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Can Credit Rating Changes Affect Corporate Carbon Emissions? Some Evidence From the S&P 500

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ABSTRACT

Using panel data on US S&P 500 firms from 2012 to 2024, this study examines how credit rating changes affect corporate carbon performance. Drawing on the resource-based view and prospect theory, we show that credit rating downgrades lead to a statistically and economically significant deterioration in emission reduction scores. Notably, a downgrade is followed by an average decline of about 1.8 points in the emissions score. In contrast, no significant effect was found for upgrades. However, the study provides evidence to suggest that among investment-grade firms, upgrades lead to significant improvement in emissions performance. Overall, the findings illustrate a reverse logic compared with the existing literature, indicating a financial-constraint channel through which credit market shocks shape firms' environmental strategies. Moreover, the study signals an apparent financial slack threshold mechanism that is apparent among investment-grade firms. Several implications and limitations are extracted along with avenues for future research.

1 | Introduction

Despite growing regulatory and investor pressure, corporate carbon emissions continue to exhibit wide variation across firms. A rich literature has examined such heterogeneity, pointing to various aspects of corporate governance structures, financial constraints, and institutional contexts as key determinants (Muttakin et al. 2021; Rehman et al. 2024). Within this context, an essential but largely underexplored research question arises, i.e., to what extent can a firm's credit rating actions influence its environmental behavior? The existing literature has tended to explore the opposite relationship, suggesting that high levels of environmental performance enhance firms' credit ratings (e.g., Safiullah et al. 2021; Yu et al. 2022; Shahrour et al. 2024; Safiullah et al. 2025). While such studies recognize the significance of emission reductions, they predominantly consider credit ratings as outcomes, rather than environmental predictors.

Although previous studies have acknowledged the theoretical possibility that credit ratings may influence environmental outcomes (e.g., Safiullah et al. 2021), such work has tended to primarily examine static credit rating levels rather than upgrades and downgrades. As such, the prior literature lacks empirical examination surrounding how dynamic rating changes affect corporate carbon performance. Moreover, research has not tended to examine this relationship within volatile climate policy contexts, i.e., following the post-Paris Agreement period, US withdrawals and significant regulatory uncertainty.

To address the gap, this study empirically investigates whether credit rating changes shape firm-level carbon performance in such a dynamic institutional setting. This research is particularly timely given the context of the United States, the world's largest economy, and historically the highest cumulative emitter of greenhouse gases. With climate regulation again under

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threat due to the political resurgence of the “Make America Great Again” movement, understanding more about carbon performance in the current economic climate is arguably more important than ever.

This study focuses on S&P 500 firms, which are closely monitored by credit rating agencies, institutional investors, and regulators. There is ample anecdotal and empirical evidence to suggest that senior managers, particularly CFOs of large corporations, actively manage credit ratings and often maintain explicit rating targets (Graham and Harvey 2001; Kisgen 2006, 2009). Rating downgrades raise borrowing costs, tighten debt covenants, and can trigger forced selling by regulated investors, creating material financial pressure even for the most resilient of firms. Research by Kisgen (2019) suggests that credit rating changes continue to exert significant influence on capital structure and investment decisions among large US firms. This setting, therefore, provides a conservative testing ground for financial-constraint mechanisms: If credit rating shocks affect environmental strategy among these firms, the effects are likely to be even stronger among smaller, more constrained companies.

The study makes several contributions to the pertinent literature. First, motivated by Kisgen's (2006, 2009) *Credit Rating–Capital Structure Hypothesis (CR-CS)*, we argue that credit rating changes may shape firms' environmental performance, thus reversing the directionality of the hypothesis for the reasons earlier suggested. The findings highlight that asymmetric responses to downgrades and upgrades can be aligned with well-established mechanisms from *prospect theory* and the *resource-based view (RBV)*. Second, we document important heterogeneity in how firms respond to credit rating changes, with distinct asymmetric effects across credit classes (investment vis-à-vis non-investment ratings). These patterns carry direct implications for targeted policy design. Third, unlike prior studies, we employ a dynamic three-equation conditional mixed process (CMP) model to address endogeneity concerns in the joint evolution of credit rating actions and firms' environmental performance. Finally, we develop and make publicly available a new state-level political landscape index that builds and extends on existing political ideology measures. The index serves as a theoretically grounded control for baseline differences in environmental norms and stakeholder pressure across US states and may also prove useful for guiding future research accordingly.

2 | Literature Review

Recent scholarship has moved beyond identifying correlates of corporate carbon performance to interrogating the mechanisms through which financial and institutional structures condition firms' environmental strategies. One strand of literature explores how firms internalize environmental expectations through capital allocation and governance processes, which are often mediated by investor pressure and regulatory threats (Flammer 2021). Yet, while environmental disclosure and ESG scores are increasingly used to signal climate responsiveness, questions remain as to whether these metrics reflect substantive behavioral change or are merely symbolic compliance (Haque and Ntim 2020).

Emerging evidence suggests that financial constraints play a key role in shaping firms' willingness and ability to decarbonize, which may be the result of capital market access, debt covenants, or credit ratings (Döttling and Rola-Janicka 2025). Attig (2024) provides evidence that easing financial constraints increases firms' CSR engagement, including environmental actions. This supports the view that sustainability investments require financial slack and are often reduced when firms face tighter financing conditions. However, no studies have investigated how shifts in financial conditions, triggered by changes in credit ratings, affect firms' carbon decisions.

Recent studies have increasingly emphasized the role of environmental performance in credit assessments, aligning with the broader shift by major rating agencies, such as S&P, Moody's, and Fitch, which have formally incorporated climate risk into their rating methodologies (Birry et al. 2024; S&P Global Ratings 2025). This evolution reflects a growing awareness that climate-related risks pose tangible financial threats to firms and their creditors. For example, Safiullah et al. (2021) investigated the effect of Scope 1 and 2 carbon emissions on the credit ratings of US firms and found a negative association. They argued that high carbon emitters face increased cash flow uncertainty, driven by regulatory risks and reputational damage, which ultimately reduces their creditworthiness. Shahrour et al. (2024) found that US firms with lower emissions scores were rewarded with higher credit ratings and lower default probabilities.

In adopting a novel methodological perspective by applying machine learning models to a sample of firms from the Eurozone, Yu et al. (2022) and Michalski and Low (2024) demonstrated that ESG scores, particularly those related to emissions, and the broader environmental pillar serve as reliable predictors of corporate ratings. More recently, research by Safiullah et al. (2025) revealed that carbon assurance disclosures can enhance firms' credit ratings by reducing information asymmetry and signaling commitment to transparency. Their study showed that this association is particularly evident among firms in states with a Democratic lean.

