain a financial cushion helps limit the impact of climate-related disruptions on its creditworthiness.

3.3.2. ESG risks

We next examine the role of a firm's environmental, social, and governance (ESG) strategy in shaping investor perceptions of transition-related credit risk. A growing body of literature suggests that strong ESG practices can reduce investor uncertainty and enhance firms' resilience to long-term risks, including those associated with climate transition (Pástor et al., 2022; Krüger, 2015; Ilhan et al., 2021). ESG alignment may signal improved risk management capabilities, greater preparedness for regulatory change, and reduced exposure to reputational or operational disruptions. Consequently, firms with more robust environmental practices may be perceived by investors as better positioned to manage transition risk, resulting in lower market-implied credit risk.

To empirically test this hypothesis, we assess whether the relationship between transition risk and firms' PD is conditioned by their environmental performance. We obtain ESG scores from S&P Capital IQ Pro, specifically utilizing the environmental pillar score (*ESG_E*). This score captures firm-level exposure to, and management of, environmental risks—such as climate change, resource depletion, pollution, and biodiversity loss. The *ESG_E* score ranges from 0 to 100, with higher

values indicating stronger environmental performance and lower exposure to environmental liabilities.

Table 6 presents the results of our analysis on how firm-level environmental performance conditions the relationship between transition risk and market-implied credit risk. In Column (1), we examine the direct effect of environmental practices on default risk. The coefficient on the *ESG_E* is negative and statistically significant, indicating that firms with stronger environmental practices are perceived by investors as less likely to default. This finding aligns with Boubaker et al. (2020), who show that higher ESG scores are associated with reduced financial distress and default probability. Strong environmental governance may reflect more forward-looking risk management, better preparedness for regulatory shifts, and enhanced stakeholder trust, which collectively lower perceived credit risk.

Importantly, the coefficient on *Scope 1* remains statistically and economically significant and in line with our baseline results, reinforcing the view that *Scope 1* emissions contain distinct informational content beyond what is captured by broader ESG assessments. This suggests that markets differentiate between a firm's current environmental footprint and its long-term environmental strategies. In Column (2), we introduce an interaction term between *Scope 1* and a binary indicator for firms with above-median *ESG_E* scores (*ESG_E High*). This allows us to test whether environmental performance moderates the relationship between carbon emissions and credit risk. The coefficient on the interaction term is negative and statistically significant, indicating that the adverse effect of emissions on default risk is less pronounced for firms with stronger environmental practices. From an economic standpoint, the positive effect of *Scope 1* on PD is approximately 50% smaller for firms with high *ESG_E* scores—similar in magnitude to the moderating effect we observe for financially unconstrained firms. This suggests that robust environmental practices may serve as a buffer or hedge against climate transition risk.

3.3.3. Capex

Investment plays a critical role in enhancing a firm's resilience and capacity to adapt to climate-related challenges. To meet the goals of the Paris Agreement, global estimates suggest that between USD 3 to 6 trillion in annual investment will be required for green infrastructure and low-carbon technologies (IEA, 2023). A substantial share of this investment must occur in emerging economies, such as India, which remain heavily reliant on coal and face significant structural and

Table 6
The role of ESG scores.

	PD (1)	PD (2)
Scope 1	0.085*** (0.023)	0.104*** (0.020)
ESG_E	-0.014*** (0.002)	
ESG_E High		0.614*** (0.195)
Scope 1 × ESG_E High		-0.051*** (0.017)
Observations	1152	1152
Firms	282	282
R-squared	0.739	0.739
Controls	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. *ESG_E* represents ESG Environmental score (ranging from 0 to 100). *ESG_E High* equals one for firms with an *ESG_E* score above the sample median. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7
The role of investments.

	PD (1)	PD (2)
Scope 1	0.065*** (0.014)	0.087*** (0.020)
CAPEX	0.005*** (0.001)	
CAPEX High		0.723*** (0.193)
Scope 1 × CAPEX High		−0.044** (0.017)
Observations	3432	3474
Firms	647	656
R-squared	0.065***	0.087***
Controls	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. CAPEX represents capital expenditures to revenues. *CAPEX High* equals one for firms with a *CAPEX* above the sample median. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

financial barriers to decarbonization.

Firms with older capital or a lower investment rate face higher exposure to technology-frontier shocks and are therefore more exposed to risk (Hsu et al., 2023). Firms that proactively invest in cleaner technologies and infrastructure are likely to be less exposed to abrupt or disruptive adjustments during the transition to a low-carbon economy. These firms may also be perceived by investors as better prepared to manage regulatory risks, maintain competitiveness, and avoid the costly consequences of a disorderly transition. Therefore, we hypothesize that high-emitting firms with higher levels of investment are penalized less by investors and face lower PD. To test this conjecture, we examine whether investment differentiates the effect of carbon emissions on default risk.

Ideally, we would directly observe green investment activity at the firm level. However, the current state of ESG disclosure in India remains limited (Srivastav and Kannadhasan, 2025). Despite growing regulatory momentum—such as SEBI's Business Responsibility and Sustainability Reporting (BRSR) framework—many firms do not yet provide detailed, verifiable data on the environmental breakdown of their capital expenditures. Given these limitations, we use the ratio of capital expenditures (*CAPEX*) to revenue as a proxy, under the assumption that general investment intensity is positively correlated with a firm's green capital expenditures. While this proxy does not isolate climate-specific spending, it serves as a relevant indicator of a firm's investment capacity and strategic orientation factors likely to impact investor expectations under heightened transition risk.

Table 7 examines whether firm-level investment activity affects the strength of the relationship between carbon emissions and market-implied credit risk. Column (1) shows that the coefficient on *CAPEX* is positive and statistically significant. This suggests that higher investment intensity is associated with increased solvency risk, potentially reflecting the external funding requirements linked to large-scale capital projects—particularly in emerging markets like India. While investment may support long-term growth, it can heighten short-term financial vulnerability by increasing leverage and financing costs.

Column (2), we interact *Scope 1* emissions with a binary indicator for firms with above-median investment intensity (*CAPEX High*). The interaction term is negative and statistically significant, indicating that

the positive association between emissions and default risk is attenuated among firms that invest more intensively. This result suggests that investment may play a risk-mitigating role in the context of the low-carbon transition. High emitting firms that allocate more resources toward capital projects may be better equipped to adapt their operations, adopt cleaner technologies, or comply with evolving regulatory standards, thereby reducing their exposure to transition risk.

3.4. Channels

We demonstrate that *Scope 1* emissions are positively associated with market-implied PDs among Indian listed firms, with the magnitude of this effect varying by firm characteristics. In this subsection, we explore two potential channels through which transition risk may be linked to default risk: the reputational channel and the cost-of-capital channel.

