Strategic Environmental Deception

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Abstract

We examine whether firms' deceptive environmental disclosures are systematically related to underlying pollution and capital market outcomes. Using a text-based measure of deceptive environmental language, we document that firms with higher emission intensity exhibit more deceptive environmental disclosure. This association is more pronounced for firms with greater profitability, stronger growth opportunities, and lower financial constraints. We interpret these patterns through a framework in which managers trade off the short-term valuation relevance of favorable environmental narratives against expected reputation and regulatory costs. Consistent with this mechanism, deceptive environmental disclosure is associated with short-run increases in stock returns, green fund inflows, and ESG ratings, and these associations attenuate as more accurate environmental information becomes available.

Keywords: Environmental Disclosure; Deceptive Language; Pollution; Financial Performance

JEL Classification Codes: M41, M14, G32, Q56

1 Introduction

To what extent do firms engage in strategic deception in their environmental disclosures, particularly when their operations cause environmental harm? This question has become increasingly salient as environmental risks gain prominence in capital market evaluations. Firms face growing incentives to shape investors' perceptions of their environmental performance (Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2022; Stroebel and Wurgler, 2021; Zhang, 2025). Investors are incorporating environmental metrics into valuation models and investment strategies (Barth et al., 2017; Grewal, Riedl, and Serafeim, 2019). However, environmental disclosure remains less standardized [1] than financial reporting and often allows managerial discretion in narrative presentation (Christensen, Hail, and Leuz, 2021), creating scope for strategic language choices that may obscure unfavorable information.

Prior research documents the prevalence of greenwashing and obfuscated ESG communication, raising concerns about the reliability of environmental reporting (Kim and Lyon, 2015; Marquis, Toffel, and Zhou, 2016; Baker et al., 2024; Fritsch, Zhang, and Zheng, 2025; Bailey et al., 2022; Duchin, Gao, and Xu, 2025). However, less is known about when firms have stronger incentives to engage in such deceptive practices and how these incentives vary across firms.

The goal of this paper is to examine whether firms strategically use environmental disclosure to obscure underlying environmental pollution. Theoretically, we develop a model-free best-response framework in which firms choose disclosure language to maximize net benefits, trading off short-term capital market gains against expected reputational and regulatory costs. Differing from classical unraveling models (Chen, 2023; Aghamolla and Smith, 2023) that predict greater transparency for high-quality firms, our framework highlights the conditions under which fi-

[1] Despite the growing importance, environmental disclosure practices remain fragmented and inconsistently regulated, especially when compared to the more standardized landscape of financial reporting (Christensen, Hail, and Leuz, 2021). The absence of a universally adopted reporting framework leaves room for subjectivity and inconsistency in how firms present their environmental performance. The lack of a common reporting framework on environmental disclosures may stem from the inherent subjectivity in determining which environmental issues materially affect a firm's long-term value (Cohen and Simnett, 2015). For instance, firms may report under varying frameworks such as the Climate Disclosures Standards Board (2016) for greenhouse gas emissions or under Section 1502 of the Dodd-Frank Act for conflict minerals—each with differing standards and priorities. In an effort to address these issues, the U.S. government began implementing mandatory climate risk disclosure requirements for public companies in March 2024. These new regulations aim to improve the consistency, comparability, and transparency of climate-related information for investors, thereby enhancing market efficiency and risk assessment. For further details on the SEC's regulation, see: www.sec.gov/newsroom/pressreleases/2024-31.

nancially stronger firms may optimally respond to higher pollution by increasing deceptive environmental disclosure [2]. Within this best-response structure, financially stronger firms exhibit a steeper pollution–deception relation.

Empirically, we focus on deceptive linguistic features—subtle manipulations of words, tone, or rhetorical structure that mislead stakeholders without crossing the line into outright falsehoods. Unlike factual misstatements, which may carry legal consequences, deceptive language is often difficult to detect and regulate, allowing firms to obscure poor environmental performance and shape external perceptions in a more favorable light (Bansal and Kistruck, 2006). [3] Leveraging insights from the disclosure literature in the context of corporate conference calls (Larcker and Zakolyukina, 2012; Henry, Jiang, and Rozario, 2024; Hassan et al., 2019; Sautner et al., 2023),[4] we construct a novel, continuous measure of environmental deception that captures the extent to which firms use vague, ambiguous, imprecise, and evasive language to avoid directly addressing environmental issues [5]. One key distinction between our revised deception measure—based on Larcker and Zakolyukina (2012)—and the uncertainty measure proposed by Loughran and McDonald (2017) is that deception-related language places greater emphasis on emotional expression [6]. Using a sample of 228,912 corporate conference call transcripts from U.S. firms between Q1 2002 and Q4 2019—restricted to those monitored by the Environmental Protection Agency (EPA)—we find strong evidence that environmental deception is negatively and