While this stream of empirical research has documented how environmental performance may influence credit assessments, the reverse hypothesis, i.e., credit rating changes influence firms' carbon behavior, remains unexplored. Safiullah et al. (2021, 7) do, however, acknowledge this possibility and state that: “It may be argued that firms with high credit ratings may be able to afford to finance at a cheaper funding cost, which may lead them to invest more in carbon abatement, resulting in lower carbon emissions.” Credit ratings could therefore influence emissions. Extensive survey evidence further confirms that managers actively adjust capital decisions to maintain or restore target ratings to enhance their firms' position (e.g., Graham and Harvey 2001; Bancel and Mittoo 2004; Servaes et al. 2009; Graham et al. 2020).

To the best of our knowledge, we are the first to extend this logic to the carbon emissions strategy context, proposing that rating downgrades may crowd out investment surrounding long-term environmental performance. At the same time, upgrades may facilitate more sustainable efforts. In doing so, we advance previous studies surrounding the *CR-CS Hypothesis* and similar

work (Kisgen 2006, 2009; Huang and Shen 2015; Wojewodzki et al. 2018). Our study is somewhat distinct from the work of Safiullah et al. (2021) and Shahrour et al. (2024) as we focus on positive and negative rating signals (upgrades and downgrades) instead of static rating levels. Moreover, we apply the CMP, which is particularly suitable for addressing the endogeneity issue (Roodman 2011). In addition, we use a composite emissions score that offers a broader and more reliable proxy for firms' environmental performance and climate risk exposure compared to raw emissions data.

However, the effect of credit rating changes on firms' environmental strategies is unlikely to be homogeneous. Firms operate within institutional environments that shape both regulatory pressure and stakeholder expectations, which may amplify or dampen their response to financial signals. The strategic value of environmental capabilities may therefore be shaped by the institutional and political environment in which firms operate. In the United States, partisan divide has produced a fragmented regulatory landscape in which Republican-led states often resist climate regulation, while Democratic-led states pursue more ambitious policies (Dietz et al. 2015). This "polarized federalism" implies that firms often face markedly different stakeholder expectations and regulatory regimes depending on their state location (Trachtman 2020). US firms in environmentally progressive states are more likely to adopt voluntary environmental management standards (Delmas and Toffel 2008), whereas those located in Democratic-leaning states frequently encounter stronger environmental pressure to conform (Adua 2021; Di Giuli and Kostovetsky 2014; Wen et al. 2016). We therefore incorporate a time-varying state-level political index as a control variable, so as to capture these baseline differences in environmental norms and stakeholder pressure across the United States.

3 | Hypotheses Development

3.1 | Credit Rating Downgrades and Emission Deterioration

RBV suggests that a firm's competitive advantage is derived from the deployment and development of valuable, rare, inimitable, and non-substitutable resources (Barney 1991). In this view, superior carbon performance, such as emissions reduction initiatives and environmental innovation, can be conceptualized as a strategic capability. Building and maintaining such a capability requires not only organizational commitment but also financial and operational flexibility to invest in long-term environmental goals.

Most existing studies examine the carbon-credit rating relationship from the perspective of credit risk, focusing on whether poor environmental performance is reflected in lower ratings or higher default risk (e.g., Safiullah et al. 2021; Shahrour et al. 2024). This direction of inquiry is important, but it treats carbon performance primarily as an input into rating assessments. Less attention has been given to the reverse channel, whereby credit rating changes may influence the firm's subsequent environmental choices. This distinction matters because rating actions can reshape the resource environment in which

firms operate. Downgrades, in particular, reduce access to capital, raise borrowing costs, and worsen financial conditions (Wojewodzki et al. 2018), thereby limiting firms' ability to fund activities that are costly, long-term, and not immediately cash-generating. From an *RBV* perspective, negative rating actions leave firms with fewer slack resources to allocate toward developing or sustaining their environmental capabilities.

In a sample of US firms, Bongaerts and Schlingemann (2024) found robust evidence of asset divestitures triggered by rating downgrades in managerial efforts to mitigate financial constraints. Zhang and Zhao (2022) showed that financially distressed firms actively reduce their environmental spending, aligning with the *RBV*'s argument that resource-constrained firms prioritize core operations over long-horizon capabilities. Kisgen (2009) and Huang and Shen (2015) demonstrated that downgraded firms adjust their capital structure at an increased speed by reducing net debt issuance, underscoring their diminished financial flexibility to regain their target ratings.

Although major credit rating agencies, such as S&P, Moody's, and Fitch, now officially integrate climate risk into their assessments, the immediate financial impact of a downgrade may shift managerial focus away from environmental commitments (Birry et al. 2024; S&P Global Ratings 2025). In such circumstances, managerial attention is redirected toward short-term financial survival, cost-cutting, and liquidity management, which is potentially at the expense of environmental initiatives that do not yield immediate returns. This can further marginalize sustainability or green R&D investment, especially in firms where environmental capabilities are not yet fully institutionalized or perceived as core strategic assets. Supporting this mechanism, recent evidence shows that higher managerial risk sensitivity leads firms to reduce long-term environmental investment. Hossain et al. (2023) demonstrate that risk-averse CEOs tend to increase carbon emissions by shifting toward short-term, low-risk decisions, mirroring the strategic retrenchment firms experience after credit-rating downgrades. This behavioral logic reinforces our expectation that downgrades heighten risk-avoidance and weaken firms' willingness to commit to costly decarbonization efforts.

Moreover, the reputational signal sent by a downgrade may further constrain firms by eroding stakeholder confidence, including that of investors, lenders, suppliers, customers, and regulators, thereby increasing the perceived risk of engaging in long-term sustainability projects. In the absence of robust internal slack or external reinforcement mechanisms, firms may deprioritize emissions reduction initiatives, leading to weaker carbon performance. Based on this argument, the following hypothesis is developed:

H1. *A firm's credit rating downgrade will lead to a deterioration in its carbon performance.*

3.2 | Credit Rating Upgrades and Emission Improvement

In contrast, credit rating upgrades signal improved creditworthiness and reduced financial constraints, granting firms greater

access to low-cost capital to enhance their financial flexibility (Kisgen 2019). According to *RBV*, such financial slack enables investment in strategic, long-term initiatives, including acquisitions, environmental innovation, emissions reduction, and sustainability disclosure (Safiullah et al. 2021, 2025). *RBV* also suggests that under conditions of abundant resources, firms are more likely to allocate capital toward non-essential but reputationally valuable investments, such as emissions reduction technologies. In ESG-conscious markets, such actions may function both as strategic differentiators and as reputational signals to capital markets, rating agencies, and sustainability-focused stakeholders (Safiullah et al. 2025).

