The Effects of Asymmetric Cost Behavior on Corporate Environmental Commitments and Actions

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ABSTRACT

We examine the effects of asymmetric cost behavior (a.k.a. "cost stickiness")—costs falling less for sales decreases than rising for equivalent sales increases—on corporate environmental commitments and real actions. Prior research suggests that corporate environmental commitments involve multi-year resource deployments and that reductions in firms' environmental commitments lead to negative investor reactions. Building on these findings, we predict that firms with higher cost stickiness will make lower initial corporate environmental commitments because they are less capable of maintaining high levels of environmental commitments in the future than firms with lower cost stickiness if sales decrease. Using measures of firms' environmental commitments based on MD&A disclosures and earnings calls, we find results consistent with our prediction. In addition, we show that firms with higher cost stickiness take weaker real environmental actions, as evidenced by economically significant increases in industry pollution and decreases in green investments. To mitigate endogeneity concern, we use two quasi-experimental designs that utilize plausibly exogenous variations in labor-adjustment costs caused by wrongful discharge laws and close-call union elections. These quasi-experimental tests yield results consistent with the main results. Cross-sectional analyses provide support for the proposed mechanisms. Our study provides novel insights about how cost behavior influences firms' environmental initiatives.

Keywords: *asymmetric cost behavior; cost stickiness; environmental commitments; sustainability*

Data Availability: Data are available from the public sources identified in the text.

1. Introduction

It is widely recognized that corporations play a pivotal role in transitioning to a low-carbon global economy (United Nations 2022; United Nations 2024). In response to increasing calls for corporate climate action, a growing number of U.S. companies are making *environmental commitments*.[1] However, significant variations exist in firms' environmental commitments (Franco and Ruetz 2024; Even-Tov et al. 2025) with cost concerns frequently cited as the greatest barrier. The U.S. Environmental Protection Agency (EPA) Office of Inspector General (2008) identified firms' "perceived emission reduction costs" as one of two greatest barriers to participation in voluntary climate programs. A 2021 survey suggests that about 40% of small and medium-sized enterprises name "the costs and fear of low returns on investment" as a major barrier to the net zero goal (Lloyds Bank 2021). Given that a firm's cost behavior influences the resources it can allocate to environmental actions, it is important to understand whether and how cost behavior affects corporate environmental commitments. Despite a large volume of studies on cost behavior, its real environmental effects remain underexplored. In this study, we examine the effect of asymmetric cost behavior (a.k.a. "cost stickiness")—costs falling less for a unit of sales decrease than rising for a unit of sales increase—on corporate environmental commitments and actions.

Cost stickiness is a well-documented phenomenon in the management accounting literature and arises from asymmetric adjustment costs for sales increasing versus decreasing periods (Anderson et al. 2003; Banker and Byzalov 2014; Banker et al. 2014). When demand increases, managers ramp up resources to the extent necessary to accommodate additional sales. Conversely, when demand decreases, managers have to weigh the expected costs of maintaining unutilized

[1] Corporate environmental commitments include actions and policies to protect the natural environment by reducing waste and emissions, adhering to environmental regulations, adopting renewable energy and innovative green technologies, and partnering with other organizations to achieve greater environmental impact (Goeller and Caldwell 2022).

resources during periods of low demand against the expected adjustment costs of reducing resources and then scaling them up again when demand rebounds in the future and are likely to cut resources to a lesser extent than sales decreases (i.e., retaining some unutilized resources). Prior literature identifies several determinants of cost stickiness, including resource-adjustment costs, managerial expectations for future sales, slack resources carried over from the prior period, and managerial incentives (e.g., Banker and Byzalov 2014; Banker et al. 2014; Chen et al. 2012; Weiss 2010). Furthermore, an emerging line of studies has documented the financial consequences of asymmetric cost behavior, such as its impact on earnings attributes, payout policies, and analyst forecasts (e.g., Banker and Chen 2006; He et al. 2020; Weiss 2010). However, empirical evidence on the real effects of cost stickiness in general—and on environmental commitments and actions in particular—remains limited.

We predict that cost stickiness is likely to reduce firms' environmental commitments for two reasons. First, prior research suggests that corporate environmental commitments involve multi-year resource deployments that are difficult to scale back proportionally if financial performance deteriorates in the future (Nagar and Schoenfeld 2023). For example, automakers like GM committed billions over a decade to reshape factories for electric vehicle production, including major infrastructure upgrades such as new body shops, automation systems, and solar panels (Colias 2021). These largescale, long-term commitments are integral to their strategic direction, making them difficult to reverse even if sales decline.

Second, prior literature documents investors' negative reactions when firms discontinue environmental, social, and governance (ESG) initiatives. Garavaglia et al. (2024) provide evidence of an "ESG stopping effect"; investors react more negatively when firms stop ESG initiatives compared to stopping general business initiatives, even when their reactions to starting the initiatives are similar. Given investors' aversion to reduced or discontinued corporate environmental initiatives (Krueger et al. 2020; Garavaglia et al. 2024) and the scrutiny from vigilant regulators, engaged communities, and activist investors regarding reductions or discontinuations in environmental initiatives (Freeman 2010), managers must consider a firm's ability to uphold future sustainability commitments when making current ones. Therefore, we predict that firms with higher cost stickiness will make lower corporate environmental commitments than their peers because they are less capable of maintaining high levels of environmental commitments in the event of future sales decreases.

Following Anderson et al. (2003) and He et al. (2020), we measure cost stickiness at a firm-year level using the most recent 16 quarters of data. Following prior literature, we use disclosure-based measures of a firm's environmental commitments. Due to the scarcity of data on firms' environmental strategies and the multi-dimensional nature of sustainability (Sautner et al. 2023a), both investors and academic researchers often use disclosure-based measures to quantify a firm's sustainability efforts (Berg et al. 2022). Additionally, we expect firms' environmental commitments to manifest through increased environmental disclosures because theory suggests managers use voluntary disclosures to credibly communicate private information about corporate strategy (Ferreira and Rezende 2007). Specifically, following Even-Tov et al. (2025), we employ both a keyword discovery algorithm and a fine-tuned large language model ClimateBERT with commitment and specificity classifications to measure corporate environmental commitments based on firms' MD&A disclosures and earnings conference calls.

In the baseline analysis, we estimate an ordinary least squares (OLS) regression with corporate environmental commitments as the dependent variable and the degree of cost stickiness as the key independent variable. We find a significantly negative relation between cost stickiness, calculated based on three types of firm costs (operating, SG&A, and total costs), and corporate environmental commitments, indicating that firms with greater cost stickiness tend to make lower environmental commitments. To alleviate reverse causality concern, we estimate the panel vector autoregression (PVAR) model (Boschen et al. 2003) and show that cost stickiness causes environmental commitments but not vice versa. In addition, we validate our disclosure-based environmental commitment measures with environmental performance ratings by prominent ESG rating agencies (i.e., KLD and ASSET4). More importantly, we find that cost stickiness is associated positively with toxic emission and negatively with green patents, and the effects are economically significant. These results suggest that cost stickiness affects not only environmental commitments but also real environmental actions. They also corroborate the validity of our disclosure-based measures of environmental commitments: they capture genuine environmental commitments, not greenwashing.

Furthermore, we validate the underlying argument that investors would react negatively to environmental commitment reductions by demonstrating that investors react unfavorably surrounding the 10-K filing date when firms reduce their environmental commitment levels in MD&A disclosures. Moreover, we document that this negative reaction is more pronounced when investor scrutiny of the firm is more intense, as proxied for by high environmentally responsible (ER) institutional ownership or high ESG performance transparency.

A key challenge in examining the relation between cost stickiness and corporate environmental commitments is the potential for simultaneous endogeneity; a firm's cost behavior and environmental commitment levels may be jointly impacted by common unobserved variables. To alleviate endogeneity concerns, we implement two quasi-experimental methods that isolate plausibly exogenous changes in cost stickiness. First, we employ a state border discontinuity approach, exploiting the quasi-random discontinuity in the wrongful discharge laws (WDLs) recognition status at state borders (i.e., with one state adopted and the bordering state not). By increasing employment protection, these laws directly increased the adjustment costs and, hence, the stickiness of labor costs (Kim et al. 2020). After entropy balancing, we compare the average environmental commitments between firms domiciled within 50 miles on either side of the border, which allows us to attribute differences in cost stickiness to whether the state recognizes the WDL. We first confirm that state-wide recognition of WDLs increases *overall* cost stickiness. We then show that the adoption of WDLs reduces firms' environmental commitments.

Second, we use a regression discontinuity design based on close-call union election victories. Although unionization itself may be endogenously chosen, prior research has shown that, by focusing on the discontinuity at the 50% victory margin, passing is asymptotically random, generating quasi-experimental variation in union presence and the resulting labor-adjustment costs (e.g., DiNardo and Lee, 2004; Bradley et al. 2017; He et al. 2020). This quasi-random assignment of unionization status for firms near the threshold helps isolate the causal impact of unionization on cost stickiness and, in turn, on corporate environmental commitments. We first document an increase in cost stickiness among firms where elections barely passed rather than barely failed, consistent with He et al. (2020). Next, we document that firms whose union elections barely passed exhibit lower environmental commitments than those whose elections barely failed. These results suggest that the increased cost stickiness caused by an exogenous union win reduces environmental commitments. The above two tests help alleviate endogeneity concerns.

Lastly, we conduct two sets of cross-sectional analyses to shed more light on the mechanisms. First, we show that our main results are stronger for firms with limited financial resources or greater resource-adjustment costs. These results are consistent with our theoretical arguments that sticky-cost firms with limited resources or greater resource-adjustments costs find it more challenging to maintain environmental commitments in future tough times. Second, because greater ER institutional ownership or greater ESG transparency would imply more investor scrutiny, we predict and find the negative relation between cost stickiness and environmental commitments to be stronger under these scenarios.

We make two primary contributions to the accounting literature. First, we connect the cost asymmetry literature with the growing accounting literature on sustainability. While past studies document the effect of cost stickiness on financial outcomes such as earnings attributes and analyst forecasts (e.g., Banker and Chen 2006; Weiss 2010) or financing activities like dividend payouts (He et al. 2020), real environmental effects of cost stickiness remain underexplored. In addition, despite the importance of costs in carrying out ESG initiatives, there is a lack of research on the effect of cost stickiness on firms' environmental initiatives. We fill this literature gap by developing and testing theory regarding the effect of asymmetric cost behavior on corporate environmental commitments and actions, which are operating and investing activities that stand in contrast to financing activities in He et al. (2020). The cross-sectional analyses provide interesting insights, suggesting stronger effects for firms with greater financial constraints and higher adjustment costs, consistent with environmental commitment decisions being driven by firms' expectation of their capability to maintain such commitments in the future if sales decrease.

Second, our study contributes to a burgeoning literature on the determinants of corporate environmental commitments. Desai et al. (2023) and Even-Tov et al. (2025) document pressure from stakeholders and government procurement as determinants of firms' environmental commitments and actions, respectively. Our study extends this emerging literature by showing that firms with greater cost stickiness are less capable of upholding environmental initiatives down the road and therefore make lower sustainability commitments initially. Essentially, analyzing cost behavior enriches our understanding of multi-period resource allocation surrounding environmental protection. Furthermore, cross-sectional analyses show that the pressure from investors for firms to maintain their initial environmental commitments serves as a channel for the main result, highlighting the role of ER institutional ownership and ESG transparency in shaping environmental commitments. Interestingly, this result suggests that, in firms facing cost stickiness, ER ownership and ESG transparency could, counterintuitively, lead to lower levels of initial environmental commitments.

Our study has important practical implications. Our results suggest that cost-sticky firms may face additional constraints in their efforts to meet net-zero goals, especially those with greater financial constraints, high asset intensity, or labor-intensive operations. In promoting corporations' sustainability efforts, policymakers, investors, financial analysts, and rating agencies could also consider firms' cost behaviors to better understand their environmental commitments.

2. Hypothesis Development

Cost stickiness has been documented in a large number of studies in the management accounting literature, and prior literature identifies several determinants of cost stickiness, including resource-adjustment costs, managerial expectations for future sales, slack resources carried over from the prior period, and managerial incentives (e.g., Anderson et al. 2003; Banker and Byzalov 2014; Banker et al. 2014; Chen et al. 2012; Chen et al. 2019; Kama and Weiss 2013). Anderson et al. (2003) find that cost stickiness increases in resource-adjustment costs; Chen et al. (2019) document the highest level of cost stickiness when there is "a low degree of unused resources, a high magnitude of adjustment costs, and optimistic managerial expectations." In terms of managerial incentives, Chen et al. (2012) show a positive association between the agency problem and SG&A cost stickiness, and Kama and Weiss (2013) find that cost stickiness is lower when managers face incentives to meet earnings targets.

Compared to the large stream of literature on the determinants of cost asymmetry, there is less empirical evidence of the consequences of cost asymmetry. Several studies document the effect of cost stickiness on financial outcomes such as earnings attributes, management earnings forecasts, and analyst earnings forecasts. For example, Banker and Chen (2006) find that incorporating cost stickiness and cost variability in earnings-prediction models leads to significant improvement in earnings forecast accuracy. Weiss (2010) documents a negative association between cost stickiness and analysts' earnings forecast accuracy. Filip et al. (2025) show that cost stickiness increases managers' income-smoothing activities. However, there is limited empirical evidence on the real effects of cost stickiness.

A notable exception is He et al. (2020), who document a negative association between cost stickiness and dividend payouts due to investors' aversion to dividend cuts and firms with greater cost stickiness being less able to maintain high dividends in the future if sales decrease. However, dividend policy (financing activities) and environmental commitments (operating and investing activities) are driven by very different factors, so findings in dividend policy do not necessarily generalize to environmental commitments for at least two reasons. First, dividend policy is shaped primarily by shareholder and stock market pressures, whereas environmental commitments can be driven by a broader range of stakeholders—including shareholders, regulators, consumers, NGOs, and the local community. Second, unlike dividend payouts, which are regularly disclosed, audited, and closely monitored by investors, environmental commitments are far less standardized and often lack transparency or enforcement. For instance, Jiang et al. (2025) document that many firms failed to report outcomes of their previously announced emissions targets and some firms failed to meet their previously announced emission targets but there were minimal market or reputational penalties. The weakness of accountability mechanisms makes it unlikely that firms face the same disciplining pressures when scaling back environmental commitments as they do when reducing dividends. .

We fill the gap in the literature and examine the consequences of cost asymmetry for corporate environmental commitments and actions. Prior research suggests that there are significant variations in firms' environmental commitments and actions (Franco and Ruetz 2024; Even-Tov et al. 2025). However, we have limited understanding of the drivers of corporate environmental commitments and actions. Using carbon-reduction pledges of publicly traded U.S. oil exploration and production companies, Desai et al. (2023) find that firms' likelihood of announcing a net-zero pledge or significant emission cuts is positively associated with energy production and ownership by BlackRock. Even-Tov et al. (2025) show that firms with high exposure to government contracts significantly increase climate commitments and actions following expanded procurement opportunities, since government procurement provides economic incentives for firms to engage in climate-mitigation actions.