[2]For classical disclosure models, please see Verrecchia (1983) and Dye (1985). In these models, firms are assumed to choose between full disclosure and nondisclosure, voluntarily releasing favorable information while withholding unfavorable news. More recent theoretical work extends this classic framework by allowing for obfuscation, where managers use vague or ambiguous language to convey less informative disclosures (Aghamolla and Smith, 2023). Such linguistic strategies can be deployed in ESG contexts to facilitate greenwashing (Chen, 2023). Building on these insights, we first propose a new model to show how environmental pollutions affect corporate deceptive disclosure behaviors.

[3]Deception can also take the form of commission, where firms provide explicitly false or biased information. However, such practices are relatively rare due to their heightened legal risk (Ge and Lennox, 2011).

[4]Conference calls offer a rich source of qualitative disclosures in natural language. Most publicly listed firms disclose environmental activities qualitatively and descriptively rather than through quantitative metrics. As such, analyzing the linguistic characteristics of these communications offers a valuable lens through which to examine firms' deceptive disclosure behavior (Archel, Husillos, and Spence, 2011; Michelon, Pilonato, and Ricceri, 2015). Although conference calls may be partially scripted and participation controlled (Mayew, 2008; Cohen, Lou, and Malloy, 2020), they nonetheless convey meaningful information to investors (e.g., Matsumoto, Pronk, and Roelofsen, 2011). We list two examples for both more deception and less deception in Appendix B and Appendix C.

[5]Prior research has developed deception metrics based on financial communication, identifying the strategic use of intentionally vague or contradictory narratives that appear informative while actually obscuring the truth (Larcker and Zakolyukina, 2012; Bertomeu and Marinovic, 2016; Dye and Sridhar, 2004; Langberg and Sivaramakrishnan, 2008).

[6]A detailed comparison is provided in Internet Appendix H.

significantly associated with firms' actual environmental performance. Specifically, we measure environmental performance using toxic release levels reported to the EPA, scaled by firm sales to capture relative pollution intensity. Our findings suggest that when environmental risks are high, firms increase the use of deceptive environmental language, consistent with strategic disclosure incentives and potentially affecting stakeholders' perceptions [7]. These results are robust across alternative measurement specifications, including large language model (LLM)-based validation tests [8].

To address potential endogeneity concerns, we first conduct a change analysis, and the results remain positive and significant. Second, we relax the fixed effects specification and instead incorporate industry differences for toxic releases. The results from this alternative interacted fixed effects model remain consistent. Finally, we exploit the expansion of the Toxic Release Inventory (TRI) chemical list between 2011 and 2019 as a plausibly exogenous shock to strengthen the identification of the link between toxic emissions and environmental deception. Firms that reported newly regulated chemical releases following this expansion exhibit significantly higher levels of deceptive environmental language. Furthermore, we explore the heterogeneity across chemical categories using the Asset4 database. We decompose toxic releases into nitrogen oxides and sulfur oxides—both scaled by firm revenues—and examine their effects within the context of the list expansion. The results indicate that sulfur oxides significantly drive environmental deception, while nitrogen oxides are close to significant at the 10% level.

Next, we investigate the relationship between financial performance and environmental deception. Consistent with our theoretical prediction, we find that firms with higher profitability and greater growth opportunities are significantly more likely to engage in deceptive environmental disclosures when their environmental performance deteriorates compared to less profitable, lower-growth firms. To arrive at these findings, we draw on classical valuation theory (Ohlson and Juettner-Nauroth, 2005; Zhang, 2000) and use a range of proxies to capture firm profitability and growth potential. Furthermore, we partition the sample based on firms' levels of financial constraint and find that financially unconstrained firms are more likely to engage

[7] Given the lack of consensus in the academic literature on how to define "greenwashing," this study takes a conservative approach by focusing narrowly on deceptive environmental disclosure.

[8] In Internet Appendix I, we provide deceptive measure distributions for both dictionary-based measures and LLM measures.

in environmental deception. This evidence is consistent with the interpretation that financially stronger firms respond more aggressively to pollution-related disclosure incentives, potentially to preserve firm value (Cheng, Ioannou, and Serafeim, 2014), rather than to alleviate financing constraints (Li, 2008; Baker et al., 2024).