Firms with upgraded ratings may also face growing pressure to align with emerging sustainability standards, particularly in sectors undergoing active decarbonization or where global investors and ESG indices closely monitor them. In this context, financially flexible firms are not only capable of developing environmental capabilities but are also incentivized to do so to maintain legitimacy and secure access to preferential financing, such as sustainability-linked bonds or green loans.

Nevertheless, the response to upgrades may not be as immediate or profound as the response to downgrades. *Prospect theory* suggests that losses loom larger than gains, meaning that firms react more strongly to adverse shocks than to positive ones (Kahneman and Tversky 1979). Empirical studies on the effects of credit ratings show that firms adjust their financial policies more aggressively after downgrades than after upgrades (Kisgen 2009; Huang and Shen 2015). *Resource dependence theory* provides further support by highlighting how strategic responses tend to intensify when external constraints become tighter (Pfeffer and Salancik 2003). In light of this discussion, we offer the following hypothesis:

H2. *A firm's credit rating upgrade will lead to improvements in its carbon emissions performance, though the effect may be weaker than for the relationship posited in hypothesis H₁.*

4 | Data and Empirical Strategy

4.1 | Variables and Sample

We constructed a panel of S&P 500 firms using firm-level financial and ESG data from LSEG Refinitiv (2012–2024) and credit ratings from Bloomberg, cross-validated with the S&P Global Ratings database. The focus on S&P 500 firms is deliberate, as these firms are closely monitored by credit rating agencies, institutional investors, and regulators, making rating actions particularly salient and economically meaningful. This setting allows us to isolate the impact of credit rating shocks on corporate environmental strategy in a context where credit signals are most informative and market reactions are immediate. The sample period aligned with the availability of environmental data and the political index. Following data cleaning, we obtained a final sample of 364 US-headquartered firms with 3821 firm-year observations.

The dependent variable is the emissions reduction score (*emis_sc*), which reflects a firm's effectiveness in managing and

reducing emissions. Scaled from 0 to 100, the score captures both realized emissions outcomes and intermediate dimensions of environmental strategy, including emissions management practices, target setting, and disclosure quality, as well as contributing to the broader Environmental (E) pillar of the ESG index. It is computed from changes in total emissions, emissions intensity, reduction targets, mitigation policies, and verifiable disclosures. While this composite structure introduces additional conceptual nuance, it reflects how firms typically adjust their environmental strategies in practice. Following financial shocks such as credit rating changes, firms may initially respond by revising disclosure practices, governance arrangements, or emissions targets before undertaking capital-intensive investments that translate into observable reductions in physical emissions. Unlike raw Scope 1, 2, or 3 emissions data, which are often incomplete, inconsistent, and slow to adjust, this composite metric provides a standardized, forward-looking, and sector-adjusted measure of climate performance and risk (LSEG 2024). The use of this aggregated score therefore enhances conceptual validity, data coverage, and aligns with recent studies employing similar measures to capture firms' environmental strategies as well as their exposure to climate risk (e.g., Rehman et al. 2024; Shahrour et al. 2024).

Credit ratings are a key measure of a firm's creditworthiness and directly influence its financial flexibility/constraints, access to and cost of capital, and strategic investment decisions (Kisgen 2019). For this research, the S&P issuer long-term local currency credit ratings were used. Following prior studies, the ratings were coded as integers from 22 (AAA) to 1 (D), with D marking a "corporate default." At the same time, higher values represent increasingly stronger (lower) creditworthiness (probability of default). Next, the binary indicators were created for rating upgrades (*up*) and downgrades (*dn*), capturing changes in credit standing (or rating signals) that have been documented to alter firms' financial behavior independently of rating levels (e.g., Kisgen 2009; Huang and Shen 2015; Bongaerts and Schlingemann 2024).

Table 1 shows the dataset records of 242 downgrades and 379 upgrades over the sample period, with downgrades peaking in 2020 (45 cases, 18.6%) and upgrades most frequent in 2013¹ (58 cases, 15.3%). These numbers reflect cyclical credit market dynamics and align with macroeconomic trends over the 2013–2024 period. Notably, 2020 exhibited the highest relative prevalence of downgrades, coinciding with the peak of economic uncertainty induced by COVID-19. In contrast, 2013 marked the most substantial upgrade dominance, reflecting the recovery momentum following the post-2008 deleveraging cycle.

We develop a new state-level political index that captures the partisan orientation of each US state on an annual basis to account for state-level differences in environmental norms potentially affecting corporate carbon performance (e.g., Delmas and Toffel 2008; Di Giuli and Kostovetsky 2014; Adua 2021). The index is constructed from six components: (1) Democratic presidential vote share, (2) Democratic gubernatorial vote share, (3–4) Democratic seat shares in the US Senate and House, and (5–6) Democratic seat shares in the state upper and lower legislative chambers. These components are continuous, measured on a 0%–100% scale, and vary across states

TABLE 1 | Annual distribution of rating changes (2013–2024).

Year	No. of downgrades	%	No. of upgrades	%
2013	10	4.13	58	15.30
2014	11	4.55	35	9.23
2015	33	13.64	30	7.92
2016	28	11.57	36	9.50
2017	16	6.61	32	8.44
2018	24	9.92	42	11.08
2019	25	10.33	24	6.33
2020	45	18.60	18	4.75
2021	22	9.09	41	10.82
2022	10	4.13	30	7.92
2023	18	7.44	31	8.18
2024	0	0.00	1	0.26
Total	242	100.00	378	100.00

Note: Data on rating changes available from 2013 onwards. Since lagged variables were used in all regressions, 2012 is excluded from the estimation sample.

Source: Bloomberg, S&P Global Ratings, and authors' calculations.

and years. The method of aggregation and the full set of annual index values by state are reported online in the Appendix (Table B1).

While several political ideology measures exist, these tend to be constructed differently or used for other purposes. For instance, research by Berry et al. (2013) focused on measuring the ideological position of state governments. In contrast, Di Giuli and Kostovetsky (2014) employed binary indicators of partisan control at the state level. In contrast, our index is designed to capture the broader political–institutional environment faced by firms. Specifically, we integrate electoral outcomes and partisan representation at both the federal and state levels. In addition, each of the components is measured as a percentage vote or via seat shares, allowing for variation in political intensity rather than relying on binary indicators of partisan control. Accordingly, the contribution of the index lies not in measuring political ideology per se, but in tailoring an institutional measure suited for the model of the US-headquartered firm-level environmental performance. By theoretically accounting for baseline shifts in state-level environmental norms and stakeholder expectations, the index serves as a reliable control variable.²

We acknowledge that large S&P 500 firms may exert some influence on state politics through lobbying or via their economic contributions, per se. The index, however, was created from broad electoral and legislative outcomes. These included presidential and gubernatorial vote shares, as well as federal and state-level legislative seat shares, shaped primarily by slow-moving demographic, historical, and cultural factors at the state level. These factors evolve gradually over time and cannot be directly manipulated by any individual corporation in the short

run, thus supporting the exogeneity of this political index with respect to firm-level environmental strategies.