We predict that cost stickiness can reduce firms' environmental commitments for two reasons. First, prior research suggests that corporate environmental commitments involve multi-year resource deployments that are difficult to reduce proportionally if financial performance declines subsequently (Nagar and Schoenfeld 2023). For example, Cisco has pledged to hit net-zero greenhouse gas emissions across the board by 2040 and aims to contribute $477 million to community programs as part of their ESG initiatives (Yamamoto 2021). UPS has invested over $1 billion since 2008 in alternative-fuel vehicles and advanced technology fueling stations to meet ambitious environmental targets (U.S. Chamber of Commerce 2020). Such capital-intensive commitments have been embedded into daily operations; for example, UPS now relies on a fleet of over 10,000 alternative-fuel vehicles, making it difficult to scale back without disrupting logistics efficiency.

Second, prior literature documents investors' negative reactions when firms stop ESG initiatives. Investors can access information about firms' environmental commitments through various channels, including Carbon Disclosure Project data, press releases, sustainability reports, regulatory filings (e.g., 10-K/Qs), and conference calls. Garavaglia et al. (2024) provide evidence of an "ESG stopping effect" in which investors react more negatively when firms stop ESG initiatives compared to stopping general business initiatives, even when their reactions to starting the initiatives are similar. Given the aversion of investors to reduced or discontinued corporate environmental initiatives (Krueger et al. 2020; Garavaglia et al. 2024) and scrutiny from vigilant regulators, engaged communities, and activist investors over reduced or discontinued environmental initiatives (Freeman 2010), managers must consider a firm's ability to uphold future sustainability commitments when making current sustainability commitments. Therefore, we predict that firms with higher cost stickiness make lower corporate environmental commitments than their peers because they are less able to maintain high levels of environmental commitments in case of sales declines. This is because firms with higher levels of cost stickiness will experience disproportionately larger earning decreases compared to other firms with lower levels of cost stickiness when sales decline (e.g., Weiss 2010). Because firms with higher cost stickiness are less able to uphold high levels of environmental commitments in the future if sales decline, we expect them to make lower environmental commitments initially.

Based on the above arguments, we predict a negative relation between a firm's cost stickiness and its environmental commitments. We posit the following hypothesis:

Hypothesis: *There is a negative association between cost stickiness and corporate environmental commitments.*

3. Sample, Variable Measurement, Model Specification, and Descriptive Statistics

3.1. *Sample*

Our initial sample comprises all firms with non-missing total assets, excluding financial firms (SIC codes 6000-6999), in Compustat from 2003 to 2019.[2] We first retain firm-years where cost stickiness measures can be calculated. Next, we require the firm-years to have cleaned texts (transcripts) of 10-Ks (conferences calls) from the Notre Dame Software Repository for Accounting and Finance (StreetEvents), which uses textual analysis to extract information from raw SEC filings (conference calls transcripts).[3] We employ the climate change bigrams developed by Sautner et al. (2023a) and a fine-tuned large language model (i.e., ClimateBERT with commitment-specificity classification) by Bingler et al. (2024) to measure corporate environmental commitments in the MD&A section of 10-Ks and the presentation sections of conference calls. This process results in a preliminary sample of 39,553 (30,269) firm-years for MD&A (conference call) analysis. Lastly, we augment our data with analyst coverage information from I/B/E/S, institutional ownership information from Thomson Reuters, executive option grant information from Execucomp, and sustainability rating information from Refinitiv ASSET4. Our final main (robustness) sample includes 35,709 (27,921) firm-year observations for MD&A (conference call) analysis, covering 5,236 (3,646) unique firms with complete information on climate commitment in MD&A (conference calls), asymmetric cost stickiness proxies, and control

[2] Jiang et al. (2019) state that the Sarbanes-Oxley Act of 2002 (SOX) may have significantly altered the contents of 10-K and 10-Q filings and that conference call transcripts become publicly available around late 2002 after the implementation of Regulation Fair Disclosure in 2000. Following their suggestion, we start our sample in 2003. Our sample ends in 2019 to avoid COVID-19's confounding influences on cost stickiness and corporate climate commitments.
[3] See https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/.

variables. Online Appendix Table OA1 reports our sample selection procedures for both the main and robustness samples.

3.2. *Measurement of cost stickiness*

To quantify firm *i*'s cost stickiness in year *t*, following Anderson et al. (2003) and He et al. (2020), we estimate the following model using a rolling window of the preceding 16 quarters (i.e., year *t*−3 to year *t*) of firm *i*'s accounting data:

$$\Delta LnOC_{i,t,q}, \Delta LnSG\&A_{i,t,q}, or\ \Delta LnTC_{i,t,q}$$
$$= \beta_0 + \beta_1 \Delta LnSales_{i,t,q} + \beta_2 Decrease_{i,t,q} \times \Delta LnSales_{i,t,q} + \varepsilon_{i,t} \tag{1}$$

where $\Delta LnOC$ is the log-change in quarterly operating costs, $\Delta LnSG\&A$ is the log-change in quarterly selling, general and administrative costs, $\Delta LnTC$ is the log-change in quarterly total costs, $\Delta LnSales$ is the log-change in quarterly sales, and $Decrease$ is a dummy variable for whether sales decrease in a quarter relative to the previous quarter. β_1 (β_1 + β_2), a firm-year measure, represents the percentage change in costs with a 1% increase (decrease) in sales. A negative β_2 indicates that costs drop less for sales decreases than they rise for sales increases and thus captures the extent to which firm costs are "sticky" and fail to adjust down proportionally during sales downturns. We define our cost-stickiness measures (*CS_OC*, *CS_SGA*, or *CS_TC*) as the *negative* of β_2, a larger value of *CS_OC*, *CS_SGA*, or *CS_TC* representing greater cost stickiness when costs are measured using operating costs, selling, general and administrative costs, and total costs, respectively. As reported in Panel A of Table 1, the means (medians) of cost-stickiness measures in our sample are 0.069 (0.017) for *CS_OC*, 0.091 (0.035) for *CS_SGA*, and 0.055 (0.010) for *CS_TC*, suggesting that firm costs are sticky on average (Banker and Byzalov 2014; He et al. 2020).

To validate our firm-year cost-stickiness measures, we test their associations with the documented economic determinants of cost stickiness including adjustment costs, managerial expectations for future demand, the slack resource level carried over from the prior period, and agency costs (e.g., Anderson et al. 2003; Banker et al. 2014; Banker and Byzalov 2014; Chen et al. 2012; Weiss 2010; He et al. 2020). Using the sample from 2003 to 2019, we regress firm *i*'s *CS_OC*, *CS_SGA*, or *CS_TC* on its asset intensity *AINT* in year *t* (indicating resource-adjustment costs); an indicator *SUCCDEC* for whether firm *i*'s sales growth rates are negative in both year *t* and *t*−1 and GDP growth rate in year *t* (both indicating managerial expectations for future demand),; a binary variable *LINC* for whether firm *i*'s sales growth rate in year *t*−1 is positive (indicating the slack resource level carried over from the prior period); and *LFCF*, the ratio of firm *i*'s free cash flows to its assets in year *t*−1 (indicating managerial empire-building incentives), either including not including 3-digit SIC-by-year fixed effect. Panel B of Table 1 shows that our stickiness measures are indeed positively related to asset intensity, current GDP growth, past sales growth, and past free cash flows and negatively related to situations where a firm consistently faces negative sales growth. Overall, the validation test results suggest that our firm-year measures capture the key economic forces behind cost stickiness.

Consistent with prior literature, we document strong correlations between cost stickiness in the current and previous quarters. In untabulated results, the Pearson (Spearman) correlation coefficients are 0.575 (0.614) between $CS\_OC_{i,t}$ and $CS\_OC_{i,t-1}$ estimates, 0.590 (0.616) between $CS\_SGA_{i,t}$ and $CS\_SGA_{i,t-1}$ estimates, and 0.563 (0.606) between $CS\_TC_{i,t}$ and $CS\_TC_{i,t-1}$ estimates. All correlations are significant at the 1% level. These results suggest that firm-level cost stickiness is relatively stable over time.

3.3. *Measurement of corporate environmental commitments*

Following prior literature (e.g., Bingler et al. 2024; Even-Tov et al. 2025; Sautner et al. 2023a), we measure environmental commitments using textual analysis of a firm's voluntary environment-related disclosures. Prior literature suggests that managers are motivated to make voluntary corporate disclosures that truthfully reveal insider information about their companies' strategic decisions, since their professional reputations are at stake (e.g., Ferreira and Rezende 2007). Also, it is inherently challenging to measure a firm's environmental strategies because of limited data availability and the complex and multi-dimensional nature of sustainability. Therefore, investors, rating agencies, and researchers often use disclosure-based measures to assess a firm's environmental strategy and efforts. For example, investors price firms' climate change exposure, which is estimated using earnings conference call transcripts (Sautner et al. 2023b); ESG rating agencies examine corporate disclosures such as sustainability reports and corporate websites to assign corporate sustainability ratings (Christensen et al. 2022); Even-Tov et al. (2025) use disclosure-based proxies to capture firms' environmental commitment levels.

Our first measure of environmental commitments (*EnvCommit1_MDA*) is adapted from Sautner et al.'s (2023a) measure of firm-level climate-related exposure. Sautner et al. (2023a) start with a small set of initial bigrams (i.e., two-word sequences) that are unambiguously related to climate change. They then use a keyword discovery algorithm to generate a larger set of bigrams that are related to the predetermined list of bigrams. Their measure of climate-related disclosure is calculated as the number of climate change bigrams in a quarterly earnings call transcript divided by the total number of bigrams in the transcript. Sautner et al. (2023a) validate their measure of environmental disclosure by demonstrating that it is useful in predicting job creation in disruptive green technologies and green patents.

We apply the Sautner et al. (2023a) climate change bigrams to measure environmental commitments in the MD&A section of the 10-K filing.[4] We examine MD&As because they contain *comprehensive* and *voluntary* narrative information about financial performance, financial statements, operations, research and development, liquidity, capital expenditures, commitments, known trends, risk factors, and forward-looking statements. As the MD&A section was solely prepared by the management team, it enables investors to view the firm's commitments through the lenses of management (SEC 2013). Our first measure of environmental commitments (*EnvCommit1_MDA*) is calculated as the number of climate change bigrams divided by the total number of bigrams in the MD&A of the 10-K filed by firm *i* in year *t*, multiplied by 100.

Our second measure of environmental commitments (*EnvCommit2_MDA*) is adapted from Bingler et al. (2024), who develop ClimateBERT, a fine-tuned large language model, to identify climate-related cheap talk and specific climate commitments in annual reports. Following Bingler et al. (2024), we identify climate-related sentences in MD&As that are related to firm actions on or commitments to climate change mitigation and adaptation. We then examine their specificity. Sentences that contain "detailed performance information, details of action, or tangible and verifiable targets" are classified as commitment-specific sentences. Specifically, our second measure of environmental commitments (*EnvCommit2_MDA*) is calculated as the number of climate-related sentences classified as commitment-specific divided by the total number of sentences in the MD&A of the 10-K filed by firm *i* in year *t*, multiplied by 100. We classify a

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[4] The climate change bigrams are downloaded from the online version of Sautner et al. (2023a) at https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.13219&file=jofi13219-sup-0002-ReplicationCode.zip.

climate-related sentence as commitment-specific based on the classification algorithm provided by Bingler et al. (2024).[5]

As a robustness check, we measure environmental commitments based on the *presentation* section of quarterly earnings calls. This disclosure offers several advantages. First, it allows us to capture voluntary disclosures made by managers instead of information elicited by analysts (Duchin et al. 2024). Earnings calls serve as a critical venue for managers to convey strategic business plans to stakeholders and garner significant attention from key audiences (Kimbrough 2005; Hollander et al. 2010; Hassan et al. 2019). Second, since the presentation section is carefully scripted and vetted by legal and investor-relations teams, it is deemed more reliable and less prone to greenwashing concerns than other disclosure channels like sustainability reports (Sautner et al. 2023a). Last, earnings call data are widely available across public firms. Our third measure of environmental commitments (*EnvCommit1_Call*) is the number of climate change bigrams divided by the total number of bigrams in the presentation section of conference call transcripts, multiplied by 100. We then average the values of all earnings calls held by firm *i* during year *t*. Our fourth measure of environmental commitments (*EnvCommit2_Call*) is the number of climate-related sentences classified as commitment-specific divided by the total number of sentences in the presentation section of conference call transcripts, multiplied by 100. We then average the values of all earnings calls held by firm *i* during year *t*. Appendix OA1 in the Online Appendix presents illustrative examples of corporate environmental commitments extracted from MD&A and earnings calls.

[5] The ClimateBERT with commitment and specificity classification models are downloaded from https://huggingface.co/climatebert/distilroberta-base-climate-commitment and https://huggingface.co/climatebert/distilroberta-base-climate-specificity, respectively.

As shown in Panel A of Table 1, the means (medians) of corporate environmental commitment measures in our main sample are 0.070 (0.027) for *EnvCommit1_MDA* and 0.058 (0) for *EnvCommit2_MDA*. In our robustness sample, the means (medians) of corporate environmental commitment measures are 0.079 (0.037) for *EnvCommit1_Call* and 0.086 (0) for *EnvCommit2_Call*.

3.4. *Main model*

To investigate the effect of cost stickiness on corporate environmental commitments, we use OLS regression to estimate the variations of the following model:

$$EnvCommit_{i,t+1} = \alpha + \delta CS_{i,t} + \Gamma Z_{i,t} + \omega_g \times \sigma_t + \varepsilon_{i,t} \tag{2}$$

where *i*, *t*, and *g* index firm, year, and industry, respectively. Our dependent variable measuring firm environmental commitments in year *t*+1 is *EnvCommit1_MDA* or *EnvCommit2_MDA*. The key independent variable is cost stickiness in year *t*, one of the three measures (*CS_OC*, *CS_SGA*, or *CS_TC*) defined earlier.[6]

Regarding $Z_{i,t}$, we first include cost elasticity (*CostElasticity*), which measures how a firm's costs change in response to changes in production levels (Chen et al. 2024). A firm with high cost elasticity (i.e., high variable costs relative to fixed costs) is flexible and can proportionately reduce costs when sales decrease. We expect that cost elasticity positively relates to environmental commitments. Another reason to control for cost elasticity is that cost stickiness could be confounded by the cost structure captured by cost elasticity (Balakrishnan et al. 2014). We include a set of additional control variables in year *t* to account for various firm characteristics, following Even-Tov et al. (2025), who also use corporate environmental commitments as a

[6] The past observation period (from year $t-3$ to year *t*) allows firms to fully understand their cost behavior before making initial environmental commitment decisions in year *t*+1. Moreover, the lead-lag specification helps resolve reverse causality concern, as environmental commitments in year *t*+1 are less likely to affect cost stickiness in year *t*.

dependent variable. We capture economies of scale using firm size (*LnSize*) and financial performances using return on equity (*ROE*) and annual stock returns (*StockReturn*). We control for firm financial flexibility using leverage ratio (*Lev*), cash holdings (*Cash*), and Whited-Wu financial constraint (*WWIndex*) and growth opportunities using the market-to-book ratio (*MTB*). We account for investment tangibility using net property, plant, and equipment (*PPE*) and capital expenditures (*CAPEX*). We control for capital market information demands using analyst coverage (*LnAnalysts*) and ESG information demands using the proportion of shares held by ESG-focused investors (*ESGOwn*), following Gantchev et al. (2022). To mitigate the concern that managerial incentives could confound our baseline relation,[7] we include managerial risk-taking incentives using the number of stock options granted to the top five executives (*Top5Options*).