3.4.1. Reputational channel

Firms operating in high-emission industries frequently face heightened exposure to environmental controversies, which can significantly harm their reputation. Reputational damage from environmental incidents can lead to substantial disruptions in business operations, including supply chain disturbances, client withdrawal, and investor reluctance, resulting in severe financial losses and potential solvency issues. For example, prominent cases involving major oil spills and chemical leaks have demonstrated pronounced financial and reputational repercussions, manifesting in elevated financing costs and diminished investor confidence (Fodor and Stowe, 2012).

Existing literature has documented the economic implications of environmental controversies. Cai et al. (2016) and Bauer and Hann (2010) report substantial increases in financing costs following major environmental incidents. Chava (2014) highlights a significant positive relationship between environmental risks and firms' credit spreads, underscoring how reputational damage stemming from ESG controversies can translate directly into increased borrowing costs. Hrazdil et al. (2024) and Nandy and Lodh (2012) investigating syndicated loan markets, find that environmental controversies are associated with elevated loan spreads, suggesting banks incorporate reputational risks into credit pricing.

India provides a particularly pertinent context for examining the reputational consequences of environmental controversies. As in many emerging markets, the institutional environment is marked by relatively weaker corporate governance, evolving disclosure norms, and significant political involvement in corporate decision-making (Sarkar et al., 2012). These features may amplify firms' susceptibility to environmental controversies, enhancing their vulnerability to reputational damage and consequent financial distress. Therefore, reputational risk may constitute an important channel through which environmental performance is associated with default probabilities among high-emission Indian firms.

To empirically investigate this channel, we utilize the Current RepRisk Index (*Current RRI*), a comprehensive measure developed by RepRisk, capturing firms' reputational exposure to environmental, social, and governance (ESG) issues based solely on recorded ESG incidents.¹⁰ The RRI ranges from 0 (lowest risk exposure) to 100 (highest risk exposure), calibrated by incident severity, frequency, recency, and reach of media coverage. We integrate RepRisk data into our primary dataset by matching firm International Securities Identification Numbers (ISIN), successfully aligning data for 283 firms across 1566 observations.

Our empirical strategy involves a two-stage regression analysis

¹⁰ We retain values of the Current RRI for a given firm-year only if the environmental component contributes to the index value, as indicated by the environmental share reported by RepRisk.

Table 8
Environmental controversies and firms' probability of default.

	Current RRI (1)	PD (2)
Scope 1	0.704*** (0.140)	0.060*** (0.017)
Assets	3.104*** (0.323)	-0.009 (0.042)
Leverage	-0.033** (0.014)	0.044*** (0.002)
ROA	0.067 (0.053)	-0.085*** (0.013)
Cash ratio	-0.021 (0.024)	-0.018*** (0.004)
Tangibility	-0.033** (0.016)	-0.002 (0.002)
CAPEX	-0.005 (0.014)	0.004*** (0.001)
P/B	0.046 (0.032)	-0.071*** (0.008)
Current RRI		0.019*** (0.004)
Observations	1566	1827
Firms	283	322
R-squared	0.388	0.699
Industry FE	No	No
Time FE	No	No

The dependent variable in Column (1) is the Current RepRisk Index (RRI), which quantifies a firm's reputational exposure to environmental, social, and governance (ESG) issues based exclusively on documented ESG-related incidents. *Current RRI* ranges from 0 (lowest risk exposure) to 100 (highest). In Column (2), the dependent variable is the natural logarithm of the firm-level 5-year market-implied PD, capturing forward-looking credit risk as assessed by financial markets. *Scope 1* is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

consistent with standard mediation frameworks.¹¹ In the first stage, we regress *Current RRI* on firm-level *Scope 1* emissions to assess whether firms with higher carbon emissions are more likely to be associated with environmental controversies. In the second stage, we regress firms' PD on both *Current RRI* and *Scope 1* emissions. Following the methodology outlined by Hayes (2013), we conduct a mediation analysis to quantify both the indirect effect of carbon emissions on PD operating through the environmental controversy channel, and the remaining direct effect of emissions after accounting for this reputational dimension (for more details see Appendix A2).

The regression results presented in Table 8 confirm a statistically significant positive relationship between *Scope 1* emissions and the *Current RRI*. Specifically, a one standard deviation increase in *Scope 1* emissions is associated with a 2.16 point increase in the *Current RRI* (3.08×0.70), corresponding to 22.2% of its sample mean. This suggests that carbon-intensive firms are more likely to be involved in environmental controversies and thus face elevated reputational risk. In Column (2), we observe a positive and statistically significant relationship between the *Current RRI* and firms' PD. A one standard deviation increase in the *Current RRI* is associated with $e^{0.90 \times 0.02} - 1 = 21.9\%$ increase in PD.

Using a mediation framework, we quantify the indirect effect of

¹¹ The channel analysis is intended to provide descriptive evidence on potential transmission mechanisms rather than to establish causal mediation. A causal interpretation would require strong assumptions, including the absence of omitted variables jointly affecting emissions, the mediator, and default risk, as well as no feedback from PD to the mediator. Given that both the cost of equity and reputational exposure may respond to changes in perceived credit risk, these assumptions may not fully hold.

Scope 1 emissions on firms' default risk operating through reputational exposure. A one-standard-deviation increase in emissions is associated with an indirect effect of $e^{3.08 \times 0.70 \times 0.02} - 1 = 4.4\%$ on the PD, via the reputational channel. This magnitude suggests that reputational risk constitutes a material pathway through which climate transition risk is priced into credit markets. This result is consistent with the notion that the likelihood of environmental incidents is substantially higher in industries such as fossil fuel extraction, mining, or petrochemical transport—sectors frequently subject to public scrutiny and controversy. In contrast, firms engaged in green technologies or renewable energy production are less likely to encounter such incidents and the associated reputational damage that could undermine their solvency. Importantly, *Scope 1* emissions remain independently and positively associated with default risk, even after controlling for reputational risk, suggesting the presence of additional transmission channels through which emissions elevate firms' credit risk.

3.4.2. Cost of capital channel

In this subsection, we examine an additional transmission channel through which transition risk may be associated with firms' PD, namely, the cost of capital. High-emitting firms are likely to require substantial investment in carbon abatement technologies, resulting in elevated capital expenditures and potentially greater leverage (European Central Bank (ECB), 2023). These financing needs may increase funding costs, either through higher interest expenses or elevated equity risk premia. Accordingly, we hypothesize that carbon-intensive firms face higher capital costs—both in debt and equity markets—due to their transition exposure.

In corporate financial management, the cost of capital refers to the financial expense associated with acquiring funds from debt and equity markets. It consists of two key components: the cost of debt (COD) and the cost of equity (COE). These components are combined to calculate the weighted average cost of capital (WACC), which reflects investors' expectations regarding the discount rate for future cash flows. Thus, the cost of capital is a fundamental metric for assessing enterprise value and guiding investment and financing decisions.