A set of firm-level control variables was used as commonly employed in studies on corporate carbon emissions modeling (Bolton and Kacperczyk 2021; Muttakin et al. 2022). Specifically, firm size (*size*) is proxied by the natural logarithm of total assets. The return on average equity represents profitability (*roe*). Leverage (*totdebt*) is the ratio of total debt to total assets, and *div_pay* is the dividend payout ratio. The governance score (*govern_sc*) captures a firm's commitment to and effectiveness in corporate governance practices, including management quality, shareholder rights, and CSR strategy, as assessed using publicly disclosed information (LSEG 2024).³

Duplicates, missing values, and outliers were all excluded. Continuous financial variables were winsorized at the 1st and 99th percentiles to reduce the influence of extreme values. The emissions score and financial indicators were aligned by the fiscal year, following literature standards (Flammer 2021). The variable definitions and sources are listed in Table A1 in the Appendix.

4.2 | Empirical Strategy

A central challenge in estimating the impact of credit rating actions on firms' environmental performance is endogeneity. Credit rating actions and emissions performance are influenced by unobservable firm-level factors, such as managerial risk aversion, and can also affect each other over time (Shahrour et al. 2024). Changes in credit ratings alter firms' financing conditions and strategic priorities, which may influence environmental policies and investments. At the same time, deteriorating emissions performance may increase climate-related credit risk and raise the likelihood of a downgrade (Birry et al. 2024). This relationship has been further strengthened by the explicit integration of climate risk into credit rating methodologies by S&P since 2017 (S&P Global Ratings 2025).

While the dynamic generalized method of moments (GMM) estimator can address endogeneity through instrumentation (Arellano and Bover 1995), it relies on assumptions that unobserved shocks affecting environmental performance and rating actions are independent. In addition, GMM requires several specification choices, such as lag depth, instrument selection, and collapsing strategies, that can materially affect results in small or moderately sized panels and are not always transparent to non-specialist readers (Roodman 2009, 2011; Hansen and Lee 2021).

This study, instead, employs a three-equation dynamic system using the CMP developed by Roodman (2011). CMP addresses endogeneity by modeling environmental performance and credit rating actions jointly and allowing correlation in their unobserved components (Alzuabi et al. 2025). This feature is well-suited to the present setting, where both outcomes may be shaped by common firm-level conditions and evolve together over time.⁴ The CMP specification is dynamic, incorporating lagged dependent variables in the emissions equation. The baseline three-equation model for testing hypotheses H₁ and H₂ is specified as follows:

$$emis_sc_{i,t} = \alpha_0 + \alpha_1 emis_sc_{i,t-1} + \alpha' X_{k,i,t} + \alpha_2 up_{i,t-1} + \alpha_3 dn_{i,t-1} + \alpha_4 index_{s,i,t} + I_j + Y_t + \varepsilon_{i,t} \quad (1)$$

$$up_{i,t} = \beta_0 + \beta_1 emis_sc_{i,t-1} + \beta' X_{h,i,t} + I_j + Y_t + \varepsilon_{i,t} \quad (2)$$

$$dn_{i,t} = \gamma_0 + \gamma_1 emis_sc_{i,t-1} + \gamma' X_{h,i,t} + I_j + Y_t + \varepsilon_{i,t} \quad (3)$$

Focusing on Equation (1), $emis_sc_{i,t}$ is the emission reduction score of firm i in year t . α_0 is the sector-specific fixed effect, α_1 to α_4 are the coefficients of unknown parameters to be estimated. α_1 captures the persistence in emissions performance, reflecting how much of the score in year $(t-1)$ carries over into year t . $emis_sc_{i,t-1}$ is the first lag of the dependent variable, while $X_{k,i,t}$ represents a vector of k firm-level explanatory variables associated with firm i 's emissions performance. $up_{i,t-1}$ and $dn_{i,t-1}$ represent binary dummy variables equal to one if S&P upgraded or downgraded the firm's credit rating in year $(t-1)$, and zero otherwise. The estimated coefficients on these two variables enable the empirical testing of hypotheses H_1 and H_2 , respectively. $index_{s,t}$ captures the prevailing political orientation of a state s in year t , where firm i is headquartered. I_j represents a set of 10 industry fixed effects based on the Global Industry Classification Standard (hereafter GICS). Y_t is a set of 12-year fixed effects capturing directly unobservable exogenous time-varying shocks. $\varepsilon_{i,t}$ is the error term. All firm-level controls are lagged to limit reverse causality. Time and industry fixed effects are included via year and industry binary dummy variables. Following Garel et al. (2024), standard errors are clustered at the firm level to account for serial correlation and unobserved heterogeneity.

Equations (2) and (3) model rating downgrades and upgrades, using a standard set of firm-level explanatory variables used in prior studies on credit rating determinants, including the first lag on the emissions score ($emis_sc_{i,t-1}$). This dynamic CMP approach (a set of three equations) isolates the direction and magnitude of rating effects on emissions while simultaneously modeling the probability of upgrades and downgrades as endogenous outcomes. This provides a comprehensive solution to the endogeneity problem.

4.3 | Summary Statistics

Table 2 reports the descriptive statistics for all the key variables used in the empirical analysis. The dependent variable, emissions reduction score ($emis_sc$), has a mean of 62.21 and a median of 69.32, with a standard deviation of 29.05, suggesting substantial variation in environmental performance across firms and over time. The 10th and 90th percentiles are 11.96 and 94.33, respectively, indicating a highly dispersed distribution and the presence of environmental leaders and laggards in the sample.

The binary variables capturing credit rating upgrades (up) and downgrades (dn) occur in 10% and 6% of firm-year observations, respectively, consistent with the rating stability of large US corporations (the sample of S&P 500-rated constituents). The state-level political index ($index$) ranges from 0.30 to 0.72 (10th–90th percentile), with a mean of 0.53, confirming substantial cross-state heterogeneity in political environments. These statistics confirm that our sample is sufficient and heterogeneous, providing a suitable empirical basis for identifying meaningful relationships between credit rating actions and emissions performance in the institutional context.