To mitigate extreme outliers, we winsorize all the continuous variables used in Equation (2) at the 1st and 99th percentiles. Following suggestions in prior literature (e.g., Anderson and Lanen 2007; Subramaniam and Weidenmier 2003), we include industry-by-year fixed effect structure ($\omega_g \times \sigma_t$) in Equation (2) to ensure that our main results from Equation (2) are not driven by time-variant industry-specific characteristics. Lastly, we cluster standard errors at the firm level to correct for heteroskedasticity.

Panel A of Table 12 reports the summary statistics of the control variables used in Equation (2). In the main sample (N = 35,709), the mean total assets (*Size*) are \$3,409 million. The mean values of financial leverage (*Lev*); market-to-book ratio (*MTB*); cash and short-term investments scaled by total assets (*Cash*); property, plant, and equipment scaled by total assets (*PPE*); and return-on-equity (*ROE*) are 0.240, 2.859, 0.182, 0.561, and 0.008, respectively. In addition, annual

[7] Managerial risk-taking incentives, such as option-based compensation, encourage managers to adopt more flexible cost structures (Aboody et al. 2018), enabling quicker cost adjustments in response to revenue changes and potentially reducing observed cost stickiness. On the other hand, Sautner et al. (2023a) suggest that managerial characteristics could partially explain a firm’s ability to commit to environment protection.

stock returns (*StockReturn*), capital expenditure scaled by total assets (*CAPEX*), and the number of analysts following (*Analysts*) are 19.8%, 0.046, and 6.406, respectively. On average, 0.6% of outstanding shares are owned by ESG-minded institutional investors (*ESGOwn*). Finally, the mean values of Whited-Wu index (*WWIndex*) and the number of options granted to top-five executives scaled by the number of shares outstanding (*Top5Options*) are −0.180 and 1.467, respectively. These statistics are comparable to Even-Tov et al. (2025).

We calculate Pearson correlations of selected variables based on our main sample (N = 35,709) and, in untabulated results, consistently observe a significantly negative correlation (p-value = 0.01) between cost stickiness (*CS_OC*, *CS_SGA*, or *CS_TC*) and corporate environmental commitments (*EnvCommit1_MDA* or *EnvCommit1_Call*), indicating that an average firm makes lower environmental commitments when it experiences a greater degree of cost stickiness.

4. Empirical Results of OLS Analyses

4.1. *Baseline results*

Table 2 reports the baseline OLS regression results of estimating Equation (2). Across all columns, we consistently observe a significant and negative relation between cost stickiness (*CS_OC*, *CS_SGA*, or *CS_TC*) and corporate environmental commitments (*EnvCommit1_MDA* or *EnvCommit2_MDA*). The economic magnitude of the baseline results is meaningful. For example, the coefficient estimates on *CS_OC* are −0.005 and −0.005 when the dependent variable is *EnvCommit1_MDA* and *EnvCommit2_MDA*, respectively. These coefficients indicate that a one-standard-deviation increase in *CS_OC* (0.695) corresponds to around a 4.96% (= −0.005 × 0.695 / 0.070) and 5.99% (= −0.005 × 0.695 / 0.058) reduction in *EnvCommit1_MDA* and *EnvCommit2_MDA*, respectively, relative to their sample means. Similarly, a one-standard-deviation increase in *CS_SGA* (*CS_TC*) corresponds to a 4.11% (4.26%) reduction in *EnvCommit1_MDA* and a 4.97% (6.42%) reduction in *EnvCommit2_MDA*.

Importantly, we include corresponding cost elasticity measures (*CE_OC*, *CE_SGA*, or *CE_TC*) as controls in baseline analysis to capture the symmetric responsiveness of costs to sales changes. In four of six specifications, cost elasticity shows a positive and significant coefficient, indicating that firms with flexible cost structure are more willing to commit to environmental initiatives. Although statistically significant in some specifications, cost elasticity's economic magnitude remains consistently smaller than that of cost stickiness.[8]

Turning to the control variables, we find significantly positive coefficients on both *LnSize* and *PPE*, suggesting that larger firms with substantial fixed assets make greater environmental commitments, likely due to greater resources and investment capacity. *MTB* has a marginally significant negative coefficient, suggesting that growth firms may prioritize other investments over environmental commitments. *LnAnalysts* has a negative and significant coefficient, implying that greater scrutiny from analysts may pressure firms to focus on short-term financial performance rather than long-term environmental goals. Similarly, *WWIndex* and *Top5Options* both have negative and significant coefficients, suggesting that financially constrained firms and those with executives holding significant stock options tend to make lower environmental commitments.

To preserve meaningful cross-industry variation in cost stickiness (Anderson and Lanen 2007), we remove the industry-year fixed effect structure in Equation (2) and find similar results

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[8] A one-standard-deviation increase in *CE_OC* (0.340) corresponds to around 0% and 5.28% (=0.009 × 0.340 / 0.058) increases in *EnvCommit1_MDA* and *EnvCommit2_MDA*, respectively; a one-standard-deviation increase in *CE_SGA* (0.532) corresponds to around 3.04% (=0.004 × 0.532 / 0.070) and 4.59% (=0.005 × 0.532 / 0.058) increases in *EnvCommit1_MDA and EnvCommit2_MDA*, respectively; and a one-standard-deviation increase in *CE_TC* (0.354) corresponds to around 0% and 4.88% (=0.008 × 0.354 / 0.058) increases in *EnvCommit1_MDA* and *EnvCommit2_MDA*, respectively.

(untabulated). Overall, our evidence suggests that firms with stickier costs tend to initially make lower environmental commitments in their MD&A.

4.2. *Robustness checks of baseline finding*

We conduct three robustness checks to corroborate the baseline finding. First, the baseline finding is based on firms' MD&A disclosures of environment commitments. For robustness, we use earnings call transcripts to calculate alternative measures of environmental commitments, *EnvCommit1_Call* and *EnvCommit2_Call*, as defined earlier. We use these as dependent variables and re-estimate Equation (2) and continue to observe a significant and negative relation between cost stickiness and environmental commitments across five out of six columns in Panel A of Table OA2 in the Online Appendix.

Second, we exploit climate-related investment opportunity bigrams from Sautner et al. (2023a) to construct alternative measures of corporate environmental commitments (*EnvCommit1_opp_MDA* and *EnvCommit2_opp_Call*). These measures capture firms' attention to environmental investment opportunities, such as renewable energy, energy storage, and emission reduction technologies, as discussed in MD&A disclosures and earnings calls. Investment opportunities represent a *tangible* dimension of environmental commitments, reflecting firms' proactive resource allocation toward sustainable initiatives. Panel B of Table OA2 in the Online Appendix consistently shows a significant and negative relation between cost stickiness and these investment-focused environmental commitments. This finding reinforces our primary results and suggests that cost stickiness constrains firms' ability to pursue climate-related investment opportunities, leading to reduced discussion of these initiatives in public disclosures.

Third, we limit the main sample to firm-year observations with positive cost-stickiness measures (*CS_OC*, *CS_SGA*, or *CS_TC*) and use this subsample to estimate Equation (2). This robustness check excludes firm-years with anti-sticky cost behavior, where firms aggressively reduce costs in response to sales downturns (Weiss 2010; Banker and Byzalov 2014). Panel C of Online Appendix Table OA2 continues to show a significant and negative relation between positive cost stickiness measures and environmental commitments.

4.3. ***Reverse causality test***

Some may argue that past environmental commitments, given their long-term nature, might drive current cost stickiness. To identify the causal direction between environmental commitments and cost stickiness, we estimate panel vector autoregression (PVAR) models to detect potential bidirectional effects in the data (e.g., Chen et al. 2022).[9] Panel A of Online Appendix Table OA3 reports our finding. As shown in column (1), the coefficient on CS_OC_{t-1} (−0.008) is significantly negative even after controlling for $EnvCommit1\_MDA_{t-1}$. The negative coefficient on *CS_OC* is consistent with our baseline model (Table 2), suggesting the cost stickiness is negatively associated with future environmental commitments. In contrast, the coefficient on $EnvCommit1\_MDA_{t-1}$ in column (2) is insignificant. These results suggest that cost stickiness affects future environmental commitments, but not vice versa, helping mitigate reverse causality concerns and rule out the alternative explanation that environmental commitments mechanically increase cost stickiness via fixed cost structure. To shed additional light on the causality direction, we perform Granger causality Wald test of the null hypothesis that the excluded variable(s) does not Granger-cause the equation variable. As presented in row (1), Panel B of Online Appendix Table OA3, the null hypothesis that cost stickiness (*CS_OC*) does not Granger-cause environmental commitments (*EnvCommit1_MDA*) is rejected. In contrast, row (2) shows that the null hypothesis that

[9] We have chosen the lag order of 1 and *instlag* (the lag order of endogenous variables used as instruments) of 5. These are chosen both to minimize the modified Bayesian information criterion and the modified Quinn information criterion, following Abrigo and Love (2016), and to mitigate the model overfitting issues, following Arnerić and Situm (2022).

environmental commitments (*EnvCommit1_MDA*) do not Granger-cause cost stickiness (*CS_OC*) cannot be rejected. These results corroborate that cost stickiness causes environmental commitments but not vice versa.

4.4. *Market reactions to corporate environmental commitment reductions*

Our hypothesis development builds upon the insight that investors would react negatively to environmental commitment reductions. Prior literature provides experimental or survey evidence that investors react negatively to any discontinuation of ESG initiatives or view climate initiative reduction unfavorably (e.g., Krueger et al. 2020; Garavaglia et al. 2024). To validate this insight with large-sample archival evidence, we test the capital market reactions to firms' environmental commitment reductions. Specifically, we use an OLS regression to estimate the following Equation (3):

$$CAR_{i,t} = \alpha + \eta EnvCommitCut_{i,t} + \theta HighERO_{i,t} \times EnvCommitCut_{i,t}$$
$$+ \kappa HighERO_{i,t} + \lambda ESGTransp_{i,t} \times EnvCommitCut_{i,t} + \mu ESGTransp_{i,t}$$
$$+ \nu CAR\_EA_{i,t} + \Omega X_{i,t} + \Gamma Z_{i,t} + \omega_g \times \sigma_t + \varepsilon_{i,t} \quad (3)$$

where the dependent variable *CAR* is firm *i*'s cumulative abnormal return measured over the seven-day window surrounding the 10-K filing date (*d*−3, *d*+3). $EnvCommitCut_{i,t}$ indicates whether firm *i* reduces its environmental commitments measured using MD&A disclosure (i.e., *EnvCommit1_MDA* or *EnvCommit2_MDA*) in year *t* compared to year *t*−1. *HighERO* is an indicator variable for whether the ER (environmentally responsible) institutional ownership of firm *i* at the end of year *t* is above the sample median of ER institutional ownership. ER ownership is calculated as the number of shares held by ER institutions (ranking top tercile value-weighted size-adjusted portfolio KLD net environmental strengths) divided by the total number of shares held by all institutions (Cao et al. 2023). *ESGTransp* is an indicator variable equal to 0 if none of the sustainability rating agencies (KLD, Sustainalytics, ASSET4, S&P, Bloomberg, or RepRisk) cover the firm *i* at the end of year *t* and 1 after the initiation of ESG rating coverage by any one or more above agencies (Lu 2024). We also control for the market reactions to Q4 earnings announcements (*CAR_EA*) because many firms issue their 10-K filings and earnings announcements either concurrently or within a short time frame (Arif et al. 2019). In addition to the control variables $Z_{i,t}$ used in our baseline model, following Goldman and Zhang (2024), we include $X_{i,t}$, a vector of textual attributes (i.e., total word count, readability, sentiment, risk, and text complexity) of 10-K filings. This inclusion mitigates the concern that our design merely captures investors' responses to general 10-K textual characteristics rather than specific environmental commitment reductions. As in the baseline model (2), we include industry-by-year fixed effects and cluster standard errors at the firm level.

Table 3 reports the test results. Columns (1) and (2) use the key independent variables *EnvCommitCut1* and *EnvCommitCut2*, respectively. The coefficients on these environmental commitment reduction variables are significant and negative, which suggests that investors on average react negatively around the 10-K filing date when a sample firm reduces its environmental commitment level compared to the previous year.

Moreover, we expect investors' negative reaction to be stronger when investor scrutiny of the firm is more intense, as proxied for by high ER institutional ownership or high ESG performance transparency. Consistent with this, we find that the coefficients on *HighERO* × *EnvCommitCut1* and *HighERO* × *EnvCommitCut2* (columns [3] and [4]) and those on *ESGTransp* × *EnvCommitCut1* and *ESGTransp* × *EnvCommitCut2* (columns [5] and [6]) are all significantly negative, suggesting that the negative reaction to environmental commitment cuts is more pronounced as investor scrutiny of firms intensifies. Overall, these results provide strong support for the argument that investors would react negatively to environmental commitment reductions.

4.5. *Validation test for environmental commitment measures*

Our baseline analysis suggests that firms with greater cost stickiness tend to make lower environmental commitments measured using corporate disclosures in annual reports and earnings calls. If these disclosure-based measures merely reflected managerial greenwashing, they would not correlate with ESG ratings. To validate our disclosure-based environmental commitment measures, we examine whether cost stickiness is indeed negatively associated with ESG ratings.

We evaluate whether cost stickiness is negatively associated with environmental performance ratings provided by two independent and prominent ESG rating agencies (i.e., KLD and ASSET4). KLD annually assesses public firms' environmental concerns (e.g., hazardous waste, regulatory problems, ozone depleting chemicals, substantial emissions, agricultural chemicals) alongside strengths (e.g., beneficial products and services, pollution prevention, recycling, clean energy). ASSET4 employs a structured framework with categories like resource use, emissions, and product innovation, supported by over 630 ESG measures derived from public firms' disclosures. Following Cao et al. (2023), we construct *KLD_envrn* and *ASSET4_envrn* to comprehensively capture firms' environmental performance ratings. While these measures differ in scope and emphasis, both share a common goal: providing objective, third-party evaluations of firms' actual environmental performance. Table OA4 in the Online Appendix reports the lead-lag regression of environmental performance ratings on cost stickiness. The results show a significant and negative association between cost stickiness measures and environmental performance ratings across five out of six columns. This finding suggests that firms with greater cost stickiness receive lower environmental performance ratings from both KLD and ASSET4, reinforcing that our disclosure-based measures reflect genuine climate commitments rather than greenwashing.