To further investigate the dynamics of environmental deception, we examine both the timing of disclosures and the role of capital market attention. To assess timing effects, we partition environmental deception based on the timing of conference calls—specifically, into the contemporary fiscal year (year t), the first half of the subsequent year (year $t+1$), and the second half of the subsequent year. Our empirical results show that firms engage in significantly more environmental deception during conference calls held in the contemporary year and the first half of the following year—periods when external stakeholders have limited information about the firm's actual environmental performance. This pattern is consistent with a temporary information wedge between regulatory monitoring and market awareness, during which investors have a limited ability to verify environmental claims. Next, we explore how capital market attention—particularly from institutional investors—influences firms' deceptive disclosure strategies. We find that firms with a higher proportion of institutional ownership exhibit a stronger pollution–deception relationship. This pattern is consistent with firms adjusting disclosure language in response to heightened capital market attention.

In the final set of analysis, we investigate the capital market rewards associated with firms that adopt a deceptive environmental disclosure strategy. Compared to firms with similar underlying environmental performance, those engaging in higher levels of deceptive environmental disclosure experience temporarily higher stock returns, lower implied costs of equity, attract greater inflows from seasonal equity offerings and green funds, and receive more favorable environmental ratings—particularly when the market has limited information to assess the credibility of their environmental claims. This evidence suggests that capital markets and environmental rating agencies may not immediately incorporate the informational content of environmental deception. Some of these effects attenuate over time as additional information becomes available. This gradual adjustment is consistent with a dynamic information diffusion process. Our theoretical framework discusses mechanisms such as jump penalties and investor short-termism that are consistent with these empirical patterns.

Our study contributes to the literature in three ways. First, there is a growing body of research on greenwashing and social-washing. For instance, Fritsch, Zhang, and Zheng (2025) document that firms trade off between hard and soft information in response to climate crises. Duchin, Gao, and Xu (2025) show that firms that divest polluting plants can gain financial benefits through behavioral perceptions rather than actual reductions in pollution. Both studies emphasize the strong external pressures from stakeholders. In contrast, our study focuses on regulated firms and examines how environmental disclosure language responds to underlying pollution within a formal monitoring environment. Our continuous measure captures variation in the intensity of deceptive environmental language, allowing us to move beyond the binary classifications commonly used in prior studies. By quantifying deceptive language within environmental narratives, our approach complements existing work on soft information and can be extended to other forms of ESG-related disclosure. Finally, our results can also serve as a supplement to findings on ESG-washing in the United Kingdom, contributing to a broader body of global evidence (Bailey et al., 2022).

Second, we contribute to the literature on disclosure and valuation by introducing perceived environmental risk through deceptive language. Traditionally, accounting-based valuation models focus solely on financial or accounting metrics (Zhang, 2000). More recent theoretical work has incorporated ESG factors into investment decisions by considering environmental and social preferences, ESG-related reputation costs, impact investing information search, and the additional cost of capital (Landier and Lovo, 2024; Oehmke and Opp, 2024; Avramov et al., 2024; Goldstein et al., 2022). Our model-free best-response framework extends obfuscation mechanisms to the ESG context and highlights how financial performance shapes disclosure incentives. Empirically, carbon intensity and other emissions-related indicators have proven useful for capital market valuations (Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2022; Stroebel and Wurgler, 2021; Zhang, 2025). Building on this literature, we show that deceptive environmental language is associated with short-term valuation effects that attenuate as additional information becomes available [9].

[9]Empirical findings have also shown a negative relationship between financial performance and diversity-washing, suggesting that firms with poor financial performance are less sensitive to ESG investors and thus less

Finally, we introduce a novel aggregate measure for information deception and apply it to environmental topics, including climate change. While prior research has primarily focused on isolated features related to different dimensions of deception or uncertainty (Larcker and Zakolyukina, 2012), our approach leverages the directional significance of deceptive coefficients. We count the net frequency of deceptive occurrences within a 20-word window centered on an environmental keyword (Hassan et al., 2019). Finally, we introduce a novel aggregate measure for information deception and apply it to environmental topics, including climate change. While prior research has primarily focused on isolated features related to different dimensions of deception or uncertainty (Larcker and Zakolyukina, 2012), our approach leverages the directional significance of deceptive coefficients. We count the net frequency of deceptive occurrences within a 20-word window centered on an environmental keyword (Hassan et al., 2019). This methodology not only simplifies the testing of environmental deception but also has the potential to extend the analysis of deception to domains beyond the environmental field, especially when it is verified by a large language model to receive both transparency and accuracy.