To examine how environmental performance is reflected in Indian firms' PD, we use balance sheet data along with market-implied measures of the cost of equity. For India, we obtain COE data from Bloomberg.¹² We calculate the effective cost of debt (COD) as the ratio of the firm's total interest expense over the past 12 months to its average total liabilities for the same period. This represents the average annual interest rate paid on outstanding debt. WACC is then calculated as the weighted average of the cost of debt and cost of equity, with weights based on the firm's capital structure.

In our empirical analysis, we regress the COD, COE, and WACC on the logarithm of *Scope 1* emissions, controlling for firm characteristics and including fixed effects, as in the benchmark model described in Eq. (1). The results are presented in Table 9. Column (1) shows no statistically significant relationship between firms' *Scope 1* emissions and the COD. This suggests that creditors may not yet be pricing climate risks into debt contracts. One possible explanation is that lending institutions in India may not face strong regulatory or market-based incentives to penalize high-emitting firms, or that loan maturities are too short for climate risks to be perceived as material.

¹² Bloomberg uses a range of inputs including stock prices, market capitalization, book value of equity, and forecasts of earnings and dividends. Bloomberg's methodology is based on the Capital Asset Pricing Model (CAPM). The risk-free rate is proxied by the yield on 10-year Indian government bonds. The equity risk premium is estimated by multiplying the firm's beta by the country-specific equity premium, which is derived from forecasted dividends and growth rates using the Dividend Discount Model (DDM) based on Bloomberg analysts' consensus. The final premium is adjusted by subtracting the country's risk-free rate.

Table 9
Transition risk and firms' cost of capital.

	COD (1)	COE (2)	WACC (3)	PD (4)
Scope 1	0.009 (0.028)	0.167*** (0.047)	0.099** (0.040)	0.054*** (0.015)
Assets	-0.039 (0.050)	-0.505*** (0.085)	-0.695*** (0.073)	0.036 (0.028)
Leverage	-0.002 (0.002)	0.041*** (0.004)	-0.026*** (0.003)	0.045*** (0.001)
ROA	0.022** (0.009)	-0.127*** (0.015)	-0.062*** (0.013)	-0.065*** (0.005)
Cash ratio	-0.036*** (0.005)	-0.050*** (0.009)	-0.019** (0.008)	-0.014*** (0.003)
Tangibility	0.005* (0.003)	-0.008* (0.005)	-0.012*** (0.004)	-0.004** (0.002)
CAPEX	-0.001 (0.003)	-0.001 (0.005)	-0.007 (0.004)	0.005*** (0.002)
P/B	-0.015** (0.006)	-0.045*** (0.010)	0.035*** (0.009)	-0.071*** (0.003)
COE				0.121*** (0.006)
Observations	2829	2829	2829	2829
Firms	629	629	629	629
R-squared	0.255	0.336	0.239	0.717
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

The dependent variables are as follows: the cost of debt (*COD*) is computed as total interest expense over the past 12 months divided by the firm's average total liabilities for the same period (Column 1); the cost of equity (*COE*) is a market-implied measure calculated using Bloomberg's methodology (Column 2); the weighted average cost of capital (*WACC*) reflects the weighted average of the cost of equity and cost of debt, with weights based on the firm's capital structure (Column 3); and the probability of default (*PD*) is the natural logarithm of the firm's five-year market-implied default probability (Column 4). The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

These findings align with recent studies documenting a persistent disconnect between firms' carbon intensity and the behaviour of credit markets. De Haas and Popov (2019) argue that banks have been largely ineffective in supporting decarbonization, primarily because they are reluctant to finance green technologies—often due to their intangible nature, uncertain cash flows, and limited collateral value. Antoniou et al. (2024) find that banks charge lower spread for high polluting EU ETS firms. Similarly, Chaudhry and Kumari (2024) show that in India's high-growth environment, lenders tend to associate energy consumption with economic potential rather than climate risk, resulting in no risk premium for high emitters.

In Column (2), we find a positive and statistically significant association between emissions and the cost of equity. The coefficient on *COE* is statistically significant at the 10% level. A one standard deviation increase in *Scope 1* emissions is associated with a 0.4 percentage point increase in *COE* (0.167×2.335), equivalent to approximately 2.9% of its sample mean. This increase in the cost of equity contributes to a higher overall cost of capital, as shown in Column (3). While modest in magnitude, the effect is not negligible and suggests that investors may require a higher return for holding equity in more carbon-intensive firms. These findings are consistent with prior studies suggesting that equity markets more effectively price climate risk, while debt markets deliver mixed results (De Haas and Popov, 2019).

In Column (4), we formally assess whether the relationship between firms' *Scope 1* emissions and their implied *PD* is mediated through the cost of equity. Specifically, we implement a mediation framework in which *COE* serves as the intermediary channel linking emissions to *PD*. To quantify the economic magnitude of the indirect effect, we compute the product of the effect of *Scope 1* emissions on *COE*, and the effect of

COE on *PD*. This yields an estimated indirect effect of $e^{3.08 \times 0.167 \times 0.121 - 1} = 6.4\%$, which represents the change in *PD* associated with a one-standard-deviation increase in emissions, transmitted through the cost of equity channel. This finding is consistent with the equity risk premium being associated with higher default probabilities among firms with greater transition exposure.

4. Extension and robustness checks

We conduct a comprehensive set of robustness checks to address endogeneity concerns and validate our identification strategy. First, we assess the parallel trends assumption underlying our DiD design and implement entropy balancing to reweight control firms based on observable characteristics. Second, we isolate idiosyncratic emissions shocks to capture unanticipated variation in firm-level emissions. Third, we estimate quantile regressions to evaluate non-linearities across the credit risk distribution. Fourth, we analyze syndicated loan-level data to assess whether lenders incorporate emissions into loan pricing. Finally, we verify that our results hold under alternative emissions metrics, default horizons, and across different sectors and regions.

4.1. Endogeneity

4.1.1. Parallel trends assumption

While both high- and low-emitting firms were subject to the Paris Agreement, our DiD design exploits the fact that investors likely revised their credit risk assessments more sharply for high emitters, given their greater exposure to transition risk. This differential response provides identifying variation across firms with different baseline emissions profiles. A central identifying assumption in this framework is that low-emitting firms constitute a valid counterfactual for high emitters, conditional on observables. The parallel trends assumption requires that, in the absence of the policy shock, the evolution of default risk would have been similar across both groups.

To evaluate this assumption, we estimate a dynamic version of Eq. (2), replacing the post-2015 indicator with a full set of event-time dummies. This specification allows for a direct test of pre-treatment trend differentials between treated (high-emitting) and control (low-emitting) firms. Fig. 1 plots the estimated coefficients and confidence intervals, using 2015 as the reference year. The pre-treatment coefficients are small in magnitude and statistically indistinguishable from zero, supporting the validity of the parallel trends assumption. Beginning one year after India's ratification of the Paris Agreement in 2016, the *PD* of high-emitting firms rises relative to control firms. This increase becomes statistically significant the following year and remains elevated thereafter, although not all post-treatment coefficients are individually significant. The results indicate that markets began incorporating transition risk into credit risk assessments shortly after the policy signal became credible.