4.6. *Real effects of cost stickiness*

We investigate real environmental actions taken by firms with sticky costs. If firms with stickier costs make lower environmental commitments, their real environmental actions will be weaker. First, following Thomas et al. (2022), we consider industrial pollution as the first measure of real environmental actions because it quantifies a firm's environmental impact, directly reflecting its efforts to mitigate negative externalities. We collect toxic emissions data from the EPA's Toxic Release Inventory database and aggregate it at the firm-year level. Second, following Cohen et al. (2023), we use green innovation as the second measure of real environmental actions, capturing a firm's investment in developing environmental technologies. We identify green patents using OECD classifications related to addressing environmental problems. Our green innovation measures include whether a firm files (and eventually is granted) any green patents in a year (*I_GreenPat*), the total count of green patents (*Ln#GreenPat*), and the total count of citations received by green patents (*Cite_GreenPat*). We replace the dependent variable in Equation (2) with these measures of corporate environmental actions and rerun Equation (2).

Table 4 reports the results. Panel A reports the lead-lag regressions of firm-year toxic emissions on cost stickiness. We observe a significant and positive coefficient on two cost stickiness measures (*CS_OC* or *CS_SGA*) when the dependent variable is a firm's total amount of toxic emissions (*ToxicEmission*) in the subsequent year, suggesting a positive association between cost stickiness and industrial pollution level. Panel B reports the lead-lag regressions of green innovation on cost stickiness. We observe a significant and negative coefficient on all cost stickiness measures when the dependent variable is *I_GreenPat*, *Ln#GreenPat*, or *Cite_GreenPat*, suggesting a negative association between cost stickiness and future green innovation outputs. Their economic magnitudes are also significant. For example, when cost stickiness is measured in

CS_OC, in respective samples, a one-standard-deviation increase in cost stickiness relates to an around 17.35% (= −0.097 × 0.517/ 0.289) increase relative to sample means of 0.289 in industrial pollution *ToxicEmission*, an around 7.13% (= −0.015 × 0.670/ 0.141) reduction relative to sample means of 0.141 in green patents *Ln#GreenPat*, and a 9.46% (= −0.047 × 0.670/ 0.333) reduction relative to sample means of 0.333 in green patent citation *Cite_GreenPat*. Together, these findings indicate a negative relationship between cost stickiness and firms' *real* environmental actions, suggesting that cost stickiness affects firms' real environmental actions, not just environmental commitments. In addition, these findings further validate that our disclosure-based measures capture genuine corporate environmental commitments, not greenwashing.

5. Results of Quasi-Experimental Analyses

A key challenge in examining the relation between cost stickiness and corporate environmental commitments is the potential for simultaneous endogeneity; a firm's cost behavior and environmental commitment levels may be jointly influenced by common unobserved variables, such as investor intervention and regulatory environment (e.g., Chen et al. 2012; Banker et al. 2013; Comello et al. 2021; Desai et al. 2023). To alleviate endogeneity concerns, we exploit two quasi-experimental designs that utilize exogenous variations in cost stickiness caused by the recognition of state WDLs and close-call union elections. Consistent inferences across two quasi-experimental tests would increase our confidence to generalize a causal link between cost stickiness and corporate environmental commitments.

5.1. *State border discontinuity: State wrongful discharge law*

Between 1974 and 1998, 14 states adopted WDLs in various years. WDL adoption constrains employers' ability to terminate employees without just cause and hence increases downward labor-adjustment costs by making layoffs more difficult (Kim, Li and Park 2020). This judicial legal setting could lead managers to retain more slack resources during periods of declining sales as they anticipate potential future reversals in demand and aim to avoid the high layoff costs (Kim et al. 2020). Hence, the adoption of WDLs could lead to slower downward adjustment to labor when sales decline, resulting in greater cost stickiness. WDLs include three common-law exceptions to the at-will employment doctrine: good faith (GF), public policy, and implied contract.[10] We focus on the GF exception as it deviates the most from at-will employment and hence is the most likely to affect cost behavior (Kugler and Saint-Paul 2004; Kim et al. 2020).

After 1998, no state adopted or rescinded the GF exception; 12 states recognized the GF exception, while all other states did not.[11] Since our data on environmental commitments is only available since 2003, we cannot use the generalized difference-in-differences method over the sample period of 1974-1998. Instead, we implement state border discontinuity analysis by exploiting the quasi-random discontinuity in GF exception recognition at state borders (i.e., one state has adopted the law while the neighboring state has not) over the sample period of 2003-2019, as shown in Online Appendix Figure OA1. We compare the average environmental commitments of firms on either side of the state border, focusing on firms domiciled within 50 miles of the border with one side governed by the GF exception and the other not. We also integrate entropy balancing based on observable firm covariates to address potential selection biases. Since demographics and economic conditions spill smoothly across state borders (Heider and Ljungqvist 2015), we attribute the average difference in environmental commitments to whether a state has

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[10] The good-faith exception implies that an employer can terminate employees only in good faith and through fair Dealing, the public-policy exception is that an employer cannot terminate an employee for declining to violate lawful public policy, and the implied-contract exception refers to the scenario in which the employment contract implicitly promises not to discharge a worker without good cause (Kim et al. 2020).

[11] Of the 14 states that adopted the GF exception between 1974 and 1998, New Hampshire and Oklahoma later rescinded it in 1980 and 1989, respectively. Consequently, after 1998, only 12 states continued to recognize the GF exception, while the others, including New Hampshire and Oklahoma, did not.

recognized the GF exception and therefore to the greater cost stickiness resulting from the GF exception.

Table 5 reports the state border discontinuity test results. In Panel A, we test whether the state-wide recognition of GF exceptions increases our cost stickiness measures. *GF* equals 1 for firms headquartered in a state in the years after the state's GF exception adoption and 0 otherwise. We find significantly positive coefficients on *GF*, indicating that the GF exception indeed increases cost stickiness, consistent with Kim et al.'s (2020) findings. In Panel B of Table 5, we test whether the greater cost stickiness, exogenously caused by the recognition of the GF exception for firms domiciled within 50 miles of the border with the GF exception, reduces firms' environmental commitments. The coefficients on *GF* remain significantly negative, which suggests environmental commitments are lower for firms domiciled near the border with the GF exception. Overall, this test alleviates endogeneity concerns via quasi-random variation in the GF exception recognition at state borders, showing that the increased cost stickiness exogenously caused by the GF exception reduces corporate environmental commitments.

5.2. *Regression discontinuity: Close-call union election*

Resource-adjustment costs, particularly those related to labor such as severance payments to dismissed workers and training costs for new employees, are a key driver of cost stickiness (Banker and Byzalov 2014). Labor unions can increase cost stickiness by making labor-adjustment costs less flexible and restructuring activities more difficult. Through collective bargaining, unions typically negotiate for rigid wage structures and strong employment protections, limiting a firm's ability to quickly adjust its labor expenses and workforce size in response to sales fluctuations. Moreover, unions often resist employers' strategic cost-cutting measures such as layoffs or plant closures, further constraining a firm's capacity to reduce costs during periods of declining demand.

We focus on the union election setting and employ a sharp regression discontinuity (RD) design that capitalizes on the availability of union election data (i.e., election voting outcomes, the number of eligible voters, firm names, and the election closing year) collected from the National Labor Relations Board. The unique feature of our RD design is that the secret-ballot elections decided by a narrow margin (leading to unionization and, thus, higher labor-adjustment costs) resemble a quasi-randomized experiment. In such *close-call* elections, neither employees nor employers can manipulate the voting outcomes around the 50% voting threshold (e.g., Lee and Mas 2012; Bradley et al. 2017; He et al. 2020). As a result, unionization is locally exogenous, meaning it is unlikely to affect unobservable firm characteristics or managerial decisions that could influence cost stickiness or corporate environmental commitments. This quasi-random assignment of unionization status for firms near the threshold helps isolate the causal impact of unionization on cost stickiness and, in turn, on corporate environmental commitments.

Following prior literature on labor union election (e.g., Ruback and Zimmerman 1984; Lee and Mas 2012; He et al. 2020), we exclude elections with missing data or fewer than 50 eligible voting participants to prevent potential precise manipulation and then use both automated and manual matching to link each firm name in the election data to its unique Compustat identifier. We estimate a nonparametric local linear regression with the optimal bandwidth and the triangular kernel.[12] We calculate ex post cost stickiness and environmental commitments of firms over the four-year window *after* the election year and compare these metrics for firms where union elections barely pass (i.e., marginally above the 50% voting threshold) to those where they barely fail (i.e.,

[12] Compared to global polynomial regression, the nonparametric local linear regression is considered the most rigorous RD model, providing superior local fit, rate optimality, and bias characteristics (He et al. 2020). The optimal bandwidth minimizes mean squared error (Imbens and Kalyanaraman 2012), and a triangular kernel is optimal for estimating local linear regressions at the boundary due to its greater weight on observations closer to the cutoff point (Fan and Gijbels 1992).

marginally below the 50% threshold). We do not include observable covariates in our specification given the assumption that firms with votes near the threshold are likely to be similar in all characteristics except voting outcomes (Imbens and Lemieux 2008; Lee and Lemieux 2010). To verify this important assumption, we estimate non-parametric local linear regressions of each ex ante cost stickiness measure (estimated using the preceding 16 quarterly observations ending in the year *before* the closing year of the union election) and ex ante environmental commitment measures and ex ante firm covariates (measured one year *before* the election year) on *Unionized* (i.e., whether the percentage of votes for unionization is greater than 50%), respectively. Panel A of Table 6 reports the coefficient on *Unionized* in each regression. None of these local linear RD coefficient estimates is significant, suggesting that ex ante cost stickiness, ex ante environmental commitments, and ex ante firm covariates do not exhibit discontinuity at the 50% voting threshold.

Next, we estimate non-parametric local linear regressions of three ex post cost stickiness measures (estimated using the subsequent 16 quarterly observations starting in the year *after* the union election) and ex post firm environmental commitment measures (calculated as the average of four environmental commitment measures in the four years *after* the union election) on *Unionized* with relative optimal bandwidth and triangular kernel, respectively. Panel B reports the RD results for ex post cost stickiness. The coefficient on *Unionized* remains positive and significant at the 1% level, indicating that cost stickiness is greater after elections for firms whose union elections barely pass than those whose elections barely fail. This finding is in stark contrast to Panel A, where we find no discontinuity in cost stickiness at the 50% voting threshold before the union election. Panel C reports the RD results for ex post environmental commitments. The coefficient on *Unionized* is negative and significant at the 1% level when the dependent variable is *EnvCommit1_MDA* or *EnvCommit2_MDA.* This indicates that, after elections, firms whose union elections barely pass exhibit lower environmental commitments than those whose elections barely fail. This finding again is in stark contrast to Panel A, where we find no discontinuity in environmental commitments at the 50% voting threshold before the union election. Collectively, our RD results suggest that the increased cost stickiness caused by exogenous union win reduces corporate environmental commitments.

Online Appendix Figure OA2 provides visual evidence consistent with the above results based on RD regressions. Figure OA2 plots the visual relation between election vote share on the horizontal axis and our dependent variables (ex post cost stickiness in Panel A and ex post environmental commitments in Panel B) on the vertical axis. To the left of the 50% cutoff, firms fail to unionize; to the right, they unionize. Each dot is an average of multiple observations falling within a narrow range of union vote share values, and the solid curve shows the fitted quartic polynomial with a 95% confidence interval. We observe a sharp increase in cost stickiness (measured by *CS_OC*, *CS_SGA*, or *CS_TC*) and a sharp drop in environmental commitments (measured by *EnvCommit1_MDA* and *EnvCommit2_MDA*) when the vote share moves from the left to the right of the 50% threshold.

6. Cross-Sectional Analyses

6.1. *Financial resources*

If the negative main relation is driven by resource-adjustment costs, environmental commitments of firms with scarce financial resources should be more affected by cost stickiness when making initial environmental commitments. We use low retained earnings (*LowErn*) and low cash flow (*LowCash*) to proxy for scarce financial resources. Table 7 reports the results of estimating Equation (2) after including a partitioning variable and its interaction with the cost stickiness measure. Panels A presents the results of estimating the modified Equation (2) using

LowErn or *LowCash* as the partitioning indicators for below-median retained earnings and below-median cash flow, respectively. The coefficient on the interaction between a cost stickiness measure and *LowErn* is significantly negative across five out of six columns. The coefficient on the interaction between a cost stickiness measure and *LowCash* is significantly negative across five columns. Collectively, these results suggest that firms with limited financial resources tend to reduce environmental commitments more substantially when facing higher cost stickiness.

6.2. *Resource-adjustment costs*

If the negative main relation is driven by resource-adjustment costs, initial environmental commitments of firms with greater adjustment costs should be affected to a greater extent by cost stickiness. Following prior literature (e.g., Anderson et al. 2003; Chen et al. 2012), we measure adjustment costs with *employee intensity*, calculated as the total number of employees divided by sales revenue, and *asset intensity*, calculated as total assets divided by sales revenue. Panel B presents the results of estimating the modified Equation (2) using *HighEINT* or *HighAINT* as the partitioning indicators for above-median employee intensity and above-median asset intensity, respectively. The coefficient on the interaction between a cost stickiness measure and *HighEINT* consistently remains negative and significant across all columns, suggesting that the negative effect of cost stickiness on firm environmental commitments is more pronounced when employee intensity is higher. We observe the negative and significant coefficient on the interaction between a cost stickiness measure and *HighAINT* in five out of six columns. The results suggest that the negative effect of cost stickiness on firm environmental commitments is more pronounced for firms with higher asset intensity.

6.3. *Firms' anticipation of investor aversion to environmental commitment reductions*

Our prediction of a negative effect of cost stickiness on environmental investments hinges on the assumption that firms anticipate negative reactions from investors when firms reduce such commitments. When a firm faces more intense scrutiny from investors, we expect the main effect to be more pronounced because managers would anticipate more negative reactions from investors in response to a reduction in environmental commitments. As in 4.4., we use high ER (environmentally responsible) institutional ownership or high ESG performance transparency to proxy for the intensity of investor scrutiny. As defined earlier, *HighERO* is an indicator variable for above-median ER institutional ownership. *ESGTransp* is an indicator variable for high ESG transparency proxied for by the initiation of ESG rating coverage by one or more rating agencies. Table 7, Panel C presents the results of estimating the modified Equation (2) using *HighERO* as the partitioning indicator for above-median ER institutional ownership. As expected, we find a significant and negative coefficient on the interaction between a cost stickiness measure and *HighERO* across all columns, suggesting that firms held by ER institutions initially make lower environmental commitments when facing higher cost stickiness. Similarly, we show a significantly negative coefficient on the interaction between cost stickiness measures and *ESGTransp* across five out of six columns. These results suggest that high ESG transparency leads sticky-cost firms to further reduce initial environmental commitments.