5 | Results and Discussion

Table 3 reports the results based on the CMP estimator. Each model includes the full set of firm-level control variables as defined in Table A1 of the Appendix. The estimated coefficients on these controls are omitted from the presented tables for brevity but are available from the authors upon request. The Wald test confirms model identification and joint significance. In Column (1) corresponding to Equation (1) in the previous section, the coefficient on the lagged dependent variable ($L1.emis_sc$) equals 0.865. This suggests that roughly 87% of a firm's emissions score is retained from one period to the next. This, in turn, implies that the S&P 500 constituents rarely undergo abrupt changes in their environmental strategies. Instead, their carbon performance typically evolves gradually over time, unless influenced by external shocks, such as regulatory intervention or changes in credit ratings.

TABLE 2 | Descriptive statistics.

Variable	N	Mean	Median	S.D.	10%	90%
<i>emis_sc</i>	3821	62.21	69.32	29.05	11.96	94.33
<i>up</i>	3821	0.10	0.00	0.30	0.00	0.00
<i>dn</i>	3821	0.06	0.00	0.24	0.00	0.00
<i>index</i>	3821	0.53	0.58	0.17	0.30	0.72
<i>govern_sc</i>	3821	62.67	65.41	19.59	35.03	86.81
<i>size</i>	3821	24.07	23.94	1.30	22.52	25.80
<i>totdebt</i>	3821	31.38	30.05	17.23	9.94	52.15
<i>roe</i>	3821	23.86	13.51	48.86	0.00	46.38
<i>div_pay</i>	3821	50.08	31.74	72.31	0.00	107.20

Note: The table presents the summary statistics for the final sample (balanced panel) over the period 2012–2024.

TABLE 3 | Credit rating effects: conditional mixed process (CMP).

Indep. vars.	CMP (1)	Indep. Vars.	CMP (2)	CMP (3)
<i>L1emission_sc</i>	0.865*** (112.60)	<i>L1emission_sc</i>	−0.002 (−1.50)	0.004*** (2.96)
<i>L1up</i>	0.621 (0.93)			
<i>L1dn</i>	−1.760*** (−2.61)			
<i>Index</i>	4.123*** (3.99)			
Firms		365		
Observations		3555		
Year dummies		Yes		
Industry dummies		Yes		
Control vars.		Yes		
Period of est.		2012–2024		
Wald test (<i>p</i> value)		0.00		
rho_12 (<i>p</i> value)		0.67		
rho_13 (<i>p</i> value)		0.21		
rho_23 (<i>p</i> value)		0.00		

Note: In equation (1), the dependent variable is the emissions score (*emis_sc*), where a higher value indicates better emissions performance. The other variables are defined in Table A1 in the Appendix. Equations (2) and (3) model the likelihood of a credit rating upgrade (*up*) and downgrade (*down*), respectively. Coefficient estimates are reported, along with z-statistics in parentheses, based on standard errors clustered at the firm level. Standard errors are clustered at the firm level to account for serial correlation and unobserved heterogeneity. The models include year and industry fixed effects. Wald test *p* values assess the joint significance of the estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Turning to the credit rating effects, the estimated coefficient on the lagged downgrade term (*L1.dn*) is negative and statistically significant at the 1% level, consistent with our first hypothesis (H_1). The coefficient's negative sign and size (−1.76) suggest that, on average, we would expect a rating downgrade to be followed by an economically meaningful deterioration in a firm's emissions score of around 1.8, *ceteris paribus*. This finding aligns strongly with *RBV*, which emphasizes how financial constraints limit a firm's ability to invest in long-term strategic capabilities, such as emissions performance (Rehman et al. 2024; Shahrour et al. 2024). A downgrade raises borrowing costs and limits capital access, forcing managers to prioritize short-term liquidity and core operations over discretionary initiatives, such as environmental sustainability. Prior research has confirmed that financially constrained firms reduce their environmental efforts (Zhang and Zhao 2022). Moreover, the downgrade also sends a negative reputational signal, potentially weakening stakeholder confidence and reducing external support for green investment. Altogether, this result confirms that credit rating downgrades impair corporate environmental performance by tightening financial slack and shifting managerial focus toward survival, as theorized in the development of hypothesis H_1 .

In contrast, while the coefficient on *L1.up* is positive, as expected, it is also statistically non-significant in the full sample, pointing to the hypothesized underlying asymmetry in how firms respond to positive versus adverse rating signals. This finding aligns with *prospect theory*, which suggests that firms are more sensitive to potential losses than gains and react more significantly to downgrades than upgrades (Kahneman and Tversky 1979). Similarly, *resource dependence theory* suggests that firms are more likely to alter their strategic priorities when external dependencies become tighter (Pfeffer and Salancik 2003). Improved credit conditions may not necessarily generate immediate pressure to reallocate resources. Such findings are aligned with those of Kisgen (2009) and Huang and Shen (2015), who document that only downgrades trigger significant changes in the capital structure of affected firms and their speed of adjustment.

The use of a composite emissions reduction score implies that the estimated effects reflect changes in firms' overall environmental strategy rather than immediate shifts in physical emissions alone. This distinction is particularly relevant in the context of credit rating shocks, where firms facing tighter financing constraints may initially respond by scaling back emissions-related

commitments, disclosure efforts, or mitigation planning before altering their actual emissions trajectory. Accordingly, the observed deterioration in emissions scores following downgrades should be interpreted as a contraction in environmental engagement, which may translate into weaker realized emissions performance over a longer horizon.

Regarding the political landscape, the estimated coefficient on the *index* (4.123) is the largest in both its magnitude and statistical significance. This indicates that firms headquartered in states with more Democratic-oriented political environments exhibit stronger emissions performance. The result supports prior findings that firms respond to the political context in which they operate, with progressive political environments offering more regulatory incentives or public pressure to improve CSR and environmental performance (e.g., Delmas and Toffel 2008; Di Giuli and Kostovetsky 2014).

To further mitigate against the concern of reverse causality, we re-estimated the baseline model using a 1-year lagged political index (*L1index*) and found that the results remained somewhat

unchanged. In addition, although some S&P 500 firms operate across multiple states, we followed standard practice from other studies (Di Giuli and Kostovetsky 2014; Huang et al. 2025), i.e., using the headquarters state as the relevant political context, as it typically reflects the firm's primary strategic and regulatory base.