Additionally, Fig. 2 reports a placebo DiD that shifts the policy date two years earlier than 2015. This test checks whether the main effect reflects spurious differential dynamics rather than a post-2015 repricing. The coefficients for 2014 and 2015 are economically small and statistically indistinguishable from zero, supporting the main identification.

4.1.2. Entropy balancing

High- and low-emitting firms often differ across multiple firm-level characteristics. These differences may confound the relationship between emissions and default risk, even after controlling for observables (Imbens, 2004). To isolate the effect of emissions, the ideal approach would compare otherwise identical firms that differ only in *Scope 1* emissions. Lacking such experimental variation, we address this concern using entropy balancing. This method reweights the sample to align the distribution of observable characteristics between high-emitting (treated) and low-emitting (control) firms. We implement the two-step

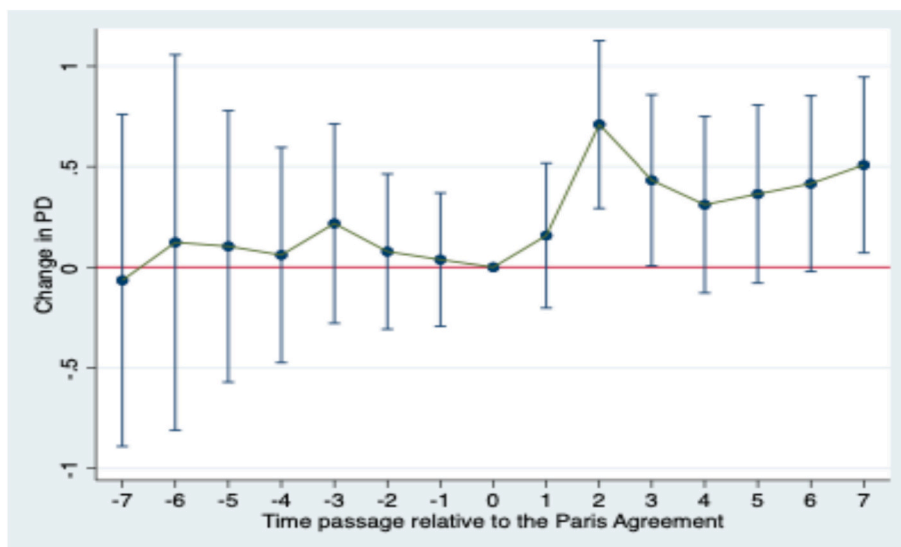


Fig. 1. Dynamic treatment effect of the Paris agreement. The figure displays the dynamic treatment effect of the Paris Agreement on firms' PD along with the 90% confidence intervals. The point estimate represents the coefficient estimate PD on relative year dummies interacted with *High Emitter*.

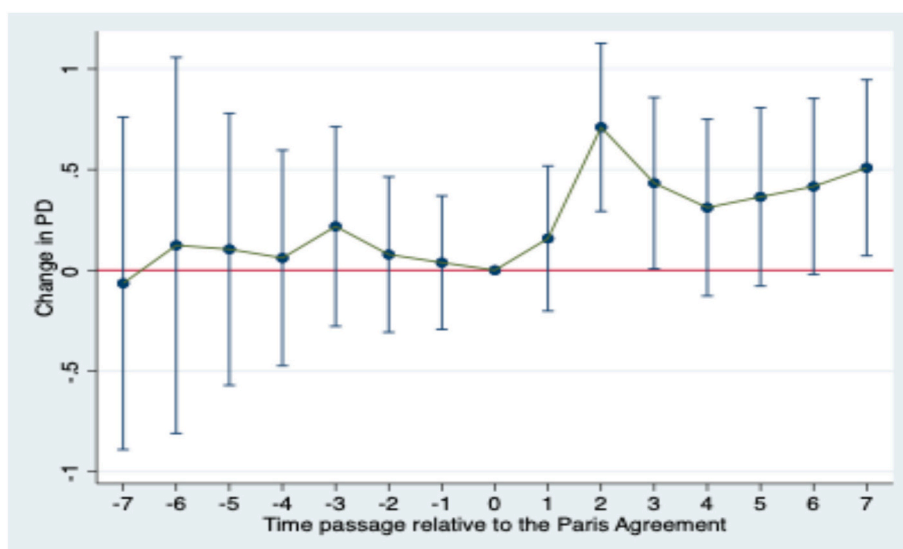


Fig. 2. Dynamic treatment effect of the placebo Paris agreement. The figure displays the dynamic treatment effect of the placebo Paris Agreement on firms' PD along with the 90% confidence intervals. The placebo indicator equals one for firm-year observations in 2014–2015, i.e., the two years immediately preceding the formal adoption of the Paris Agreement.

procedure in Hainmueller (2012). First, we construct weights for control firms that match the first moments of the covariates among treated firms.¹³ This step includes all firm-level controls from the baseline model. We define treatment using a median split of *Scope 1* emissions, consistent with earlier sections. Second, we estimate a weighted regression on the reweighted sample, following the specification in Eq. (1).

Fig. 3 shows the standardized percentage bias in covariates before and after entropy balancing. Table 10 reports covariate means for treated firms and for control firms before and after reweighting, together with standardized mean differences (and variance ratios). After reweighting, the treated and control groups exhibit substantially

improved covariate balance, with most standardized biases falling below commonly used threshold of 10% (Rosenbaum and Rubin, 1983). Table 11 reports the unweighted (Column 1) and weighted (Column 2) regression results. In both specifications, the coefficient on *High Emitter* remains positive and statistically significant, suggesting that the estimated effect of emissions is not driven by differences in observable firm characteristics between high- and low-emitting firms.¹⁴ While this approach does not eliminate endogeneity from unobserved factors, it reduces selection on observables sufficiently to make it unlikely that omitted differences across firms are responsible for the result.

¹³ Results remain qualitatively unchanged when higher-order moments are added.

¹⁴ The bias is the percentage difference of the sample means in the treated and non-treated subsamples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (Rosenbaum and Rubin, 1985).