The remainder of the paper is organized as follows. **Section 2** discusses the related literature. **Section 3** develops a theory and proposes research hypotheses. **Section 4** introduces data and research design. **Section 5** describes the main empirical results. **Section 6** addresses additional tests on deception timing and attention. **Section 7** documents deception consequences. Finally, **Section 8** provides concluding remarks.

2 Related Literature

Literature has provided evidence on firms' capital market incentives in deciding their disclosure strategies when experiencing negative earnings surprises. Studies suggest that firms have greater incentives to withhold negative information to avoid the market penalty associated with negative surprises (Kasznik and Lev, 1995). In contrast, firms may choose to voluntarily disclose (truthfully) the negative information to preempt litigation risks associated with non-disclosure if opportunistic withholding is more likely to be detected (Lev, 1992; Skinner, 1994). Rather than treating

likely to engage in diversity-washing to attract financing (Baker et al., 2024).

the disclosure as a dichotomous decision, Li (2008) examines how firms disclose when having negative earnings news. He shows that firms choose to use complex and difficult-to-understand language to obfuscate investors and reduce the information content in the disclosures so that capital markets react less completely to negative news.

With rising demand for firms' environmental information, many firms provide environmental disclosures to meet the expectations of regulators, communities, NGOs, customers, and investors (Al-Tuwaijri, Christensen, and Hughes Ii, 2004; Hughes, Anderson, and Golden, 2001; Patten, 2002). While environmental transparency can generate potential benefits—such as improved reputation, enhanced brand value, employee motivation, and stronger internal controls (Hahn and Kühnen, 2013)—the absence of a broadly accepted theory on the objectives of environmental disclosure has resulted in heterogeneous disclosure practices driven by diverse incentives. With rising demand for firms' environmental information, many firms provide environmental disclosures to meet the expectations of regulators, communities, NGOs, customers, and investors (Al-Tuwaijri, Christensen, and Hughes Ii, 2004; Hughes, Anderson, and Golden, 2001; Patten, 2002). While environmental transparency can generate potential benefits—such as improved reputation, enhanced brand value, employee motivation, and stronger internal controls (Hahn and Kühnen, 2013)—the absence of a broadly accepted theory on the objectives of environmental disclosure has resulted in heterogeneous disclosure practices driven by diverse incentives.

When firms directly engage with investors—where complete non-disclosure is typically not feasible—they may adopt more strategic linguistic choices when communicating negative information to divert attention from unfavorable content. Such strategies can impede investors' ability to fully process disclosures and may dampen capital market penalties associated with poor environmental performance (Bloomfield, 2002; Cho, Roberts, and Patten, 2010; You and Zhang, 2009). Cho, Roberts, and Patten (2010) examine opportunistic bias and concealment in environmental disclosure within 10-K reports as a means of managing environmental reputation. Building on this literature, we examine deceptive environmental language in relation to firms' underlying pollution and financial conditions within a regulated disclosure setting [10].

[10]Our paper also differs from Cho, Roberts, and Patten (2010) by measuring environmental performance using operational environmental outcomes rather than rating-based KLD scores, which may be influenced by disclosure practices.

Our measurement of obfuscated and deceptive linguistic features draws on conceptual frameworks from linguistics, psychology, and deception detection research (Vrij, 2008). Prior work suggests that deceptive communication is characterized by more general, non-specific language, fewer self-references, and indirect or evasive statements. Consistent with this literature, we operationalize deceptive environmental language based on linguistic features associated with obfuscation and concealment [11].

3 Theoretical Framework and Hypothesis Development

This section develops a model-free game-theoretic framework to study firms' incentives to engage in deceptive ESG disclosure. The framework is deliberately kept model-free, in the sense that we do not commit to a specific signal and information structure, equilibrium refinement, or functional form, nor do we structurally estimate its parameters in the empirical analysis. We first present a static comparative-statics analysis, then provide a minimal two-period dynamic foundation and several illustrative cases. Finally, we derive empirical hypotheses that map the theory into our baseline regressions.