6 | Robustness Tests

6.1 | Benchmarking Against Alternative Estimators

To assess the robustness of the baseline CMP estimates from Table 3, we re-estimated Equation (1) using four alternative approaches commonly employed in carbon performance studies: ordinary least squares (OLS), fixed effects (FE), two-step system GMM (2SGMM), and hierarchically nested general linear model (HNGLM). The results are reported in Table 4. While OLS and FE models confirm the negative and statistically significant effect of credit rating downgrades on emission scores, these estimators are not ideally suited to dynamic panel settings due to

TABLE 4 | Tests of the rating effects using alternative estimators.

Indep. vars.	OLS (1)	FE (2)	2SGMM (3)	HNGLM (4)
<i>L1emission_sc</i>	0.865*** (112.23)	0.709*** (46.36)	0.884*** (58.69)	0.865*** (117.20)
<i>L1up</i>	0.596 (0.89)	0.100 (0.14)	1.240 (1.57)	0.596 (1.00)
<i>L1dn</i>	−1.751*** (−2.58)	−1.283* (−1.88)	−1.739** (−2.13)	−1.751** (−2.40)
<i>Index</i>	4.109*** (3.96)	−4.523 (−1.26)	3.610*** (2.85)	4.109*** (3.54)
Firms	357	357		357
Observations	3459	3459		3459
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	No (absorbed by FE)	Yes	Yes
Control vars.	Yes	Yes	Yes	Yes
Period of est.	2012–2024	2012–2024	2012–2024	2012–2024
<i>F</i> test (<i>p</i> value)	0.00	0.00		
Wald test (<i>p</i> value)				0.00
m1 (<i>p</i> value)			0.00	
m2 (<i>p</i> value)			0.27	
Hansen test (<i>p</i> value)			0.31	
<i>R</i> ²	0.87	0.68		

Note: The dependent variable is the emissions score (*emis_sc*), where a higher value indicates better emissions performance. The key explanatory variables include lagged credit rating changes (*L1up* and *L1dn*). The other variables are defined in Table A1 in the Appendix. The Wald test *p* values assess the joint significance of the estimated coefficients. m1 and m2 are tests for first-order and second-order serial correlation in the first-differenced residuals under the null hypothesis of no serial correlation. The Hansen test is a test of the overidentifying restrictions under the null hypothesis of instrument validity. t-Statistics (z-statistics in the case of the estimates from HNGLM) based on robust standard errors clustered at the firm level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

potential bias arising from lagged dependent variables and endogeneity (Wojewodzki et al. 2018).

To address these concerns, we applied the 2SGMM estimator in Column (3). The instrument count remains within acceptable boundaries, and both the Hansen and Arellano-Bond m2 tests confirm validity, as well as the absence of second-order serial correlation, respectively (Roodman 2009). The 2SGMM results remain consistent with the CMP estimates, reinforcing the credibility of the findings. As a final robustness check, we employed HNLGM to account for the hierarchical structure of the data, with firm-year observations nested within industries. Although HNLGM does not correct for endogeneity, its flexibility captures firm and industry-level heterogeneity. The results in Column (4) remain robust. Such consistency across four different estimators underscores the overall robustness of the study's primary conclusions.

6.2 | Sectoral Heterogeneity

To validate the robustness of the findings and explore sectoral heterogeneity, the sample was stratified into carbon-intensive and non-carbon-intensive industries. Carbon-intensive firms

have been defined in the literature (e.g., Safiullah et al. 2025) and typically belong to one of the GICS sectors in Energy, Materials, or Utilities.⁵ These industries are widely recognized for their high emissions profiles and are typically subject to stricter environmental regulation, heightened stakeholder scrutiny, and elevated exposure to climate-related financial risks (Shui et al. 2025). Recent research also highlights that ESG pressures and credit rating constraints are particularly salient for firms in these sectors (Safiullah et al. 2025). Against this backdrop, credit shocks may provoke asymmetric behavioral responses depending on the sector's regulatory scope and cost structure.

To examine potential asymmetries, the baseline model was re-estimated separately for firms in carbon-intensive and non-carbon-intensive sectors. The results, reported in Table 5, indicate a clear sectoral asymmetry in the credit ratings–carbon performance relationship. Among non-carbon-intensive firms (Column 1), credit downgrades are associated with economically significant declines in emissions performance in line with H_1 . By contrast, there is no evidence that either downgrades or upgrades materially affect the environmental performance of firms operating in carbon-intensive sectors (Column 2). Overall, the findings show that the financial burden of sustainability is unevenly shared, with credit shocks shaping environmental

TABLE 5 | Rating effects for carbon-intensive vis-à-vis non-carbon-intensive sectors.

	Carb-Int	Non-Carb-Int		Carb-Int	Non-Carb-Int	Carb-Int	Non-Carb-Int
Indep. Vars.	(1)	(2)	Indep. Vars.	(3)	(4)	(5)	(6)
<i>L1emission_sc</i>	0.842*** (33.06)	0.866*** (107.08)	<i>L1emission_sc</i>	−0.004 (−1.19)	−0.002 (−1.12)	−0.000 (−0.12)	0.004*** (2.67)
<i>L1up</i>	−1.222 (−0.90)	1.134 (1.51)					
<i>L1dn</i>	−1.581 (−1.08)	−1.713** (−2.30)					
<i>Index</i>	4.987* (1.92)	4.151*** (3.71)					
Firms	56	309					
Observations	560	2995					
Year dummies	YES	YES					
Industry dummies	YES	YES					
Control vars.	YES	YES					
Period of est.	2012–2024	2012–2024					
Wald test (<i>p</i> value)	0.00	0.00					
rho_12 (<i>p</i> value)	0.63	0.73					
rho_13 (<i>p</i> value)	0.26	0.26					
rho_23 (<i>p</i> value)	0.00	0.00					

Note: In Columns (1) and (2), the dependent variable is the emissions score (*emis_sc*), where a higher value indicates better emissions performance. Columns (3)–(5) and (4)–(6) model the likelihood of a credit rating upgrade (*up*) and downgrade (*dn*), respectively. Coefficient estimates are reported, with z-statistics shown in parentheses, based on standard errors clustered at the firm level. The key explanatory variables include lagged credit rating changes (*L1up* and *L1dn*). The other variables are defined in Table A1 in the Appendix. Standard errors are clustered at the firm level to account for serial correlation and unobserved heterogeneity. The models include year and industry fixed effects. Wald test *p* values assess the joint significance of the estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

outcomes more strongly in sectors where environmental investments are more discretionary.

6.3 | Temporal Analysis

This section examines whether the relationship between credit rating actions and emission performance has changed following the ratification of the Paris Agreement, signed in December 2015. In line with prior studies (Palea and Drogo 2020), the pre-(post) Paris period covers 2012–2015 (2016–2024). The results, reported in Table 6, show that the adverse effect of downgrades (*L1dn*) on corporate emissions scores remains robust and statistically significant, mirroring the baseline estimates in Table 3.