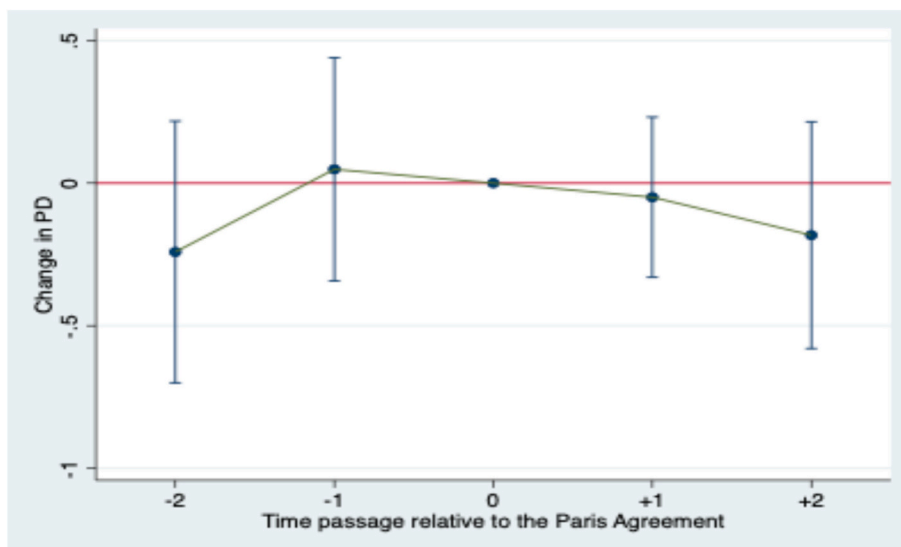


Fig. 3. Covariate balance before and after entropy balancing. This figure shows the standardized percentage bias in covariates for high- and low-emitting firms before and after entropy balancing, based on the variables used for reweighting.

Table 10
Covariate balance before and after entropy balancing.

	Treated (1)	Control (2)	t-test (3)
Panel A: Before reweighting			
Assets	7.34	6.20	30.35***
Leverage	53.57	49.02	6.66***
ROA	7.77	6.67	5.54***
Cash ratio	6.40	6.75	-1.22
Tangibility	40.34	24.76	24.84***
CAPEX	12.59	9.57	5.10***
P/B	5.05	6.65	-6.32***
Panel B: After reweighting			
Assets	7.34	7.30	1.01
Leverage	53.57	51.90	2.52**
ROA	7.77	7.51	1.20
Cash ratio	6.40	6.05	1.27
Tangibility	40.34	40.61	-0.38
CAPEX	12.59	12.27	0.57
P/B	5.05	5.02	0.11

This table reports means of the firm characteristics used for entropy balancing for high-emitting firms (treated) and low-emitting firms (control), before and after reweighting. Panel A reports raw (unweighted) covariate means. Panel B reports covariate means after reweighting the control group using entropy balancing weights to match treated-group covariate means. The t-statistics test differences in means between the treated group and the (raw/reweighted) control group. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.1.3. Brown shocks

A key identification concern in our baseline specification is potential endogeneity in firms' emissions. Emissions may correlate with unobserved firm characteristics that also affect credit risk. In this case, our estimates would confound the effect of emissions with omitted variables. To mitigate this concern, we adopt an alternative identification strategy, following the procedure in Bottero and Cascarano (2025), that isolates idiosyncratic, unforecastable changes in emissions i.e. shocks that plausibly capture information unexpected by the market.

We define these shocks as residuals from a first-stage regression of log Scope 1 emissions on firm-level observables (Scope 1 Shock). Specifically, we regress emissions on the log of revenues (which strongly correlates with emissions), and contemporaneous firm controls, along with firm and year fixed effects. This specification accounts for both

Table 11
Entropy balancing.

	PD (1)	PD (2)
High Emitter	0.154** (0.063)	0.193*** (0.072)
Observations	3432	3432
Firms	647	647
R-squared	0.665	0.738
Controls	Yes	Yes
Industry FE	Yes	Yes
Time FE	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. The main explanatory variable, *High Emitter* equals one if a firm's absolute Scope 1 GHG emissions exceed the median value of the sample distribution. The procedure implements entropy balancing, reweighting the control group (low-carbon-emitting firms) to match the covariate means of the treated group (high-carbon-emitting firms). The resulting weights are then applied in the regression model. Column (1) reports estimates from the unweighted sample. Column (2) presents results using the reweighted sample. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

time-invariant firm characteristics and time-specific country conditions. The residual component reflects deviations from predicted emissions and captures unexpected changes—positive shocks when emissions exceed predicted levels (“brown shocks”), and negative shocks when emissions fall short (“green shocks”). This approach strengthens identification by focusing on unexpected emissions that are orthogonal to firm fundamentals and country-specific trends. While the fixed effects absorb a substantial portion of the systematic variation in emissions, the model preserves enough residual variation to plausibly reflect investor-relevant surprises.

In the second stage, we regress market-implied PD on the estimated emission shocks. Table 12 presents the results. Column (2) shows that brown shocks significantly increase the PD, consistent with the interpretation that markets respond to abnormal increases in emissions by repricing credit risk upward.

Table 12
Brown shock and firms' probability of default.

	Scope 1 (1)	PD (2)
Scope 1 Shock		0.089* (0.052)
Assets	0.111** (0.056)	0.060** (0.024)
Leverage	0.001 (0.001)	0.053*** (0.001)
ROA	-0.005 (0.004)	-0.064*** (0.005)
Cash ratio	-0.006*** (0.002)	-0.023*** (0.003)
Tangibility	0.002 (0.002)	-0.003** (0.002)
CAPEX	-0.002** (0.001)	0.002 (0.002)
P/B	0.004 (0.003)	-0.078*** (0.004)
Revenues	1.046*** (0.042)	
Observations	3429	3215
Firms	596	596
R-squared	0.961	0.673
Industry FE	No	Yes
Time FE	Yes	Yes
Firm FE	Yes	No

The dependent variables are as follows: *Scope 1* defined as the natural logarithm of absolute *Scope 1* GHG emissions (Column 1) and the probability of default (*PD*) defined as the natural logarithm of the firm's five-year market-implied default probability (Column 2). The shock (*Scope 1 Shock*) is computed as the residual from a regression of *Scope 1* emissions on contemporaneous firm-level controls, log revenues, and firm and year fixed effects. The regression in Column (2) includes firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2. Non-linear effects

Firms with higher probabilities of default may exhibit greater sensitivity to climate-related risks due to their weaker financial positions. To further explore this heterogeneity, we conduct quantile regressions, which allow us to assess how the effect of *Scope 1* emissions varies across the distribution of firm-level credit risk. Quantile regression is particularly suitable in this context, as it is robust to outliers, does not rely on homoskedasticity assumptions, and provides insights into nonlinear effects that standard mean-based regression models may obscure. Table 13 presents the results across the 10th, 25th, 50th, 75th, and 90th percentiles of the PD distribution, capturing both the tails and the center of the distribution. The results reveal significant variation in the marginal effect of carbon emissions across quantiles. A clear pattern emerges: the sensitivity of default risk to transition risk increases from the lower to the median quantiles, reaching its strongest effect at the 50th percentile, where the coefficient is statistically significant at the 1% level. For instance, a one-standard-deviation increase in log-transformed *Scope 1* emissions raises the PD by 0.21% at the 10th percentile (Column 1), and by 0.29% at the 50th percentile (Column 3).