These results, combined with those in columns (3)–(6) of Table 3 showing that the negative investor reaction to environmental commitment cuts is more pronounced when a firm has higher ER ownership or high ESG transparency, provide strong support for our argument that anticipated investor aversion to environmental commitment reductions drives the negative relation between cost stickiness and environmental commitments.

7. Conclusion

We document asymmetric cost behaviour as a determinant of corporate environmental commitments and real actions. We predict and find that firms with higher cost stickiness make lower environmental commitments initially than their peers with lower cost stickiness. We also provide large-sample evidence supporting the assumption that investors react negatively to reduced or discontinued firm environmental commitments. Importantly, we show that firms with higher cost stickiness take weaker real environmental actions, as evidenced by more severe industry pollution and lower green investments. Cross-sectional analyses suggest that resource-adjustment costs and managers' concern about investors and other stakeholders' aversion to future commitment cuts serve as two non-mutually exclusive channels for the baseline relation. We provide novel insights that a firm's environmental commitments and actions are driven not only by the firm's resource constraints but also by its expectation about its capability to maintain the same level of environmental commitments or actions in the future when sales decline.

This study is not without limitations. First, disclosures-based measures of environmental commitments may not fully capture the scope or quality of a firm's sustainability efforts, as they are susceptible to managers' selective reporting. For example, managers might highlight favorable aspects of their environmental initiatives while downplaying less-favorable ones. Second, although we provide some evidence of environmental actions, our analyses are limited to industrial pollution and green innovation. Real environmental actions are wide-ranging, and our analysis cannot capture the changes in other dimensions of sustainability actions, such as waste management and water usage, due to data unavailability.

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Appendix A: Variable Definitions

Variable name	Definitions
Dependent variables:	
$EnvCommit1\_MDA_{i,t+1}$	The number of bigrams related to climate change divided by the total number of bigrams in the Management Discussion and Analysis of 10-Ks filed by firm *i* in year *t*+1, multiplied by 100. We obtain the climate change bigrams from Sautner et al. (2023a). (Source: Self-constructed based on climate change bigrams and Notre Dame Software Repository for Accounting and Finance)
$EnvCommit2\_MDA_{i,t+1}$	The number of climate-related sentences classified as commitment-specific divided by the total number of sentences in the Management Discussion and Analysis of 10-Ks filed by firm *i* in year *t*+1, multiplied by 100. We classify a climate-related sentence as commitment-specific based on the classification algorithm provided by Bingler et al. (2024). (Source: Self-constructed based on Climate BERT model and Notre Dame Software Repository for Accounting and Finance)
$EnvCommit1\_Call_{i,t+1}$	The number of bigrams related to climate change divided by the total number of bigrams in the presentation section of conference call transcripts, multiplied by 100. We then average the values of all earnings calls held by firm *i* during year *t*+1. We obtain the climate change bigrams from Sautner et al. (2023a). (Source: Self-constructed based on climate change bigrams and StreetEvents)
$EnvCommit2\_Call_{i,t+1}$	The number of climate-related sentences classified as commitment-specific divided by the total number of sentences in the presentation section of conference call transcripts, multiplied by 100. We then average the values of all conference calls held by firm *i* during year *t+1*. We classify a climate-related sentence as commitment-specific based on the classification algorithm provided by Bingler et al. (2024). (Source: Self-constructed based on ClimateBERT model and StreetEvents)
$EnvCommit1\_opp\_MDA_{i,t+1}$	The number of bigrams related to climate investment opportunities divided by the total number of bigrams in the Management Discussion and Analysis of 10-Ks filed by firm *i* in year *t*+1, multiplied by 100. We obtain climate-related investment opportunities bigrams from Sautner et al. (2023a). (Source: Self-constructed based on climate change bigrams and Notre Dame Software Repository for Accounting and Finance)
$EnvCommit1\_opp\_Call_{i,t+1}$	The number of bigrams related to climate investment opportunities divided by the total number of bigrams in the presentation section of conference call transcripts, multiplied by 100. We then average the values of all earnings calls held by firm *i* during year *t*+1. We obtain climate-related investment opportunities bigrams from Sautner et al. (2023a). (Source: Self-constructed based on climate change bigrams and StreetEvents)
$ToxicEmission_{i,t+1}$	Total toxic emissions in thousand pounds of firm *i* in year *t*+1 divided by the lagged total assets. (Source: Toxic Release Inventory)
$I\_GreenPat_{i,t+1}$	An indicator that equals one if the firm filed (and eventually was granted) any green patents in year *t*+1. (Source: Kogan et al., 2017)
$\#GreenPat_{i,t+1}$	Total number of green patents filed by (and eventually granted for) firm *i* in year *t*+1. (Source: Kogan et al., 2017)
$Ln\#GreenPat_{i,t+1}$	Natural logarithm of one plus total number of green patents filed by (and eventually granted for) firm *i* in year *t*+1. (Source: Kogan et al., 2017)
$Cite\_GreenPat_{i,t+1}$	Total number of citations received on all green patents filed by (and eventually granted for) firm *i*, divided by the average number of citations of all patents filed by (and eventually granted for) all firms in year *t*+1 to adjust for truncation. (Source: Kogan et al., 2017)
$KLD\_envrn_{i,t+1}$	The sum of environmental strengths minus the sum of environmental concerns from KLD by firm *i* in year *t*+1. (Source: KLD)

$ASSET4\_envrn_{i,t+1}$	The environmental score from ASSET4 by firm *i* in year *t*+1. (Source: ASSET4)

Independent variables:

$CS\_OC_{i,t}$	The cost stickiness measure constructed following He et al. (2020). Specifically, we first estimate the following model using a rolling window of the preceding 16 quarters (i.e., year *t*−3 to year *t*) of accounting data: $\Delta LnOC_{i,t,q} = \beta_0 + \beta_1 LnSales_{i,t,q} + \beta_2 Decrease_{i,t,q} \times LnSales_{i,t,q} + \mu,$ where $\Delta LnOC$ is the log-change in quarterly operating costs (i.e., the difference between sales and operating income after depreciation), $\Delta LnSales$ is the log-change in quarterly sales, and $Decrease$ is an indicator that equals 1 if $\Delta LnSales$ is less than zero and 0 otherwise. We then define $CS\_OC_{i,t}$ as the negative of estimated β_2. (Source: Compustat)
$CS\_SGA_{i,t}$	The cost stickiness measure that is calculated similarly to $CS\_OC_{i,t}$ but using $\Delta LnSG\&A$, which is the log-change in quarterly selling, general, and administrative expenses, as the dependent variable when estimating Equation (1). (Source: Compustat)
$CS\_TC_{i,t}$	The cost stickiness measure that is calculated similarly to $CS\_OC_{,t}$ but uses $\Delta LnTC$, which is the log-change in quarterly total costs (i.e., the sum of costs of goods sold and the selling, general and administrative expenses), as the dependent variable when estimating Equation (1). (Source: Compustat)
$CE\_OC_{i,t}$	The cost elasticity measure that is constructed by estimating the following model using a rolling window of the preceding 16 quarters (i.e., year *t*−3 to year *t*) of accounting data following Chen et al. (2024): $\Delta LnOC_{i,t,q} = \beta_0 + \beta_1 LnSales_{i,t,q} + \beta_2 EINT_{i,t,q} + \beta_3 AINT_{i,t,q} + \beta_4 LnSize_{i,t,q} + \mu,$ where $\Delta LnOC$ is the log-change in quarterly operating costs (i.e., the difference between sales and operating income after depreciation), $\Delta LnSales$ is the log-change in quarterly sales, $EINT$ is total number of employees (assumed to remain constant in year *t*) divided by quarterly sales (adjusted using 2019 dollars), *AINT* is the quarterly total assets divided by quarterly sales (adjusted using 2019 dollars), and *LnSize* is natural logarithm of quarterly total assets. We define $CE\_OC_{i,t}$ as the coefficient on $LnSales$, β_1. (Source: Compustat)
$CE\_SGA_{i,t}$	The cost elasticity measure that is constructed similarly to $CE\_OC_{i,t}$ but using $\Delta LnSG\&A$, which represents the log-change in quarterly selling, general, and administrative expenses, as the dependent variable when estimating the same equation used for constructing $CE\_OC_{i,t}$. (Source: Compustat)
$CE\_TC_{i,t}$	The cost elasticity measure that is constructed similarly to $CE\_OC_{i,t}$ but using $\Delta LnTC$, which represents the log-change in quarterly total costs (i.e., the sum of costs of goods sold and the selling, general and administrative expenses), as the dependent variable when estimating the same equation used for constructing $CE\_OC_{i,t}$. (Source: Compustat)
$Size_{i,t}$	Total assets of firm *i* at the end of year *t*. (Source: Compustat)
$LnSize_{i,t}$	Natural logarithm of total assets of firm *i* at the end of year *t*. (Source: Compustat)
$Lev_{i,t}$	Total liabilities divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
$MTB_{i,t}$	The ratio of market capitalization to the book value of equity of firm *i* at the end of year *t*. (Source: Compustat)
$Cash_{i,t}$	Cash and short-term investments divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
$PPE_{i,t}$	Property, plant, and equipment divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
$ROE_{i,t}$	The earnings before interest and taxes scaled by the difference between total assets and total liabilities. (Source: Compustat)
$StockReturn_{i,t}$	Firm *i*'s annual stock returns during year *t*. (Source: Compustat)
$CAPEX_{i,t}$	Capital expenditures divided by total assets. (Source: Compustat)

$Analysts_{i,t}$	The number of analysts following firm *i* at the end of year *t*. (I/B/E/S)
$LnAnalysts_{i,t}$	Natural logarithm of one plus the number of analysts following firm *i* at the end of year *t*. (I/B/E/S)
$ESGOwn_{i,t}$	The proportion of firms' outstanding shares owned by ESG-minded institutional investors of firm *i* at the end of year *t*, constructed following the approach of Gantchev et al. (2022). (Source: Thomson Reuters and Refinitiv ASSET4)
$WWIndex_{i,t}$	The Whited–Wu (WW) (2006) index is defined as (−0.091 × CF) − (0.062 × DIVPOS) + (0.021 × TLTD) − (0.044 × LNTA) + (0.102 × ISG) − (0.035 × SG), where CF is a ratio of cash flow divided by total assets, DIVPOS is an indicator that equals to 1 if the firm pays a dividend and 0 otherwise, TLTD = long-term debt to total assets, LNTA = logarithm of total assets, ISG = 2-digit SIC industry sales growth, and SG = firm sales growth. Higher values of the WW index indicate greater levels of financial constraint. (Source: Compustat)
$Top5Options_{i,t}$	The number of stock options granted to the top-five executives scaled by firm *i*'s total shares outstanding in year *t* in which stock options are granted, multiplied by 1,000. (Source: Execucomp and Compustat)
$AINT_{i,t}$	The total assets divided by sales revenue (adjusted using 2019 dollars) for firm *i* in year *t*. (Source: Compustat)
$SUCCDEC_{i,t}$	An indicator variable for whether firm *i*'s sales growth rates are negative in both year *t* and *t*−1. (Source: Compustat)
$GDPgrowth_{i,t}$	The GDP growth rate for firm *i* in year *t*. (Source: U.S. Bureau of Labor Statistics)
$LINC_{i,t-1}$	An indicator variable for whether firm *i*'s sales growth rate in year *t*−1 is positive. (Source: Compustat)
$LFCF_{i,t-1}$	The ratio of firm *i*'s free cash flows to its assets in year *t*−1. (Source: Compustat)
$GF_{s,t}$	An indicator variable that equals 1 for firms headquartered in state *s* in the years after the state's Good Faith exception adoption and 0 otherwise. (Source: Bai et al. 2020, Table 1)
$Unionized_{i,t}$	An indicator variable for whether firm *i*'s percentage of votes for unionization in year *t* is greater than 50%. (Source: National Labor Relations Board)
$CAR_{i,t}$	The cumulative abnormal return around the seven-day window (*d*−3, *d*+3) of firm *i*'s 10-K filing date in year *t*. (Source: CRSP; SEC Analytics Suite)
$CAR\_EA_{i,t}$	The cumulative abnormal return around the seven-day window (*d*−3, *d*+3) of firm *i*'s Q4 earnings announcement date in year *t*. (Source: CRSP; Compustat)
$EnvCommitCut1_{i,t}$	An indicator variable for whether firm *i*'s value of *EnvCommit1_MDA* in year *t* is lower than its value of *EnvCommit1_MDA* in year *t*−1. (Source: Self-constructed based on climate change bigrams and Notre Dame Software Repository for Accounting and Finance)
$EnvCommitCut2_{i,t}$	An indicator variable for whether firm *i*'s value of *EnvCommit2_MDA* in year *t* is lower than its value of *EnvCommit2_MDA* in year *t*−1. (Source: Source: Self-constructed based on climate change bigrams and Notre Dame Software Repository for Accounting and Finance)
$LitigiousProportion_{i,t}$	The ratio of words related to litigation or legal disputes, based on the Loughran-McDonald dictionary's litigious word count, divided by the total number of words at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
$GunningFogIndex_{i,t}$	The Gunning Fog index at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
$LnWordCount_{i,t}$	The natural logarithm of the total number of words at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
$Sentiment_{i,t}$	The Loughran-McDonald dictionary's positive word count minus negative word count, scaled by the total word count at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
$UncertaintyProportion_{i,t}$	The proportion of words reflecting uncertainty, calculated using the Loughran-McDonald dictionary's uncertainty word count, scaled by the total word count at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
$LnComplexWordCount_{i,t}$	The natural logarithm of the total number of complex words at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)

Partitioning variables:

LowErn$_{i,t}$	An indicator variable for whether the retained earnings of firm *i* in year *t* is below the sample median of retained earnings. (Source: Compustat)
LowCash$_{i,t}$	An indicator variable for whether the cash flow of firm *i* in year *t* is below the sample median of cash flow. (Source: Compustat)
HighEINT$_{i,t}$	An indicator variable for whether the employee intensity of firm *i* in year *t* is above the sample median of employee intensity. Employee intensity is calculated as the total number of employees divided by sales revenue (adjusted using 2019 dollars) for firm *i* in year *t*. (Source: Compustat and U.S. Bureau of Labor Statistics)
HighAINT$_{i,t}$	An indicator variable for whether the asset intensity of firm *i* in year *t* is above the sample median of asset intensity. Asset intensity is calculated as the total assets divided by sales revenue (adjusted using 2019 dollars) for firm *i* in year *t*. (Source: Compustat and U.S. Bureau of Labor Statistics)
HighERO$_{i,t}$	An indicator variable for whether the environmentally responsible (ER) institutional ownership of firm *i* at the end of year *t* is above the sample median of ER institutional ownership. ER ownership is calculated as the number of shares held by ER institutions (ranking top tercile value-weighted size-adjusted portfolio KLD net environmental strengths) divided by the total number of shares held by all institutions. (Source: Thomson Reuters and KLD)
ESGTransp$_{i,t}$	An indicator variable equal to 0 if none of the sustainability rating agencies (KLD, Sustainalytics, ASSET4, S&P, Bloomberg, or RepRisk) cover the firm *i* at the end of year *t* and 1 after the initiation of ESG rating coverage by any one or more above agencies. (Source: KLD, Sustainalytics, ASSET4, S&P, Bloomberg, and RepRisk)

Table 1 Descriptive Statistics and Validation Test on Cost Stickiness Measures

This table presents the descriptive statistics for the samples used in the empirical tests and validation test about our firm-year cost stickiness measures. Panel A reports the summary statistics. Since our baseline analysis is based on two distinct test samples, we present the summary statistics for each variable in the larger sample size for brevity. Panel B reports the validation test results on our firm-year cost stickiness measures (i.e., *CS_OC*, *CS_TC*, and *CS_SGA*). Appendix A provides variable definitions.