At the same time, the coefficient on the Paris variable is positive and statistically significant (3.74), indicating a general improvement in emissions performance among S&P 500 firms in the post-Paris era. This finding confirms recent work (e.g., Bolton and Kacperczyk 2025) and reflects higher regulatory expectations, strengthened climate-related disclosure norms, and increased reputational pressures following the Paris Accord. However, the interaction terms (*Paris*L1dn* and *Paris*L1up*) were statistically non-significant, suggesting that firms' responsiveness to credit rating shocks has not materially changed since the Paris Agreement was adopted. These results suggest that although the Paris Accord raised the overall environmental baseline, it did not alter the way credit rating actions influence firms' emissions strategies.

TABLE 6 | Rating effects before and after the Paris Agreement.

Indep. vars.	CMP (1)	Indep. Vars.	CMP (2)	CMP (3)
<i>L1emission_sc</i>	0.865*** (112.42)	<i>L1emission_sc</i>	−0.002 (−1.51)	0.004*** (2.96)
<i>L1up</i>	0.614 (0.92)			
<i>L1dn</i>	−1.759*** (−2.59)			
<i>Paris</i>	3.740* (1.70)			
<i>Paris*L1up</i>	−2.837 (−0.69)			
<i>Paris*L1dn</i>	−1.987 (−0.53)			
<i>Index</i>	4.440*** (−3.99)			
Firms			365	
Observations			3555	
Year effects			Yes	
Industry effects			Yes	
Period of estimation			2012–2024	
Wald test (<i>p</i> value)			0.00	
rho_12 (<i>p</i> value)			0.66	
rho_13 (<i>p</i> value)			0.22	
rho_23 (<i>p</i> value)			0.00	

Note: In Equation (1), the dependent variable is the emissions score (*emis_sc*), where a higher value indicates better emissions performance. The Equations (2) and (3) model the likelihood of a credit rating upgrade (*up*) and downgrade (*dn*), respectively. Coefficient estimates are reported, with *z*-statistics shown in parentheses, based on standard errors clustered at the firm level. The key explanatory variables include lagged credit rating changes (*L1up* and *L1dn*). Equation (1) also includes a post-Paris dummy variable (*Paris*) equal to 1 for years 2016–2024, and zero otherwise, as well as its interactions with lagged rating upgrades (*Paris*L1up*) and downgrades (*Paris*L1dn*), to test the robustness of rating effects before and after the Paris Agreement. The other variables are defined in Table A1 in the Appendix. Standard errors are clustered at the firm level to account for serial correlation and unobserved heterogeneity. The models include year and industry fixed effects. Wald test *p*-values assess the joint significance of the estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

6.4 | Credit Ratings Class Segmentation

To examine the potentially heterogeneous impact of credit rating actions on corporate emissions performance, the sample was split based on credit class, distinguishing between investment-grade firms (rated BBB- and above) and non-investment-grade firms (rated BB+ and below). The intention was to test whether credit quality moderates the impact of rating actions on emissions performance. This distinction is economically meaningful, as credit ratings remain deeply integrated into regulatory frameworks and institutional investment mandates in the United States. Thus, downgrades below the investment-grade threshold significantly reduce the pool of eligible bondholders, trigger forced selling by regulated financial institutions, and increase the cost of debt and equity financing alike (Kisgen 2019).

The results reported in Table 7 demonstrate pronounced asymmetry. Among investment-grade firms (Column 1), the first lag of credit downgrades (*L1dn*) has a substantial adverse effect on emission scores, consistent with *RBV*'s argument that adverse

rating actions constrain the resources available for discretionary environmental initiatives. In contrast, the *L1up* variable has a smaller, albeit statistically significant and positive coefficient (1.355), providing empirical support for H_2 , although only within the subset of financially flexible (investment-grade rated) S&P 500 firms.

However, speculative-grade firms (Column 2) exhibit no meaningful response to either downgrades or upgrades. One possible explanation is that these firms already face elevated borrowing costs and restricted investor access, which have depleted any discretionary capacity to adjust carbon performance (Kisgen 2019). Another interpretation may relate to a financial slack threshold mechanism. Investment-grade firms, with their superior access to low-cost capital and greater financial flexibility, possess sufficient slack to convert rating upgrades into discretionary environmental investments.

Conversely, even after upgrades, speculative-grade firms often experience financing constraints and therefore lack the "green slack" necessary to enhance their emissions performance meaningfully. This threshold logic complements *prospect theory* by highlighting that positive rating signals only translate into behavioral change when firms have adequate resources to act upon them. The findings mirror earlier results for carbon-intensive sectors and underscore that credit rating effects on emissions performance are contingent on a firm's capacity to respond, varying systematically by sector and credit quality. In such situations, good intentions are no match for hard constraints.

TABLE 7 | Rating effects by credit rating class.

Indep. vars.	Investment (1)	Non-Investment (2)
<i>L1emission_sc</i>	0.860*** (97.77)	0.859*** (42.20)
<i>L1up</i>	1.355* (1.77)	−2.459 (−1.60)
<i>L1dn</i>	−2.386*** (−3.22)	0.521 (0.29)
<i>Index</i>	5.062*** (4.26)	2.812 (0.99)
Firms	331	85
Observations	2981	479
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Period of est	2012–2024	2012–2024
Wald test (<i>p</i> value)	0.00	0.00
rho_12 (<i>p</i> value)	0.58	0.42
rho_13 (<i>p</i> value)	0.63	0.13
rho_23 (<i>p</i> value)	0.00	0.00

Note: The dependent variable is the emissions score (*emis_sc*), where a higher value indicates better emissions performance. The estimated results from the upgrade and downgrade equations are omitted for brevity, as their primary role is to account for potential endogeneity in rating actions. Coefficient estimates are reported, with z-statistics shown in parentheses, based on standard errors clustered at the firm level. The key explanatory variables include lagged credit rating changes (*L1up* and *L1dn*). The other variables are defined in Table A1 in the Appendix. Standard errors are clustered at the firm level to account for serial correlation and unobserved heterogeneity. The models include year and industry fixed effects. Wald test p-values assess the joint significance of the estimated coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

7 | Conclusion

This study examines the role of credit rating signals in shaping corporate environmental behavior. Using longitudinal panel data on S&P 500 firms from 2012 to 2024 and a dynamic conditional mixed process (CMP) model, we find that credit rating downgrades are associated with a deterioration in firms' emissions reduction performance. By contrast, rating upgrades are associated with only modest environmental improvements, and only among investment-grade firms. We also show that firms headquartered in Democratic-leaning states exhibit stronger baseline environmental performance.