One possible explanation is that firms in the lower tail of the PD distribution—those perceived as relatively safe—possess greater financial flexibility and operational resilience, which enable them to absorb the costs of climate-related adjustments more effectively. As a result, investors perceive them as less exposed to transition risk, and their credit risk is less sensitive to emissions. By contrast, firms in the middle of the distribution may be more marginal in terms of creditworthiness, making their valuation and risk perception more sensitive to adverse climate-related signals. Beyond the median, however, the marginal effect of emissions declines. At the 90th percentile (Column 5), the coefficient becomes statistically insignificant, suggesting that for firms

Table 13
Scope 1 emissions and loan spreads.

	Spread (1)	Spread (2)	Spread (3)	Spread (4)
Scope 1	-0.014 (0.032)	-0.015 (0.028)	-0.010 (0.031)	-0.019 (0.036)
Tenor			0.003*** (0.001)	0.003*** (0.001)
Loan amount			-0.032 (0.035)	-0.031 (0.031)
Nr of lenders			-0.001 (0.006)	-0.000 (0.005)
Assets				-0.030 (0.029)
Leverage				0.004*** (0.001)
ROA				0.004 (0.008)
Cash ratio				0.001 (0.004)
Tangibility				0.005*** (0.002)
Observations	9902	9832	9661	8497
Firms	591	586	575	515
R-squared	0.001	0.502	0.565	0.604
Industry FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes

The dependent variable is the loan spread (*Loan spread*) is defined as the “all-in-spread-drawn” obtained from DealScan. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

already priced as highly risky, climate risk factors are overshadowed by broader concerns about solvency and survival. In such cases, investors may focus on short-term liquidity and debt service capacity rather than long-term environmental exposures. These results reinforce the earlier findings on the amplifying role of financial constraints: firms with weaker balance sheets or higher default risk are more vulnerable to climate transition risks, but only up to a point. Once firms enter the extremely high-risk category, credit market signals appear dominated by fundamental financial distress, rather than climate-related considerations.

4.3. Syndicated loan-level dataset

Previous analyses based on firm-level balance sheet data did not reveal a statistically significant relationship between the effective cost of liabilities and carbon emissions. However, the effective interest rate on debt, as derived from financial statements, may obscure meaningful variation across loans extended to borrowers with heterogeneous emissions profiles. In addition, utilizing firm-level data does not allow for control for loan-specific attributes—such as maturity, collateral, or contract type—that are critical determinants of pricing and may introduce omitted variable bias. To enhance robustness and address these limitations, we extend our empirical investigation to the syndicated loan market, drawing on detailed loan-level data from the DealScan database.

To examine whether lenders incorporate climate transition risk into credit pricing, we use a loan-level approach based on syndicated lending data. We construct a matched dataset of Indian firms and their syndicated loan facilities between 2005 and 2023, covering 216 firms and 586 loan tranches. We regress the loan spread—defined as the all-in-drawn spread over LIBOR—on firm-level *Scope 1* emissions, controlling for loan-specific and firm-level characteristics, along with industry and year fixed effects. Appendix A3 provides a detailed description of the data construction, matching procedures, and empirical specification.

The regression results are detailed in Table 14. Column (1) presents a

Table 14
Quintile regression results.

	PD_q10 (1)	PD_q25 (2)	PD_q50 (3)	PD_q75 (4)	PD_q90 (5)
Scope 1	0.092* (0.049)	0.078** (0.034)	0.126*** (0.024)	0.078*** (0.019)	0.002 (0.022)
Observations	3433	3433	3433	3433	3433
Firms	648	648	648	648	648
R-squared	0.281	0.436	0.476	0.420	0.248
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variable represents the 10th, 25th, 50th, 75th, and 90th percentiles of the natural logarithm of the 5-year market-implied PD at the firm level, respectively. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. The sample covers the period 2005–2023. All variable definitions are provided in Appendix A1. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

baseline model, progressively extended by adding industry and firm fixed effects (Column 2), loan-specific controls (Column 3), and finally firm-level controls (Column 4). Consistently across all specifications, firm-level *Scope 1* emissions exhibit no statistically significant relationship with loan spreads. Moreover, unreported results also suggest no significant differences when comparing pre- and post-Paris Agreement periods, nor when testing emissions of different scopes (*Scope 2* and *Scope 3*). These findings align with the initial firm-level analysis of effective liability costs.

Several institutional features of the Indian banking system may explain this result. First, bank lending is dominated by public sector banks, which account for the majority of corporate credit and operate under policy-oriented mandates in addition to profit objectives. In such an environment, credit allocation may reflect growth and sectoral priorities rather than forward-looking climate risk assessments. Second, until very recently, climate-related financial disclosure and supervisory guidance in India have been limited (RBI, 2022). Absent regulatory capital incentives or binding disclosure requirements, banks may have limited incentives to incorporate transition risk into pricing. Third, corporate loans in India tend to have relatively short maturities and are frequently rolled over, which reduces lenders' exposure to long-horizon transition risk.¹⁵ When expected climate policy tightening lies beyond the typical loan horizon, pricing effects may be attenuated. Finally, priority sector lending requirements and relationship-based banking structures can further weaken risk-based pricing incentives, particularly for large industrial borrowers. Taken together, these features imply that the absence of a significant emissions premium in the cost of debt for India firms might be related with institutional constraints in credit markets rather than evidence that transition risk is immaterial.¹⁶

4.4. Other robustness tests

4.4.1. Emission intensity and indirect emissions

We measure a firm's exposure to climate transition risk using its absolute *Scope 1* emissions, following Bolton and Kacperczyk (2023), who argue that transition risk scales with total greenhouse gas output. However, Aswani et al. (2024) note that absolute emissions may conflate firm size with carbon efficiency. They propose emission intensity as a more appropriate proxy for relative carbon risk. To address this concern, we construct an (log) intensity measure by dividing each firm's *Scope 1*

emissions by total revenues (*Scope 1 Intensity*). We also assess the robustness of our findings across alternative emission scopes. *Scope 2* captures indirect emissions from purchased energy sources (e.g., electricity, steam, heat), while *Scope 3* includes upstream and downstream emissions related to a firm's broader value chain. For each scope, we examine both absolute and intensity-based metrics.

Table 15 presents the results. Column (1) shows that *Scope 1 Intensity* remains positively associated with default risk and statistically significant at the 1% level. Columns (2) and (3) report similar findings for *Scope 2* and *Scope 3* intensity measures, respectively. We repeat the analysis using absolute emissions for indirect scopes. Although the coefficients on both *Scope 2* and *Scope 3* are positive, only *Scope 2* is statistically significant (Column 4). Taken together, these results indicate that our core findings are robust to the choice of emissions metric. The relationship holds for both absolute and intensity-based measures, and for both direct and indirect emissions. For *Scope 3*, the evidence is inconclusive, consistent with well-documented measurement challenges, exacerbated by limited disclosure among Indian firms.