Panel A: Summary statistics

Variables	N	Mean	Std. Dev.	25%	Median	75%
Dependent variables:						
EnvCommit1_MDA	35,709	0.070	0.132	0	0.027	0.074
EnvCommit2_MDA	35,709	0.058	0.154	0	0	0
EnvCommit1_Call	27,921	0.079	0.128	0.015	0.037	0.087
EnvCommit2_Call	27,921	0.086	0.213	0	0	0.078
Key explanatory variables:						
CS_OC	35,709	0.069	0.695	−0.197	0.017	0.294
CS_SGA	35,709	0.091	1.440	−0.449	0.035	0.615
CS_TC	35,709	0.055	0.745	−0.212	0.010	0.284
Control variables:						
CE_OC	35,709	0.692	0.340	0.518	0.759	0.920
CE_SGA	35,709	0.383	0.532	0.078	0.352	0.662
CE_TC	35,709	0.710	0.354	0.538	0.781	0.939
Size	35,709	3,409	9,976	101	503	2,089
LnSize	35,709	6.123	2.194	4.614	6.220	7.645
Lev	35,709	0.240	0.262	0.018	0.186	0.358
MTB	35,709	2.859	4.893	1.140	2.006	3.537
Cash	35,709	0.182	0.185	0.039	0.117	0.268
PPE	35,709	0.561	0.460	0.215	0.425	0.786
ROE	35,709	0.008	0.870	−0.045	0.078	0.164
StockReturn	35,709	0.198	0.848	−0.216	0.047	0.350
CAPEX	35,709	0.046	0.052	0.015	0.029	0.056
Analysts	35,709	6.406	7.154	1	4	10
LnAnalysts	35,709	1.500	1.060	0.693	1.609	2.398
ESGOwn	35,709	0.006	0.012	0	0	0
WWIndex	35,709	−0.180	0.253	−0.328	−0.233	−0.115
Top5Options	35,709	1.467	3.303	0	0	1.350

Panel B: Validation tests for *CS_OC*, *CS_SGA*, and *CS_TC*

	(1) *CS_OC*	(2) *CS_OC*	(3) *CS_SGA*	(4) *CS_SGA*	(5) *CS_TC*	(6) *CS_TC*
AINT	0.048***	0.042***	0.046***	0.048**	0.038***	0.036***
	(6.05)	(4.43)	(2.79)	(2.32)	(4.16)	(3.38)
SUCCDEC	−0.034***	−0.031***	−0.059***	−0.066***	−0.036***	−0.035***
	(−4.83)	(−3.96)	(−4.21)	(−4.42)	(−4.74)	(−4.14)
GDPgrowth	0.837***		1.423***		1.063***	
	(3.40)		(2.77)		(3.95)	
LINC	0.058***	0.057***	0.093***	0.105***	0.052***	0.051***
	(6.36)	(5.69)	(4.92)	(5.16)	(5.21)	(4.73)
LFCF	0.028**	0.034***	0.035*	0.038*	0.024*	0.030**
	(2.26)	(2.67)	(1.79)	(1.94)	(1.89)	(2.30)
Industry×Year FE	No	Yes	No	Yes	No	Yes
N	46,482	45,949	48,304	47,767	46,790	46,265
Adjusted R^2	0.005	0.065	0.002	0.073	0.003	0.061

Table 2 Cost Stickiness and Environmental Commitments

This table shows the effects of asymmetric cost behavior on environmental commitments based on firm disclosure in 10-K filings. *EnvCommit1_MDA*$_{i,t+1}$ is the number of bigrams related to climate change divided by the total number of bigrams in the Management Discussion and Analysis of 10-Ks filed by firm *i* in year *t+1*, multiplied by 100. *EnvCommit2_MDA*$_{i,t+1}$ is the number of climate-related sentences classified as commitment-specific divided by the total number of sentences in the Management Discussion and Analysis of the 10-K filed by firm *i* in year *t+1*, multiplied by 100. Following He et al. (2020), we measure a firm-year degree of cost stickiness (i.e., *CS_OC*, *CS_SGA*, and *CS_TC*) using the preceding 16 quarterly observations. The sample period spans 2003 to 2019. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values are presented in parentheses calculated using standard errors clustered by firm. *, **, and *** indicate p < 0.10, p < 0.05, and p < 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
CS_OC	−0.005***			−0.005***		
	(−3.58)			(−3.39)		
CS_SGA		−0.002***			−0.002**	
		(−3.80)			(−2.13)	
CS_TC			−0.004***			−0.005***
			(−3.25)			(−3.47)
CE_OC	0.002			0.009***		
	(0.79)			(2.86)		
CE_SGA		0.004**			0.005***	
		(2.48)			(2.75)	
CE_TC			0.001			0.008***
			(0.42)			(2.74)
LnSize	0.004***	0.003**	0.003***	0.004**	0.002	0.003**
	(2.82)	(2.48)	(2.65)	(2.23)	(1.11)	(2.05)
Lev	−0.006	−0.007	−0.006	0.005	0.003	0.005
	(−1.00)	(−1.23)	(−1.03)	(0.77)	(0.44)	(0.75)
MTB	−0.000*	−0.000*	−0.000*	−0.000	−0.000	−0.000
	(−1.91)	(−1.93)	(−1.90)	(−0.91)	(−0.89)	(−0.91)
Cash	0.002	0.002	0.002	0.026**	0.026**	0.026**
	(0.22)	(0.17)	(0.24)	(2.36)	(2.35)	(2.37)
PPE	0.011**	0.011**	0.011**	0.017***	0.017***	0.017***
	(2.53)	(2.51)	(2.55)	(3.29)	(3.28)	(3.31)
ROE	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.78)	(−0.77)	(−0.79)	(0.19)	(0.33)	(0.20)
StockReturn	0.001	0.001	0.001	0.001	0.001	0.001
	(0.67)	(0.63)	(0.68)	(0.49)	(0.48)	(0.49)
CAPEX	0.015	0.014	0.016	0.026	0.025	0.027
	(0.38)	(0.35)	(0.39)	(0.54)	(0.54)	(0.57)
LnAnalysts	−0.006***	−0.006***	−0.006***	−0.005**	−0.005**	−0.005**
	(−2.60)	(−2.66)	(−2.63)	(−2.00)	(−2.21)	(−1.98)
ESGOwn	0.034	0.031	0.034	0.067	0.066	0.062
	(0.28)	(0.25)	(0.28)	(0.54)	(0.54)	(0.51)
WWIndex	−0.014***	−0.014***	−0.014***	−0.002	−0.002	−0.002
	(−3.19)	(−3.19)	(−3.21)	(−0.25)	(−0.26)	(−0.30)
Top5Options	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(−4.64)	(−4.72)	(−4.72)	(−3.12)	(−3.59)	(−3.11)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.0%	9.1%	9.0%	3.8%	3.7%	3.8%

Table 3 Market Reactions to Corporate Environmental Commitment Reductions

This table shows the results of the capital market reactions to firms' environmental commitment reductions. The dependent variable *CAR* is a sample firm's cumulative abnormal return over the seven-day window surrounding its 10-K filing date. *EnvCommitCut1* is an indicator variable for whether a sample firm's current year *EnvCommit1_MDA* value is lower than its previous year's *EnvCommit1_MDA* value. *EnvCommitCut2* is an indicator variable for whether a sample firm's current year *EnvCommit2_MDA* value is lower than its previous year's *EnvCommit2_MDA* value. *HighERO* is an indicator variable for whether the environmentally responsible (ER) institutional ownership of a firm-year is above the sample median of ER institutional ownership. *ESGTrans* is an indicator variable that equals 0 if none of the sustainability rating agencies (KLD, Sustainalytics, ASSET4, S&P, Bloomberg, or RepRisk) cover a firm and 1 after the initiation of ESG rating coverage by any one or more above agencies. We include several 10-K filing textual attributes and the same set of control variables in our baseline model specification. Appendix A provides other variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values are presented in parentheses calculated using standard errors clustered at the firm level. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			CAR			
EnvCommitCut1	−0.008**		−0.001		0.010	
	(−2.14)		(−0.18)		(0.89)	
EnvCommitCut2		−0.006**		0.003		0.013
		(−2.02)		(0.69)		(1.43)
HighERO×EnvCommitCut1			−0.012*			
			(−1.73)			
HighERO×EnvCommitCut2				−0.014**		
				(−2.26)		
HighERO			0.006	0.005		
			(0.87)	(0.84)		
ESGTransp×EnvCommitCut1					−0.020*	
					(−1.68)	
ESGTransp×EnvCommitCut2						−0.023**
						(−2.34)
ESGTransp					0.027**	0.024**
					(2.22)	(2.50)
CAR_EA	0.295***	0.295***	0.298***	0.298***	0.301***	0.301***
	(2.91)	(2.91)	(2.86)	(2.86)	(2.86)	(2.86)
LitigiousProportion	−0.444	−0.446	−0.418	−0.409	−0.462	−0.459
	(−1.03)	(−1.04)	(−0.95)	(−0.93)	(−1.05)	(−1.04)
GunningFogIndex	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−0.36)	(−0.39)	(−0.41)	(−0.46)	(−0.56)	(−0.60)
LnWordCount	0.044	0.044	0.044	0.043	0.048	0.049
	(1.18)	(1.19)	(1.16)	(1.14)	(1.25)	(1.28)
Sentiment	0.304***	0.307***	0.285***	0.286***	0.284***	0.288***
	(3.22)	(3.25)	(2.96)	(2.97)	(2.93)	(2.97)
UncertaintyProportion	−1.464	−1.492	−1.420	−1.432	−1.635	−1.648
	(−1.34)	(−1.37)	(−1.28)	(−1.29)	(−1.48)	(−1.49)
LnComplexWordCount	−0.038	−0.038	−0.038	−0.037	−0.041	−0.042
	(−1.03)	(−1.05)	(−1.02)	(−1.00)	(−1.11)	(−1.13)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,361	27,361	26,409	26,409	26,205	26,205
Adjusted R^2	2.1%	2.1%	2.1%	2.1%	2.2%	2.2%

Table 4 Real Effects of Cost Stickiness

This table shows the real effects of cost stickiness. In Panel A, the dependent variable $ToxicEmission_{i,t+1}$ is the total toxic emissions in thousands of firm *i* in year *t+1* divided by the lagged total assets. In Panel B, we use three dependent variables to proxy for corporate green innovation. $I\_GreenPat_{i,t+1}$ is an indicator that equals 1 if the firm filed any green patents (and eventually granted) in year *t+1*. $Ln\#GreenPat_{i,t+1}$ is the natural logarithm of one plus the total number of green patents filed by (and eventually granted for) firm *i* in year *t+1*. $Cite\_GreenPat_{i,t+1}$ is the total number of citations received on all green patents filed by (and eventually granted for) firm *i*, divided by the average number of citations of all patents filed by (and eventually granted for) all firms in year *t+1* to adjust for truncation. Appendix A provides variable definitions. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Cost stickiness and industrial pollution

	(1)	(2)	(3)	(4)	(5)	(6)
		ToxicEmission			*ToxicEmission*	
CS_OC	0.097**			0.094**		
	(1.96)			(1.97)		
CS_SGA		0.041***			0.040***	
		(2.82)			(2.76)	
CS_TC			0.041			0.040
			(1.20)			(1.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
N	9,875	9,875	9,875	9,885	9,885	9,885
Adjusted R^2	10.0%	9.9%	9.9%	10.6%	10.6%	10.5%

Panel B: Cost stickiness and green innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		I_GreenPat			*Ln#GreenPat*			*Cite_GreenPat*	
CS_OC	−0.006**			−0.015***			−0.047**		
	(−2.55)			(−2.98)			(−2.34)		
CS_SGA		−0.002**			−0.006***			−0.022**	
		(−1.98)			(−2.70)			(−2.50)	
CS_TC			−0.005**			−0.012***			−0.041**
			(−2.28)			(−2.72)			(−2.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,238	44,238	44,238	44,238	44,238	44,238	44,238	44,238	44,238
Adjusted R^2	24.9%	24.8%	25.4%	23.5%	23.1%	24.7%	14.2%	13.7%	15.1%

Table 5 State Border Discontinuity Analysis on Cost Stickiness and Environmental Commitments: Evidence from Wrongful Discharge Laws

This table shows the results of the state border discontinuity analysis. We estimate the state border discontinuity (SBD) model after entropy balancing between the treatment and control groups. State borders are those where one state has recognized the Good Faith (GF) exception, and its neighboring state has not. We use the SBD samples including firms headquartered in counties whose centroids are within 50 miles of state borders. In Panel A, we test the effect of the state-wide recognition of the GF exception on our cost stickiness measures (*CS_OC*, *CS_SGA*, or *CS_TC*). *GF* equals 1 for firms headquartered in a state in the years after the state's GF exception adoption and 0 otherwise. In Panel B, we test the effect of GF exception recognition on corporate environmental commitments. The set of controls includes those in our baseline specification, Implied Contract exception, Public Policy exception, and other state characteristics. After 1998, no state adopted or rescinded the GF exception; 12 states recognized the GF exception, while the other states did not. The SBD sample period is from 2003 to 2019. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values are presented in parentheses calculated using standard errors clustered by firm. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: GF exception and cost stickiness

	Within 50 miles of state borders		
	(1)	(2)	(3)
	CS_OC	*CS_SGA*	*CS_TC*
GF	0.095**	0.166*	0.129**
	(2.04)	(1.87)	(2.31)
Controls	Yes	Yes	Yes
Border×Year FE	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	13,710	13,710	13,710
Adjusted R^2	3.1%	2.6%	3.0%