3.1 A Model-Free Static Framework

Theoretically, we differentiate between cheating and the use of deceptive language. Cheating refers to the intentional misreporting or manipulation of factual information (Dechow, Sloan, and Sweeney, 1996; Dyck, Morse, and Zingales, 2010), such as falsifying environmental performance metrics, underreporting emissions, or concealing regulatory violations. It constitutes a direct violation of rules or objective truth and is typically verifiable through independent audits or third-party data. In contrast, deceptive language involves the strategic use of vague, ambiguous, or overly optimistic wording in corporate disclosures (Larcker and Zakolyukina, 2012; Bushee, Gow, and Taylor, 2018). This form of impression management does not necessarily entail factual inaccuracies but instead aims to mislead stakeholders through selective emphasis, omission, or

[11] Similar to Larcker and Zakolyukina (2012), we assume that managers possess private information about firms' environmental performance and that formal narratives may provide cues about disclosure strategies.

linguistic obfuscation.

We model the interaction as a sequential game in which managers privately observe firm fundamentals and pollution intensity, choose disclosure language at date 0, and face potential regulatory and market detection at date 1. Following Aghamolla and Smith (2023), consider a firm that chooses the intensity of deceptive ESG language (ESG obfuscated disclosure) $d \geq 0$ as a function of two observable states: (i) its overall fundamental strength θ and (ii) its environmental exposure, proxied by emissions e. Let $B(d; \theta, e)$ denote the short-run valuation or reputational benefit from deceptive disclosure, and let $C(d; \theta, e)$ denote the implementation and compliance cost. Monitoring and enforcement are summarized by a detection technology $p(e, d) \in [0, 1]$, which denotes the probability that deception is detected once additional verifiable ESG information becomes available. Detection imposes a discounted loss $L(\theta) > 0$, such as regulatory penalties, litigation risk, or reputational damage. We do not impose any specific functional form on B, C, or p; instead, we work with the following reduced-form objective:

$$U(d; \theta, e) = B(d; \theta, e) - C(d; \theta, e) - \beta\, p(e, d) L(\theta), \tag{1}$$

where $\beta \in (0, 1]$ is a discount factor that captures the fact that detection typically occurs with a delay. This reduced-form objective can be interpreted as the manager's expected payoff in a two-player game between the firm and external monitors, where detection probabilities reflect equilibrium monitoring intensity rather than a structural parameter to be estimated. For an interior solution $d^*(\theta, e)$, the first-order condition (FOC) is

$$B_d(d^*; \theta, e) - C_d(d^*; \theta, e) - \beta\, p_d(e, d^*) L(\theta) = 0, \tag{2}$$

where subscripts denote partial derivatives. Equation (2) summarizes the trade-off behind deceptive disclosure: the marginal valuation benefit B_d is balanced against the marginal implementation cost C_d and the discounted marginal increase in expected detection losses $\beta\, p_d L(\theta)$.

3.1.1 Camouflage Channel and Average Positive Effect

We are interested in how emissions affect the optimal level of deception. Differentiating the FOC with respect to e yields

$$\frac{\partial d^*(\theta, e)}{\partial e} \propto -\frac{\partial}{\partial e}\Big(\beta\, p_d(e, d^*) L(\theta)\Big) + \frac{\partial}{\partial e}\Big(B_d(d^*; \theta, e) - C_d(d^*; \theta, e)\Big), \tag{3}$$

Hence, the sign of $\partial d^{*}/\partial e$ depends on how emissions change (i) the marginal detection risk and expected loss, and (ii) the marginal benefits and costs of using ESG language to support polluting operations.

In our institutional setting, which focuses on regulated EPA-registered firms, we assume that the marginal enforcement and reputation costs of ESG deception do not increase one-for-one with emissions. This assumption reflects institutional features such as limited monitoring capacity, delayed public disclosure of regulatory findings, and heterogeneous investor attention. Intuitively, firms can expand polluting activities while relying less on external finance, and regulatory and reputational sanctions do not increase one-for-one with emissions. Under this condition, the *camouflage channel* dominates the disciplinary channel, so that for any given firm type θ,

$$\frac{\partial d^{*}(\theta, e)}{\partial e} > 0. \tag{4}$$

That is, among polluting firms, higher emissions are associated with more deceptive ESG language, independent of their current financial performance.

Equation (4) is a model-free comparative static: it relies only on the relative slopes of marginal benefits and expected detection costs with respect to emissions, rather than on a specific signal structure or on whether θ and d enter additively.

3.2 Two-Period Dynamic Foundation and Illustrative Cases

We now embed the static framework in a minimal dynamic environment and use simple specifications to illustrate the policy functions that our empirical tests are designed to detect. The timing captures a simple asymmetric information environment: managers observe (θ, e) at date 0, choose disclosure language d_0, and outside investors update their beliefs only after new verifiable signals arrive at date 1.