4.4.2. Alternative default horizons

Our main specification uses the 5-year market-implied PD to capture the long-term nature of transition risk, which unfolds over multi-year horizons. As a robustness check, we examine whether our results are sensitive to alternative PD maturities. Specifically, we re-estimate the baseline model using shorter-dated PDs—1-month, 3-month, 6-month, 12-month, 24-month, and 36-month horizons—available from the CRI database. Table 16 reports the results. Across all maturities, the coefficient on *Scope 1* emissions remains positive and statistically significant at the 1% level. The magnitude of the effect exhibits minimal variation across specifications, suggesting that the relationship between emissions and default risk holds consistently across both short- and medium-term horizons. These findings reinforce the robustness of our baseline results to the choice of PD horizon.

4.4.3. High vs. low emitters

GHG emissions are disproportionately generated by sectors characterized by high energy intensity, such as power generation, heavy manufacturing, and resource extraction. These sectors pose the greatest challenge in meeting global climate targets due to their substantial contributions to global warming. Given that our analysis encompasses a diverse set of firms, including low-emission sectors such as services, there may be a concern that the estimated effects are predominantly driven by low-emission firms rather than reflecting the conditions faced by high emitters. To address this potential issue, we perform a robustness check by partitioning our sample into high- and low-emission sectors based on median emissions. Table 17 reports these results: Column (1) presents estimates for low-emission sectors, and Column (2) for high-emission sectors. In both subsamples, the coefficient on *Scope 1* emissions remains positive and statistically significant, suggesting that the association between emissions and perceived credit risk persists across the sectoral distribution. In Column (3), we estimate the model on the full sample, adding an interaction term between *Scope 1* emissions and a high-emission sector indicator to test for differential effects. The interaction coefficient is positive and statistically significant at the 5% level, indicating that the relationship between emissions and PD is stronger among high-emission firms. This mitigates the concern that our results are primarily driven by low-polluting sectors.

5. Conclusions

This paper provides new evidence that climate transition risk is priced into corporate credit risk in emerging markets. Using firm-level data from India, we document a strong and robust positive association between carbon emissions and market-implied PD. We find that financial markets began pricing transition risk more actively following the 2015 Paris Agreement, consistent with the hypothesis that the

¹⁵ In our sample only 20% of loans have maturity greater than four years.

¹⁶ We also acknowledge the limited size of our sample, advising caution in interpretation. Future studies utilizing administrative credit registry data could provide further robustness and deeper insights into these relationships.

Table 15
Emission intensity, indirect emissions and firms' probability of default.

	PD (1)	PD (2)	PD (3)	PD (4)	PD (5)
Scope 2	0.036** (0.016)				
Scope 3		0.002 (0.021)			
Scope 1 Intensity			0.098*** (0.015)		
Scope 2 Intensity				0.082*** (0.018)	
Scope 3 Intensity					0.084*** (0.027)
Observations	3432	3432	3432	3432	3432
Firms	647	647	647	647	647
R-squared	0.665	0.664	0.669	0.666	0.665
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. *Scope 2* and *Scope 3* represent firms' absolute indirect emissions. *Scope 1/2/3 Intensity* is defined as the natural logarithm of the ratio of absolute *Scope 1, 2, or 3* emissions to total revenues. *Scope 2* and *Scope 3* emissions are reported cumulatively, with each scope including emissions from the preceding scope. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 16
Alternative maturities.

	PD_m1 (1)	PD_m3 (2)	PD_m6 (3)	PD_m12 (4)	PD_m36 (5)
Scope 1	0.072*** (0.017)	0.071*** (0.017)	0.071*** (0.017)	0.070*** (0.017)	0.070*** (0.016)
Observations	3389	3432	3432	3432	3432
Firms	647	647	647	647	647
R-squared	0.657	0.669	0.671	0.671	0.671
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

The dependent variable is the natural logarithm of the market-implied probability of default (PD) at the firm level, measured at 1-month, 3-month, 6-month, 24-month, and 36-month horizons. The main explanatory variable, *Scope 1*, is defined as the natural logarithm of absolute *Scope 1* GHG emissions. The regressions include firm-level controls, industry and year fixed effects. The sample covers the period 2005–2023. All variable definitions are provided in Appendix A1. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Agreement altered investor expectations regarding future regulatory exposure and the cost of carbon-intensive operations. Firms misaligned with Paris-aligned decarbonization trajectories and those more exposed

Table 17
Low- vs. high-emitting firms.

	PD (1)	PD (2)	PD (3)
Scope 1	0.082** (0.036)	0.053** (0.021)	0.005 (0.030)
High Emitter			−0.708** (0.319)
High Emitter × Scope 1			0.077** (0.033)
Observations	1645	1787	3432
Firms	362	285	647
R-squared	0.638	0.718	0.667
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

The dependent variable is the natural logarithm of the 5-year market-implied PD at the firm level. *Scope 1* is defined as the natural logarithm of absolute *Scope 1* GHG emissions. *High Emitter* equals one if a firm's absolute *Scope 1* GHG emissions exceed the median value of the sample distribution. Column (1) reports results for the subsample of low-emitting firms, Column (2) for high-emitting firms, and Column (3) for the full sample of firms. The regressions include firm-level controls, industry and year fixed effects. All variable definitions are provided in Appendix A1. The sample covers the period 2005–2023. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

to future carbon pricing face significantly higher credit risk.

We further document heterogeneity in investor responses. The relationship between emissions and default risk is most pronounced among financially constrained firms. In contrast, firms with strong environmental performance and higher capital expenditures exhibit lower sensitivity, suggesting that credible mitigation efforts and forward-looking investment strategies reduce perceived risk. We also identify two transmission channels linking emissions to credit risk. Reputational exposure and the cost of equity both contribute significantly to higher default probabilities for carbon-intensive firms, while we detect no meaningful effect through the cost of debt. Overall, our findings underlying the growing relevance of climate transition risk in emerging markets and highlight mechanisms through which investors incorporate firm-level environmental exposure into credit risk assessments.

Our results also have direct policy implications. For high-emitting firms, they suggest a higher likelihood of tighter financing conditions or higher capital costs if transition exposure persists. We further find that ESG practices moderate this association, indicating that firms can partially shape their risk profile through credible governance structures and transition commitments. From a regulatory perspective, the weaker association between emissions and the cost of debt relative to capital markets implies that transition exposure may accumulate on bank balance sheets. This pattern supports incorporating transition risk explicitly into supervisory monitoring and stress-testing frameworks. More comprehensive emissions disclosure and credible transition plans can reduce information asymmetries and support a more orderly reallocation of capital during the low-carbon transition.

CRedit authorship contribution statement

Marcin Borsuk: Software, Methodology, Investigation, Formal analysis, Conceptualization. **Gireesh Shrimali:** Writing – review & editing.

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Appendix A

A.1. Appendix A1. Variable definitions

Definitions and source of the variables employed in the study.