The research contributes to the literature on the effects of credit ratings by extending the analysis to corporate environmental behavior. The findings deepen our understanding of how credit signals function not only as reflections of firm risk but also as catalysts of behavioral change in environmental strategy. In particular, the results are consistent with a *resource-based view* (*RBV*) mechanism, whereby adverse rating events tighten financing conditions, reduce financial slack, and constrain firms' ability to sustain environmental investments. Moreover, the asymmetric responses to downgrades and upgrades reinforce *prospect theory*'s prediction that firms react more strongly to losses than gains.

From a practical perspective, firms should prioritize by continuing to invest in sustainability investments during periods of financial stress, recognizing that cutting back on environmental initiatives may only offer temporary relief but risks undermining long-term strategic resilience, stakeholder trust, and regulatory

alignment. Furthermore, investors and credit rating agencies must better account for the unintended environmental consequences of credit events, especially considering the increasing materiality of climate risk to financial performance.

From a policy perspective, the findings call for a differentiated rather than a uniform response. For investment-grade firms, incentive-based instruments (such as green tax credits or sustainability-linked financing) may encourage positive environmental responses when ratings improve. For speculative-grade firms, where upgrades do not translate into better carbon performance, vulnerability-mitigating mechanisms, such as government-backed green loan guarantees or countercyclical credit enhancement, are needed to build financial slack and enable environmental investment. Broader countercyclical green financing mechanisms (government-backed credit guarantees, sustainability-linked loan programs, and green bond guarantees) remain valuable to insulate environmental investment from adverse credit shocks across the board. These tools align with existing US practices in development finance and can be used to prevent short-term financial stress from crowding out long-term environmental investment.

A limitation of this study is its focus on large US firms. Smaller firms typically face tighter financing constraints and may therefore respond more strongly to credit shocks and institutional pressures. As such, the estimated effects should be interpreted with caution as a conservative benchmark rather than a general trend. Extending the analysis to relatively smaller or mid-sized, or non-US firms would be a valuable avenue for future research, particularly in jurisdictions where political regimes, regulatory frameworks, and credit market structures differ substantially. In addition, emerging analytical approaches, including machine learning techniques, may complement traditional econometric methods by capturing nonlinear dynamics and uncovering additional predictors of sustainability outcomes. Finally, while this study focuses on carbon-related performance, future research could extend the framework to broader ESG dimensions to assess whether similar mechanisms operate across other aspects of corporate sustainability. Another promising avenue may include the development of weighted multi-state political exposure measures to gauge how firms operate across different jurisdictions. Finally, further work could focus on the exploration of nonlinear threshold effects surrounding political ideology and how firms respond to credit rating shocks.

Author Contributions

Michał Wojewodzki led the study and made the primary contribution, including developing the core idea, collecting the data, shaping the theoretical framework, designing the research strategy, carrying out the empirical work, overseeing the interpretation of findings, and drafting the manuscript. Mohamad H. Shahrou assisted in data gathering and management, empirical analysis, formulation of the hypotheses, and manuscript review. Alireza Rohani contributed to the literature development, helped refine the theoretical framework, and methodological approach. Bradley R. Barnes provided overall supervision and strategic direction, delivered key conceptual contributions throughout the project, and critically reviewed the manuscript in full. Chi Keung Marco Lau supported the interpretation and discussion of findings and helped develop the practical and policy implications.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

¹ In cases where multiple rating changes occurred within the same year, e.g., a downgrade from A– to BBB+ in February 2015, followed by another downgrade to BBB– in August 2015, the final rating (BBB–) is retained. This approach is standard in the related empirical literature (see Wojewodzki et al. 2018).

² Untabulated tests of our baseline model indicate that, empirically, the inclusion of the *index* variable demonstrably improves the model's relative fit according to both the Bayesian information criterion (BIC) and Akaike information criterion (AIC).

³ We intentionally exclude overall ESG scores, environmental pillar scores, and the environmental innovation score from the emissions reduction score model (*emis_sc*). These factors are constructed using the *emis_sc* variable as one of their ingredients and are thus highly correlated with it. Including them would introduce circularity, as well as inflate multicollinearity.

⁴ For robustness, we also report findings based on more conventional estimation approaches, including OLS, fixed effects (FE), and GMM applied to the emissions equation alone (see Section 6.1).

⁵ To further confirm the robustness of the empirical results, additional (unreported) tests were conducted using an alternative definition of carbon-intensive industries based on the Carbon Disclosure Project's classification: oil and gas, chemicals, construction materials, metals and mining, paper and forest products, electric utilities, gas utilities, multi-utilities, and independent power producers (GICS: 151010, 151,020, 151,040, 151,050, 551,010, 551,020, 551,030, 551,050). The results remain virtually unchanged.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table B1** Complete annual (2012–2024) index values for 50 US states.

Appendix A

TABLE A1 | Definitions and sources of the employed variables.

Name	Definition	Data source
<i>emis_sc</i>	LSEG ESG emissions reduction score measures a company's commitment and effectiveness in reducing environmental emissions in its production and operational processes, winsorized at the 1st and 99th percentiles. The higher the emissions score, the better the firm's environmental performance.	LSEG Refinitive
<i>index</i>	State-level political ideology index (0–1 scale). Higher values indicate a more Democratic-leaning political environment. Constructed annually from six components: (1) Democratic presidential vote share, (2) Democratic gubernatorial vote share, (3–4) Democratic seat shares in the US Senate and House, and (5–6) Democratic seat shares in the state upper and lower legislative chambers.	Authors' calculations
<i>L1up</i>	First lag of a dummy variable equal to one if, in the given year, S&P upgraded the firm's credit rating and zero otherwise.	Bloomberg
<i>L1dn</i>	First lag of a dummy variable equal to one if, in the given year, S&P downgraded the firm's credit rating and zero otherwise.	Bloomberg
<i>size</i>	Natural logarithm of the firm's total assets, winsorized at the 1st and 99th percentiles.	LSEG Refinitive
<i>totdebt</i>	Total debt as a percentage of the firm's total assets, winsorized at the 1st and 99th percentiles.	LSEG Refinitive
<i>roe</i>	Return on average total equity, winsorized at 1st and 99th percentiles.	LSEG Refinitive
<i>div_pay</i>	Dividend payout ratio, winsorized at the 1st and 99th percentiles.	LSEG Refinitive
<i>govern_sc</i>	LSEG ESG governance pillar score, winsorized at the 1st and 99th percentiles.	LSEG Refinitive