Panel B: GF exception and corporate environmental commitments

	Within 50 miles of state borders			
	(1)	(2)	(3)	(4)
	EnvCommit1_MDA	*EnvCommit2_MDA*	*EnvCommit1_Call*	*EnvCommit2_Call*
GF	−0.024***	−0.031**	−0.034***	−0.026**
	(−2.83)	(−2.46)	(−2.80)	(−2.45)
Same Controls as Equation (2)	Yes	Yes	Yes	Yes
Border×Year FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
N	12,094	12,094	9,493	9,493
Adjusted R^2	7.9%	2.8%	6.8%	6.3%

Table 6 Regression Discontinuity Analysis on Cost Stickiness and Environmental Commitments: Evidence from Close-Call Union Elections

This table shows the results of the regression discontinuity analysis on ex post cost stickiness and corporate environmental commitments, respectively. We estimate the nonparametric local linear regression that exploits the optimal bandwidth following Imbens and Kalyanaraman (2012) and the triangular kernel. In Panel A, we regress an ex ante firm characteristic on *Unionized* (i.e., examine the effect of labor-adjustment costs caused by union election on ex ante firm characteristics) and report the coefficient on *Unionized* in each regression. Ex ante cost stickiness (based on *CS_OC*, *CS_SGA*, or *CS_TC*) is calculated using the preceding 16 quarterly observations *before* the closing year of the union election. Other ex ante firm characteristics (based on our control variables in the baseline analysis) are measured at one year *before* the closing year of the union election. In Panel B, we examine the effect of labor-adjustment costs caused by union election on firms' ex post cost stickiness. Ex post cost stickiness (based on *CS_OC*, *CS_SGA*, or *CS_TC*) is calculated using the subsequent 16 quarterly observations starting in the year *after* the union election. In Panel C, we examine the effect of labor-adjustment costs caused by union election on firms' ex post environmental commitments. Ex post environmental commitments (based on *EnvCommit1_Call*, *EnvCommit2_Call*, *EnvCommit1_MDA*, or *EnvCommit2_MDA*) are calculated as the average of four values in the four years *after* the union election. *Unionized* is a dummy variable for whether more than half of the employees cast their votes in favor of unionization in a union election. The relevant optimal bandwidth is presented at the bottom of both panel tables. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Ex ante firm characteristics before the election

Variables		Variables (Continued)	
CS_OC	0.064	*MTB*	−0.217
	(1.25)		(−0.77)
CS_SGA	0.111	*Cash*	−0.005
	(0.80)		(−0.69)
CS_TC	0.036	*PPE*	0.038
	(0.76)		(1.23)
CE_OC	0.002	*ROE*	−0.086
	(0.09)		(−1.07)
CE_SGA	−0.022	*CAPEX*	0.001
	(−0.46)		(0.44)
CE_TC	−0.001	*StockReturn*	−0.022
	(−0.06)		(−0.40)
EnvCommit1_MDA	0.005	*LnAnalysts*	−0.062
	(0.48)		(−0.77)
EnvCommit2_MDA	0.017	*ESGOwn*	0.001
	(0.59)		(1.05)
LnSize	−0.140	*WWIndex*	0.001
	(−0.98)		(0.05)
Lev	−0.002	*Top5_Options*	−0.024
	(−0.10)		(−0.13)

Panel B: Ex post cost stickiness after the election

	(1) *CS_OC*	(2) *CS_SGA*	(3) *CS_TC*
Unionized	0.135***	0.346***	0.163***
	(4.59)	(4.04)	(3.99)
N	593	806	916
Bandwidth	±0.113	±0.141	±0.163

Panel C: Ex post corporate environmental commitments after the election

	(1) *EnvCommit1_MDA*	(2) *EnvCommit2_MDA*
Unionized	−0.022***	−0.013***
	(−2.61)	(−4.84)
N	747	476
Bandwidth	±0.096	±0.062

Table 7 Cross-sectional Variation Analysis

This table shows the results of estimating Equation (2) after including the partitioning variable and its interaction with a cost stickiness measure. Only the results on the interaction terms are reported. In Panel A, we conduct cross-sectional analyses related to financial resources. We test whether the effect is more pronounced for firms with below-median retained earnings or below-median cash flows. In Panel B, we conduct cross-sectional analyses related to resource-adjustment costs. We test whether the effect is more pronounced for firms with above-median employee intensity or above-median asset intensity. In Pane C, we conduct cross-sectional analyses related to firms' anticipation of investor aversion to environmental commitment reduction. We test whether the effect is more pronounced for firms with high environmentally responsible institutional ownership or firms with high ESG performance transparency. Our sample period spans from 2003 to 2019. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values are presented in parentheses calculated using standard errors clustered by firm. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Cross-sectional analyses related to financial resources

Retained earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
LowErn×CS_OC	−0.010***			−0.007**		
	(−3.82)			(−2.29)		
LowErn×CS_SGA		−0.003**			−0.001	
		(−2.15)			(−0.91)	
LowErn×CS_TC			−0.010***			−0.006**
			(−3.73)			(−2.04)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.2%	9.2%	9.2%	4.2%	4.1%	4.1%

Cash flow

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
LowCash×CS_OC	−0.007***			−0.011***		
	(−3.26)			(−3.98)		
LowCash×CS_SGA		−0.001			−0.003*	
		(−1.14)			(−1.88)	
LowCash×CS_TC			−0.007***			−0.008***
			(−3.44)			(−3.26)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.3%	9.3%	9.3%	4.4%	4.3%	4.4%

Panel B: Cross-sectional analyses related to resource-adjustment costs

Employee intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
HighEINT×CS_OC	−0.007***			−0.009***		
	(−2.97)			(−2.96)		
HighEINT×CS_SGA		−0.004***			−0.004***	
		(−3.40)			(−2.65)	
HighEINT×CS_TC			−0.007***			−0.011***
			(−3.04)			(−3.73)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.1%	9.2%	9.1%	3.8%	3.7%	3.9%

Asset intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
HighAINT×CS_OC	−0.006**			−0.007**		
	(−2.27)			(−2.48)		
HighAINT×CS_SGA		−0.002			−0.003*	
		(−1.32)			(−1.89)	
HighAINT×CS_TC			−0.005**			−0.006**
			(−2.26)			(−2.33)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.1%	9.1%	9.1%	4.1%	4.0%	4.1%

Panel C: Cross-sectional analyses related to firms' anticipation of investor reaction to environmental commitment reduction

Environmentally responsible ownership

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
HighERO×CS_OC	−0.011***			−0.011***		
	(−4.58)			(−3.63)		
HighERO×CS_SGA		−0.003**			−0.003*	
		(−2.45)			(−1.90)	
HighERO×CS_TC			−0.010***			−0.009***
			(−4.28)			(−3.10)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.7%	9.7%	9.7%	4.9%	4.8%	4.9%

ESG transparency

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
ESGTransp×CS_OC	−0.010**			−0.023***		
	(−2.06)			(−3.86)		
ESGTransp×CS_SGA		−0.003*			−0.004*	
		(−1.95)			(−1.82)	
ESGTransp×CS_TC			−0.009**			−0.022***
			(−2.04)			(−3.99)
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,709	35,709	35,709	35,709	35,709	35,709
Adjusted R^2	9.1%	9.1%	9.1%	4.0%	3.9%	4.0%

The Effects of Asymmetric Cost Behavior on
Corporate Environmental Commitments and Actions

Online Appendix

In this online appendix, we present Appendix OA1, Figure OA1-OA2, and Table OA1-OA4.

Appendix OA1: Examples of Corporate Environmental Commitments

Southern Company 2018 Annual Report:

In April 2018, Southern Company established an intermediate goal of a 50 reduction in carbon emissions from 2007 levels by 2030 and a long-term goal of low to no carbon operations by 2050. To achieve these goals, the Southern Company system expects to continue growing its renewable energy portfolio, optimize technology advancements to modernize its transmission and distribution systems, increase the use of natural gas for generation, complete ongoing construction projects, including Georgia Powers interest in Plant Vogtle Units 3 and 4, invest in energy efficiency, and continue research and development efforts focused on technologies to lower GHG emissions.

WEC Energy Group 2014 Annual Report:

Climate Change: We continue to take measures to reduce our emissions of Greenhouse Gas (GHG). We support flexible, market-based strategies to curb GHG emissions, including emissions trading, emission offset projects and credit for early actions. We support an approach that encourages technology development and transfer and includes all sectors of the economy and all significant global emitters. We, along with our affiliates, have taken, and continue to take, several steps to reduce our emissions of GHG, including: Repowered the Port Washington Power Plant from coal to natural gas-fired combined cycle units. Added coal fired units as part of the Oak Creek expansion that are the most thermally efficient coal units in our system. Increased our investment in energy efficiency and conservation. Added renewable capacity. Converting the fuel source at the VAPP from coal to natural gas, scheduled for completion in 2015. Retired coal units 1-4 at PIPP.

Brown–Forman Corporation 2010 Annual Report:

To accomplish our vision, we have five strategic aspirations we will focus on as we move through the next decade towards our 150th anniversary in 2020: …… Be responsible in everything we do. We endeavor to be responsible in everything we do – from reducing our environmental footprint to managing how we market our brands…… Our approach to corporate responsibility includes our civic obligations and our products' entire environmental life cycle: how we produce or source our raw materials, how we set and maintain production standards, and how we package and distribute our products. Environmental stewardship is central to our broader social responsibilities, as is our commitment to contribute to the quality of life in the communities where our employees live, work, and raise their families.

Q4 2017 Vectren Corp Earnings Call:

Eric J. Schach - COO and EVP: …… we expect to significantly diversify our generation portfolio over the next 7 years as we replace our aging coal-fired fleet with efficient, cleaner and diverse energy sources. To accomplish this, in the next 10 years, we plan to invest about $1 billion to add 800- and 900-megawatt generation from the combined-cycle natural gas plant and a total of 54 megawatt of universal solar generation. At the same time, we will continue to provide robust energy efficiency programs to our customers, such as the ones recently approved through 2020, and retire over 800 megawatts of mostly coal-fired generation. As a result, we are pleased to have a generation plan that, once approved and executed, will achieve a reduction in carbon emissions of 60% by 2024 from 2005 levels. The 60% carbon emission reduction will represent another significant step-up from the over 30% carbon emissions reduction through 2017 from 2005 levels achieved through energy efficiency programs, exiting purchase power agreements with neighboring municipal utilities, retirement of a small coal-fired unit and improved efficiency of our generation turbines.

Q3 2007 Sierra Pacific Resources Earnings Conference Call:

Michael Yackira - President, CEO: To make sure we will continue to provide our customers with clean, reliable electricity at reasonable and predictable prices, we are following a three-part strategy…… Second, we are expanding our renewable energy initiatives and investments that have already made us a national leader in renewables, and third, we are building new generating plants that will use the best available technology to improve the environment and efficiency of our portfolio of assets. Because of the importance of energy efficiency, we recently joined forces with seven other utilities to announce plans to increase our investment in conservation. These eight utilities in total serve nearly 20 million electric customers in 22 states. We share a common belief that energy efficiency is the most readily available resource in the near-term for addressing climate change……We also plan to test new technologies for capturing and storing carbon dioxide, and to expand those technologies when they have become proven and economically viable.

Figure OA1 Map of Counties within 50 Miles of State Borders

This figure presents the counties within 50 miles of state borders where neighboring states differ in their recognition of the good faith (GF) exception. Our focus is on those counties whose centroids are located within 50 miles of the state border. Counties are color-coded: blue for counties in states with the GF exception and red for those in states without the GF exception. Source: Bai et al. (2020, Table 1).

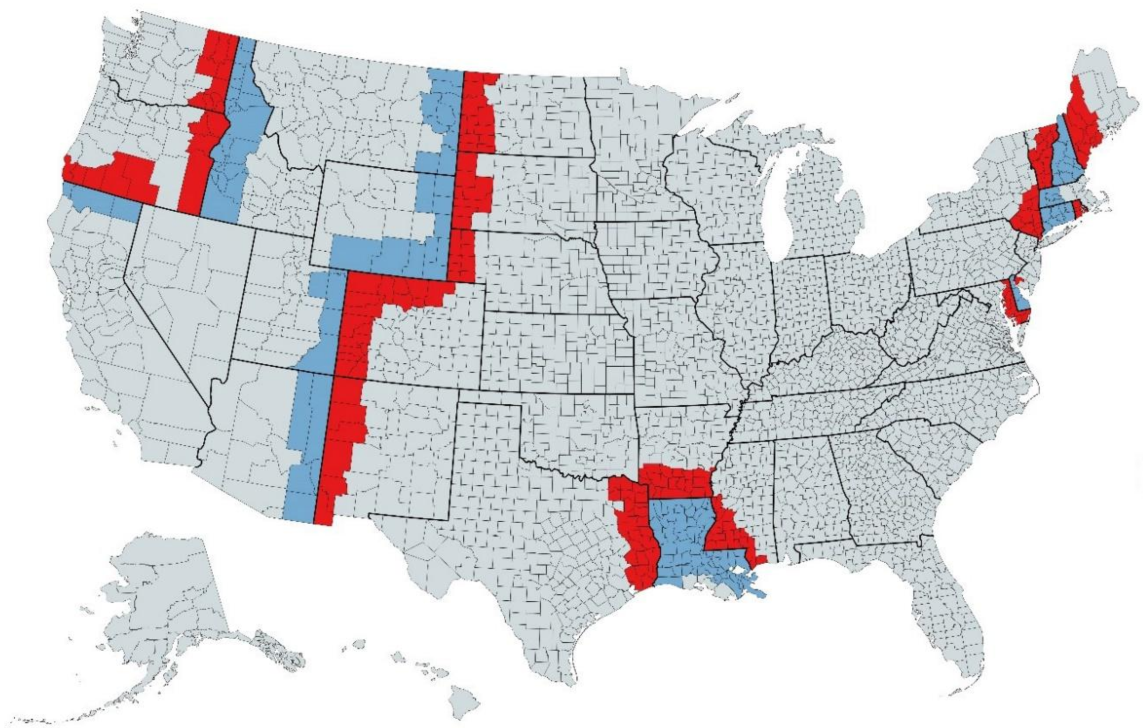
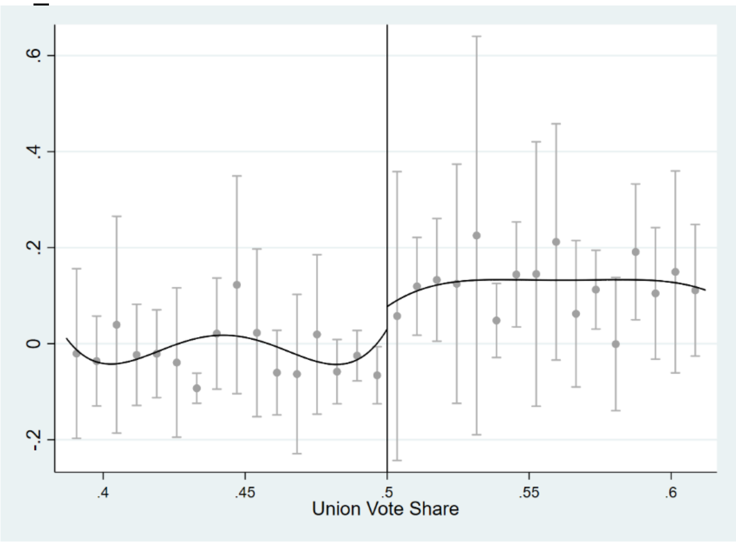