3.2.1 Two-Period Bellman Equation

Time is $t = 0, 1$. At $t = 0$, the firm observes its state (θ, e) and chooses deceptive disclosure $d_0 \geq 0$. At $t = 1$, additional verifiable information arrives (for example, external assurance reports, regulatory filings, or realized incident data), and past deception can be detected and punished.

Let $V_1(\theta, e)$ denote the continuation value before detection. If deception is detected, the firm incurs a loss $L(\theta)$; otherwise, it retains $V_1(\theta, e)$. The date-0 Bellman equation is

$$\begin{aligned} V_0(\theta, e) = \max_{d_0 \geq 0} \Big\{ & B(d_0; \theta, e) - C(d_0; \theta, e) \\ & + \beta \big[(1 - p(e, d_0)) V_1(\theta, e) + p(e, d_0)(V_1(\theta, e) - L(\theta)) \big] \Big\}. \end{aligned} \tag{5}$$

Because $V_1(\theta, e)$ does not depend on d_0, the firm's choice problem is equivalent to maximizing

$$B(d_0; \theta, e) - C(d_0; \theta, e) - \beta\, p(e, d_0) L(\theta), \tag{6}$$

which coincides with the reduced-form objective in Equation (1). The resulting FOC is identical to Equation (2). Thus, the two-period DP provides a timing interpretation of the model-free framework without imposing additional structure or requiring structural estimation.

3.2.2 Illustrative Policy Functions

To visualize how pollution affects deceptive disclosure, we consider several simple specifications of $U(d; \theta, E)$, all consistent with Equations (1)–(2). These examples are meant to be illustrative; the main comparative statics do not rely on any particular specification. In all cases, the optimal deception choice $d^*(\theta, E)$ solves the model-free first-order condition

$$B_d(d^*; \theta, E) - C_d(d^*; \theta, E) - \beta\, p_d(E, d^*)\, L(\theta) = 0,$$

and the goal is not to impose a structural model but to illustrate robust economic channels through which emissions E affect deception.

Throughout the examples, we distinguish two firm types, $\theta = \alpha$ ("strong" firms) and $\theta = \beta$ ("weak" firms). Strong firms have greater access to internal funds and a better ability to manage reputational risks, which we capture through higher marginal benefits and/or lower expected losses from detection. This yields both higher levels of deception and steeper responses to changes in pollution while preserving the positive sign in Equation (4) for both types. These parameterized examples are provided solely for illustration. The empirical analysis does not estimate these parameters, and the numerical magnitudes should not be interpreted as structural calibrations.

Case A: Linear Policy with Affine Detection. Suppose that the reduced-form payoff for type θ is

$$U_\theta(d_0; e) = a_\theta d_0 - \frac{1}{2} b_\theta d_0^2 - \beta L_\theta \big(p_{d,\theta} d_0 + p_{ed,\theta} e d_0 \big), \tag{7}$$

up to terms independent of d_0. The FOC is linear and yields a closed-form linear policy

$$d_\theta^*(e) = \frac{a_\theta - \beta L_\theta (p_{d,\theta} + p_{ed,\theta} e)}{b_\theta}, \tag{8}$$

with slope

$$\frac{\partial d_\theta^*(e)}{\partial e} = -\frac{\beta L_\theta p_{ed,\theta}}{b_\theta}. \tag{9}$$

Choosing $p_{ed,\theta} < 0$ for the firms in our sample produces an upward-sloping policy function consistent with Equation (4).

Economically, this specification captures environments where the marginal enforcement intensity is approximately linear and where incremental ESG embellishment incurs smoothly increasing costs. This corresponds to settings in which SEC/EPA monitoring increases gradually with the extent of deception and where public relations, legal, and compliance costs scale proportionally with the amount of language management. Strong firms place a higher value on maintaining a green narrative and face weaker financing discipline, implying a larger marginal benefit of deception and, therefore, a steeper pollution–deception slope.

Case B: Logistic Detection and Nonlinear Policy. To capture bounded detection probabilities and nonlinear monitoring, consider

$$p(e, d_0) = \sigma(g_0 + g_e e + g_d d_0), \quad \sigma(x) = \frac{1}{1 + e^{-x}}, \tag{10}$$

and a quadratic instantaneous benefit and cost. The FOC becomes

$$a_\theta - b_\theta d_0 - \beta L_\theta \sigma'(g_0 + g_e e + g_d d_0) g_d = 0, \tag{11}$$

which has no closed-form solution. The optimal policy $d_\theta^*(e)$ is defined implicitly and obtained via numerical root-finding. The shape of $d_\theta^*(e)$ reflects the same positive emissions–deception relationship as in Case A, but with smooth nonlinearities.