Variable	Definition	Source
PD	Natural logarithm of 5-year market-implied probability of default	CRI
Assets	Natural logarithm of total assets	S&P IQ Pro
Tangibility	Tangible assets to total assets	S&P IQ Pro
CAPEX	Capital expenditures to revenues	S&P IQ Pro
P/B	Price-to-book value	S&P IQ Pro
ROA	Net income to total assets	S&P IQ Pro
Leverage	Debt to total assets	S&P IQ Pro
Revenues	Natural logarithm of revenues	S&P IQ Pro
Misalignment	The difference between actual emissions and projected Paris-aligned emissions, divided by actual emissions	Trucost
Carbon-at-risk	Natural logarithm of unpriced carbon cost (as a share of EBITDA)	Trucost
ESG E	ESG Environmental score (ranging from 0 to 100)	Trucost
Scope 1	The natural log of <i>Scope 1</i> GHG-equivalent emissions	Trucost
Scope 1 Intensity	The natural log of <i>Scope 1</i> GHG-equivalent emissions	Trucost
Scope 1 Shock	The residual from a regression of <i>Scope 1</i> on contemporaneous firm-level controls, and firm and year fixed effects.	Trucost
Current RRI	Firms' reputational exposure to environmental, social, and governance (ESG) issues based solely on recorded ESG incidents (ranging from 0 to 100)	RepRisk
Z-score	The sum of a firm's average return on assets and equity-to-asset ratio, divided by the standard deviation of its return on asset	S&P IQ Pro
COE	Market-implied measures of the cost of equity calculated based on Bloomberg's methodology	Bloomberg
COD	Firms' total interest expense over the past 12 months to its average total liabilities for the same period	S&P IQ Pro
WACC	The weighted average of the cost of debt and cost of equity, with weights based on the firm's capital structure.	Bloomberg
Loan spread	The "all-in-spread-drawn" obtained from DealScan	DealScan

A.2. Appendix A2. Mediation analysis

To examine potential transmission channels linking carbon emissions to firms' credit risk, we implement a mediation-style analysis. Mediation analysis enables us to decompose the total effect of *Scope 1* emissions on firm's PD into indirect effects operating through specific mediators, namely, reputational exposure and the cost of equity, and a residual direct effect not explained by these channels. In this framework, a mediator (*COE/RRI*, *M*) lies on the causal path from the independent variable (*Scope 1*, *A*) to the dependent variable (*PD*, *Y*) (Fig. A1).

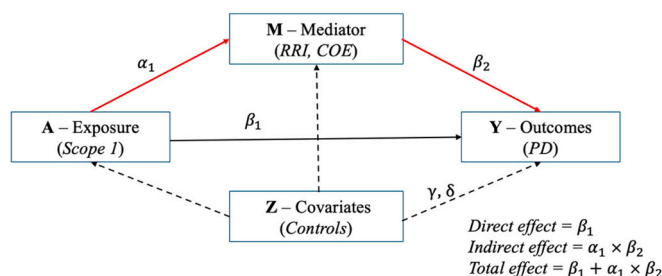


Fig. A1. Mediation analysis framework.

This figure displays the schematic framework used to quantify the transmission channels through which *Scope 1* emissions are associated with firms' market-implied PD.

The analysis proceeds in two stages. First, we estimate the effect of emissions on the mediator:

$$M_{i,t} = \alpha_1 \ln(\text{Scope } 1)_{i,t} + \beta_2 Z_{i,t-1} + \gamma_t + \alpha_s + \epsilon_{i,t} \tag{A2.1}$$

where $M_{i,t}$ is either the Current RepRisk Index (RRI), capturing reputational exposure, or the cost of capital, capturing investor-required return. In the second stage, we regress PD on both emissions and the mediator:

$$\ln(\text{PD})_{i,t} = \beta_1 \ln(\text{Scope } 1)_{i,t} + \beta_2 M_{i,t-1} + \beta_3 Z_{i,t-1} + \gamma_t + \alpha_s + \epsilon_{i,t} \tag{A2.2}$$

The indirect effect of emissions on PD via the mediator is calculated as the product $\alpha_1 \times \beta_2$. This term captures the portion of the emissions–PD relationship explained by the mediator. The coefficient β_1 represents the direct effect of emissions on PD after accounting for the mediator. The total effect can be obtained either by summing the direct and indirect effects or through an unmediated regression of PD on emissions

A.3. Appendix A3. Loan-level analysis

We utilize DealScan, a syndicated loan database widely used in academic and industry research, which provides detailed historical data on global loan contracts, including borrower and lender identities, loan terms, and syndicate composition. The data collection and processing involve multiple steps. Initially, we extract syndicated loan details and characteristics from DealScan for 523 Indian borrowers participating in international debt markets. To link these data with firm-level financial characteristics, we employ the linking (updated) table provided by Chava and Roberts (2008). Given that Compustat predominantly covers publicly traded firms, we complement this data with information from S&P Capital IQ Pro for non-public firms. This integration leverages Legal Entity Identifier (LEI) codes and fuzzy name matching techniques to ensure accurate data alignment. Subsequently, we merge the resulting dataset with environmental data sourced from Trucost. The final estimation sample comprises 216 Indian firms spanning various industries over the period from 2005 to 2023, encompassing a total of 586 loan facilities.

To empirically examine the relationship between transition risk and the loan interest rate we estimate the following regression model:

$$\text{Loan spread}_{i,j,t} = \beta_1 \text{Scope } 1_{i,t} + \beta_2 X_{i,j,t} + \beta_3 Z_{i,t-1} + \gamma_t + \alpha_s + \epsilon_{i,t} \quad (\text{A3.1})$$

where the loan spread (*Loan spread*) is defined as the “all-in-spread-drawn” obtained from DealScan, consistent with methodologies used in Chava (2014) and Ivashina (2009). This measure captures the borrower's cost in basis points (bps) above a benchmark interest rate (LIBOR), per dollar drawn. It encompasses both the loan spread and any annual facility fees paid to the syndicate banks. Transition risk exposure is proxied by the logarithm of firms' absolute *Scope 1* emissions. Our model incorporates loan-specific characteristics as controls, including loan size, maturity, presence of covenants, refinancing status, secured status, the number of lenders, and loan types ($X_{i,j,t}$). Additionally, we control for firm-level financial characteristics and include the same set of fixed effects as in Eq. (1).

The primary unit of analysis in DealScan is a loan facility or tranche, which is typically grouped into larger deals or packages. Consistent with prior literature, we focus exclusively on lead arrangers, as they are primarily responsible for setting loan terms and pricing (e.g., Sufi, 2007; Ivashina, 2009). Lead arrangers conduct the bulk of the due diligence and exert the greatest influence over syndicate structure, monitoring, and contractual arrangements, making their role central to understanding how banks assess and price credit risk.

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2026.109315>.

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