Figure OA2 Regression Discontinuity Plots for Ex Post Cost Stickiness and Corporate Environmental Commitments

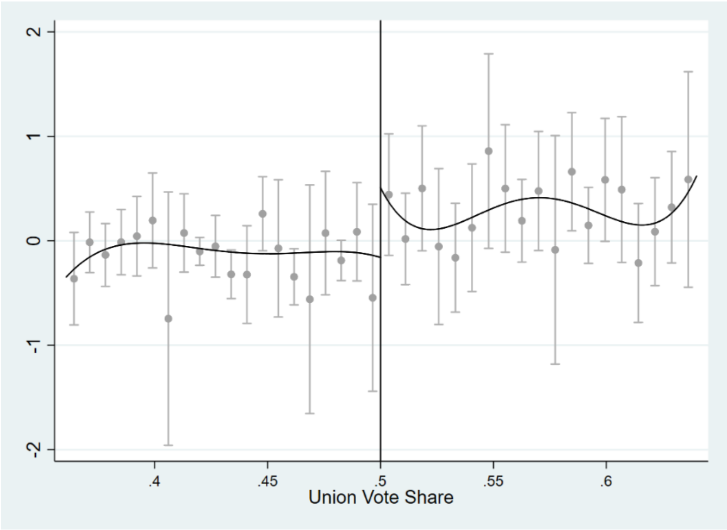
This figure shows regression discontinuity plots using a fitted quartic polynomial with a 95% confidence interval surrounding the fitted values. The horizontal axis represents the union vote share, which is the percentage of votes in favor of unionization in an election. Each dot is an average of multiple sample observations that fall within a narrow range of union vote share values. The dots indicate ex post cost stickiness or firm environmental commitments for the average of sample firms over the four-year period following union elections.

Panel A: Ex post cost stickiness after the election

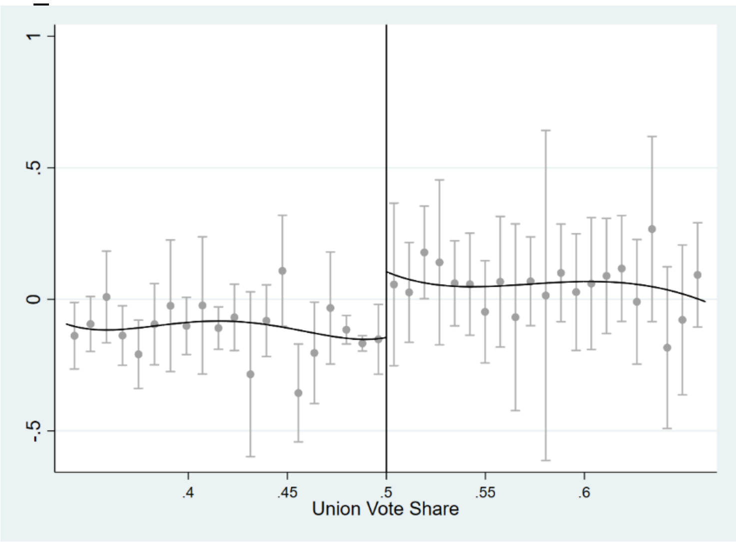
CS_OC



CS_SGA

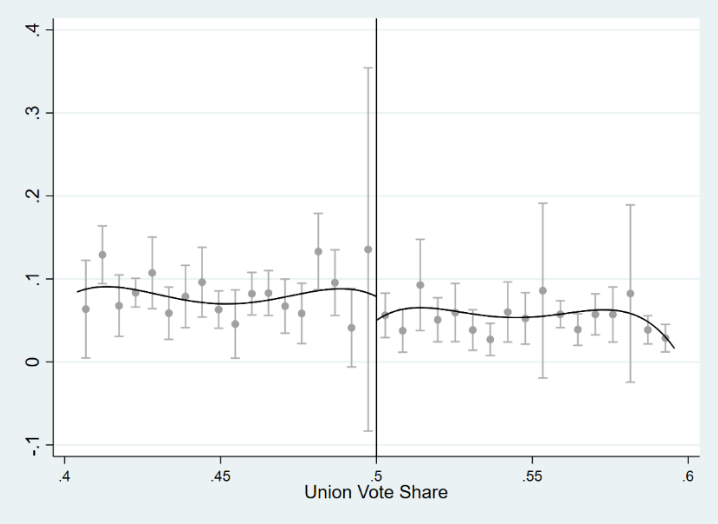


CS_TC



Panel B: Ex post corporate environmental commitments after the election

EnvCommit1_MDA



EnvCommit2_MDA

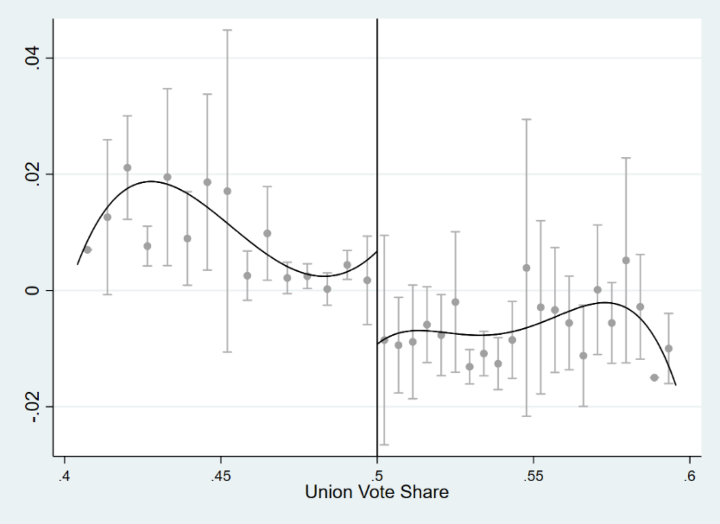


Table OA1 Sample Selection

The table lists the sample-selection procedures. Our main sample includes 35,709 firm-year observations in 2003–2019 for MD&A analysis, covering 5,236 unique U.S. public firms. Panel A lists its sample-selection procedures. Our robustness sample includes 27,921 firm-year observations in 2003–2019 for conference call analysis, covering 3,646 unique U.S. public firms.

Panel A: MD&A main sample

Firm-years with non-missing total assets in Compustat for 2003–2019	151,955
Less:	
Firm-years in the financial sector (SIC codes 6000–6999)	(29,869)
Firm-years without available data for calculating *CS_OC*, *CS_SGA*, and *CS_TC*	(72,071)
Firm-years without clean texts of 10-Ks from Notre Dame Software Repository for Accounting and Finance	(10,462)
Firm-years without data for calculating the control variables in our main model	(3,844)
Our main sample in firm-years	35,709

Panel B: Earnings call robustness sample

Firm-years with non-missing total assets in Compustat for 2003–2019	151,955
Less:	
Firm-years in the financial sector (SIC codes 6000–6999)	(29,869)
Firm-years without available data for calculating *CS_OC*, *CS_SGA*, and *CS_TC*	(72,071)
Firm-years without clean transcripts of conference calls from StreetEvents	(19,746)
Firm-years without data for calculating the control variables in our main model	(2,348)
Our robustness sample in firm-years	27,921

Table OA2 Robustness Checks of Baseline Findings

This table shows the results of the robustness checks on the baseline findings. In Panel A, we replace the dependent variables in Equation (2) with corporate environmental commitments constructed based on the presentation section of earnings calls (*EnvCommit1_Call* and *EnvCommit2_Call*). In Panel B, we replace the dependent variables in Equation (2) with investment-focused environmental commitments constructed based on the MD&A disclosure and the presentation section of earnings calls (*EnvCommit1_opp_MDA* and *EnvCommit2_opp_Call*). In Panel C, we restrict our main sample to observations with positive values of cost stickiness measures and use this subsample to re-estimate our baseline specification. In Panel D, we restrict our main sample to observations with negative values of cost stickiness measures and use this subsample to re-estimate our baseline specification. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values or z-values are presented in parentheses calculated using standard errors clustered by firm level. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Alternative measures of environmental commitments based on earnings calls

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_Call			*EnvCommit2_Call*		
CS_OC	−0.004***			−0.004**		
	(−3.14)			(−2.01)		
CS_SGA		−0.002***			−0.002**	
		(−3.09)			(−2.09)	
CS_TC			−0.004***			−0.003
			(−3.61)			(−1.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,921	27,921	27,921	27,921	27,921	27,921
Adjusted R^2	7.6%	7.7%	7.7%	4.8%	4.9%	4.8%

Panel B: Alternative measures of environmental commitments in investment opportunities based on MD&A disclosure or earnings calls

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_opp_MDA			*EnvCommit2_opp_Call*		
CS_OC	−0.002***			−0.001***		
	(−3.79)			(−3.12)		
CS_SGA		−0.001***			−0.001*	
		(−3.56)			(−1.82)	
CS_TC			−0.002***			−0.001**
			(−3.53)			(−2.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	29,568	29,568	29,568	23,766	23,766	23,766
Adjusted R^2	1.7%	1.7%	1.7%	5.2%	5.2%	5.2%

Panel C: Subsample of firms with positive cost stickiness measures

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA			*EnvCommit2_MDA*		
CS_OC	−0.011***			−0.008***		
	(−5.28)			(−3.33)		
CS_SGA		−0.002**			−0.003***	
		(−2.34)			(−2.70)	

CS_TC			−0.010***			−0.008***
			(−4.78)			(−3.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18,668	18,605	18,319	18,668	18,605	18,319
Adjusted R^2	9.2%	8.4%	9.0%	3.7%	3.6%	3.6%

Table OA3 Reverse Causality Test

This table reports the results of analyses that address reverse causality between cost stickiness and environmental commitments. Panel A reports the results from panel vector autoregression (PVAR) model of corporate environmental commitments (measured by *EnvCommit1_MDA* or *EnvCommit2_MDA*), asymmetric cost behavior (measured by *CS_OC*, *CS_SGA*, or *CS_TC*), and respective control variables used in our baseline model specification. Corporate environmental commitments and asymmetric cost behavior are treated as endogenous variables, and controls are treated as exogenous variables in PVAR. We include the first-order lag of endogenous variables in the PVAR and use the first five lags of endogenous variables as instruments in the model both to minimize the modified Bayesian information criterion and the modified Quinn information criterion (Abrigo and Love 2016) and to mitigate the model overfitting issues (Arnerić and Situm 2022). Panel B reports the Chi-square statistics for the Granger causality Wald tests of the null hypothesis that the excluded variable does not Granger-cause equation variable. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values or z-values are presented in parentheses calculated using standard errors clustered by firm level. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Panel vector autoregression coefficient estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	EnvCommit1_MDA$_t$	*CS_OC*$_t$	*EnvCommit2_MDA*$_t$	*CS_OC*$_t$	*EnvCommit1_MDA*$_t$	*CS_SGA*$_t$
EnvCommit1_MDA$_{t-1}$	0.530*** (10.22)	0.141 (0.44)				
CS_OC$_{t-1}$	−0.008*** (−2.65)	0.653*** (15.36)				
EnvCommit2_MDA$_{t-1}$			0.502*** (5.85)	−0.014 (0.14)		
CS_OC$_{t-1}$			−0.023*** (−2.92)	0.652*** (17.49)		
EnvCommit1_MDA$_{t-1}$					0.539*** (9.32)	0.821 (0.47)
CS_SGA$_{t-1}$					−0.003* (−1.92)	0.604*** (10.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

	(7)	(8)	(9)	(10)	(11)	(12)
	EnvCommit2_MDA$_t$	*CS_SGA*$_t$	*EnvCommit1_MDA*$_t$	*CS_TC*$_t$	*EnvCommit2_MDA*$_t$	*CS_TC*$_t$
EnvCommit2_MDA$_{t-1}$	0.460*** (4.87)	0.428 (1.34)				
CS_SGA$_{t-1}$	−0.017*** (−2.69)	0.606*** (17.60)				
EnvCommit1_MDA$_{t-1}$			0.524*** (10.02)	0.049 (0.14)		
CS_TC$_{t-1}$			−0.006** (−2.17)	0.648*** (14.88)		
EnvCommit2_MDA$_{t-1}$					0.507*** (5.79)	−0.001 (−0.01)
CS_TC$_{t-1}$					−0.020** (−2.62)	0.651*** (16.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Granger causality tests

Equation variable	Excluded variable	Chi-square
(1) *EnvCommit1_MDA*	*CS_OC*	7.026***
(2) *CS_OC*	*EnvCommit1_MDA*	0.193
(3) *EnvCommit2_MDA*	*CS_OC*	8.532***
(4) *CS_OC*	*EnvCommit2_MDA*	0.019
(5) *EnvCommit1_MDA*	*CS_SGA*	3.697*
(6) *CS_SGA*	*EnvCommit1_MDA*	0.222
(7) *EnvCommit2_MDA*	*CS_SGA*	7.230***
(8) *CS_SGA*	*EnvCommit2_MDA*	1.792
(9) *EnvCommit1_MDA*	*CS_TC*	4.722***
(10) *CS_TC*	*EnvCommit1_MDA*	0.019
(11) *EnvCommit2_MDA*	*CS_TC*	6.876***
(12) *CS_TC*	*EnvCommit2_MDA*	0.000

Table OA4 Validation Test for Environmental Commitment Measures

This table shows the validation test for our disclosure-based environmental commitment measures. We use two dependent variables to capture firms' environmental performance ratings. $KLD\_envrn_{i,t+1}$ is the sum of environmental strengths minus the sum of environmental concerns from KLD by firm *i* in year *t*+1. $ASSET4\_envrn_{i,t+1}$ is the environmental score from ASSET4 by firm *i* in year *t*+1. The sample period spans from 2003 to 2019. Appendix A provides variable definitions. The t-values are presented in parentheses calculated using standard errors clustered by firm. *, **, and *** indicate p < 0.10, p < 0.05, and p < 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	KLD_envrn	*KLD_envrn*	*KLD_envrn*	*ASSET4_envrn*	*ASSET4_envrn*	*ASSET4_envrn*
CS_OC	−0.011**			−0.005**		
	(−2.39)			(−2.57)		
CS_SGA		−0.002			−0.002*	
		(−0.68)			(−1.80)	
CS_TC			−0.009**			−0.005**
			(−2.09)			(−2.34)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	44,590	44,590	44,590	44,590	44,590	44,590
Adjusted R^2	10.8%	10.9%	11.2%	30.1%	29.9%	30.2%