In many empirical settings, the probability that ESG deception is detected is bounded due to limited regulatory resources or the inherent noise in text-based scrutiny. Logistic detection captures this realistic feature: as pollution and deception increase, detection becomes more likely but eventually saturates. This specification shows that our main prediction–that higher emissions raise optimal deception–does not require linearity or closed-form solutions. Even under highly nonlinear and bounded monitoring, the pollution–deception relation remains positive, and the slope is larger for strong firms.

Case C: Cubic First-Order Condition (Convex Reputational and Legal Costs). Finally, to allow for richer curvature while keeping the structure simple, consider a quartic penalty

$$U_\theta(d_0; e) = a_\theta d_0 - \frac{1}{2} b_\theta (1 + \kappa_\theta e) d_0^2 - \frac{1}{4} c_\theta d_0^4. \tag{12}$$

The FOC is a cubic equation given by:

$$a_\theta - b_\theta(1 + \kappa_\theta e) d_0 - c_\theta d_0^3 = 0, \tag{13}$$

whose unique positive root defines $d_\theta^*(e)$ for each e. Numerical solutions again deliver upward-sloping policy functions under parameter values consistent with Equation (4).

In industries subject to strong public scrutiny, the marginal cost of ESG deception can rise sharply as deception increases. For example, when legal, reputational, or third-party assurance risks escalate. This environment can be captured with quartic cost structures, generating a cubic first-order condition. Although the exact shape of $d^*(\theta, E)$ depends on parameter curvature, the pollution–deception slope remains positive across firm types, and slope heterogeneity emerges naturally because strong firms internalize larger reputational stakes.

Case D: Attention-Amplified Narrative Benefits. We model institutional attention A as affecting the marginal benefit of environmental narratives rather than the probability of detection. Specifically, suppose the short-term narrative payoff satisfies $B_d(d; \theta, E, A)$ with $\partial B_d / \partial A > 0$. Closer institutional attention increases the capital market impact of environmental narratives, thereby amplifying the marginal benefit of deceptive language in the early information stage. As a result, the pollution–deception slope becomes steeper for high-attention firms:

$$\frac{\partial^2 d^*(\theta, E, A)}{\partial E \partial A} > 0.$$

This mechanism is consistent with the empirical evidence showing that the association between pollution and deception is stronger when institutional ownership and market attention are higher.

Case E: Financially Strong Firms More Sensitive to Deception. The existing theoretical literature argues that firms with strong financial performance should have lower emissions and, therefore, correspond to lower deception (Chen, 2023). Our case shows that the strong-type firm is more sensitive to the level of deception, exhibiting a steeper pollution–deception relation. This preceding case is consistent with our empirical findings and repositions Chen's (2023) example as a special case. To illustrate this distinction, consider a quadratic specification:

$$U_\theta(d;E) = a\,d - \tfrac{1}{2}b\,d^2 - \beta L(\theta)\big(p_0 + p_E E\big)\,d,$$

with $L(\alpha) > L(\beta) > 0$ capturing larger reputational losses for high-profile firms and $p_0 > 0 > p_E$ capturing a modestly declining marginal detection intensity as pollution rises. The optimal deception level is

$$d^*_\theta(E) = \frac{a - \beta L(\theta)\big(p_0 + p_E E\big)}{b}.$$

For any θ, $\partial d^*_\theta(E)/\partial E > 0$, such that more polluted firms optimally resort to more deceptive ESG disclosures. At the same time, because $L(\alpha) > L(\beta)$, strong firms choose less deception at every E:

$$d^*_\alpha(E) - d^*_\beta(E) < 0,$$

but respond more strongly to changes in pollution:

$$\frac{\partial d^*_\alpha(E)}{\partial E} > \frac{\partial d^*_\beta(E)}{\partial E} > 0.$$

Thus, slope heterogeneity holds even when level ordering is reversed. This example aligns precisely with our empirical tests based on pollution–performance interactions: the effect of emissions on deceptive ESG language is more pronounced for financially stronger firms.

Case F: Staggered Information Revelation. To illustrate the dynamic timing structure underlying our empirical findings, we consider a simple two-period sequential game with staggered information arrival. The dates (date 0, date 1, and date 2) in this illustrative structure represent information stages rather than fixed calendar intervals. In the empirical analysis, we proxy these stages using semiannual windows within fiscal year $t + 1$, reflecting the gradual incorporation of regulatory information into market prices. The model does not require that these stages correspond exactly to half-year periods; instead, it captures the qualitative timing wedge between early market reactions and later regulatory disclosure.

At date 0, managers privately observe firm fundamentals and pollution intensity (θ, E) and choose environmental disclosure language d_0. At date 1, capital market participants observe a noisy signal about environmental performance, while regulatory authorities may acquire more precise information but do not immediately disclose it publicly. At date 2, regulatory findings become publicly available, allowing investors to fully update their beliefs. Let the manager's expected payoff at date 0 be:

$$U(d_0; \theta, E) = B(d_0; \theta, E) - p_1(E, d_0)L_1(\theta) - \delta\, p_2(E, d_0)L_2(\theta), \tag{14}$$

where $B(d_0; \theta, E)$ captures short-term capital market benefits from favorable environmental narratives; $p_1(E, d_0)$ is the probability that deception is detected by markets in the early stage (date 1); $p_2(E, d_0)$ is the probability that regulatory information is eventually revealed (date 2); $L_1(\theta)$ and $L_2(\theta)$ denote short- and long-run losses from detection; and $\delta \in (0, 1)$ is a discount factor.

Importantly, we allow for $p_2(E, d_0) > p_1(E, d_0)$ to reflect that regulatory monitoring may be more precise than early market inferences, even though regulatory information becomes public with a delay. The manager's best response satisfies the first-order condition:

$$B_d(d_0; \theta, E) = p_{1d}(E, d_0)L_1(\theta) + \delta\, p_{2d}(E, d_0)L_2(\theta). \tag{15}$$

This condition highlights a key timing mechanism: when early-stage detection is limited (i.e., p_{1d} is small), short-term narrative benefits may dominate expected penalties, leading to higher optimal deception at date 0. However, once regulatory information becomes public, the long-run loss component materializes, attenuating any short-term capital market benefits.

This staggered information structure generates a temporary window during which deceptive environmental disclosure can influence market outcomes before regulatory signals are fully incorporated into prices. The mechanism does not require persistent market inefficiency; rather, it reflects gradual information diffusion across institutional channels. We emphasize that this formulation is illustrative and does not impose a fully specified equilibrium structure. The empirical analysis does not estimate the structural parameters (p_1, p_2, L_1, L_2); instead, the framework serves to clarify the comparative statics underlying the observed timing patterns.

Illustrative Implications of the Framework. Across a range of functional specifications (Appendix J), the model generates three robust qualitative predictions. First, Deception increases with pollution under limited early detection. Second, financially stronger firms exhibit a steeper pollution–deception slope. Third, Short-term valuation benefits attenuate after delayed regulatory revelation. The numerical examples in Appendix J demonstrate that these comparative statics arise under linear, nonlinear, and cubic detection structures.

3.3 Hypothesis Development

Hypothesis 1 (Emissions and Deceptive ESG Language) *Firms increase their ESG deceptive language when their environmental pollution is higher.*

Within the model-free framework developed in Section 3, and in the sequential information structure described in Case F, the firm's optimal level of deceptive ESG language is given by $d^*(\theta, E)$, which solves the first-order condition:

$$B_d(d^*; \theta, E) - C_d(d^*; \theta, E) - \beta\, p_d(E, d^*)\, L(\theta) = 0.$$

Totally differentiating the first-order condition with respect to emission intensity E yields:

$$\frac{\partial d^*}{\partial E} \;\propto\; \frac{\partial}{\partial E}\big[B_d(d^*; \theta, E) - C_d(d^*; \theta, E)\big] - \frac{\partial}{\partial E}\big[\beta\, p_d(E, d^*)\, L(\theta)\big].$$

The sign of $\partial d^*/\partial E$ therefore depends on the relative rate at which emission intensity affects the marginal operational benefits of maintaining a green image and the marginal expected costs of detection and punishment. In the staggered information environment of Case F, emission intensity affects both short-term narrative benefits and expected detection losses. When early-stage market detection is limited and regulatory information becomes public with a delay, higher pollution increases the short-term marginal benefits of favorable narratives more rapidly than the discounted expected penalties. Under these conditions, the short-term disclosure incentive dominates, implying that:

$$\frac{\partial d^*(\theta, E)}{\partial E} > 0.$$

That is, holding firm fundamentals constant, higher environmental pollution leads firms to optimally engage in more deceptive ESG disclosures during the early information stage. This prediction does not rely on persistent market inefficiency; rather, it reflects a temporary timing wedge between early market inference and later regulatory revelation. This comparative static is consistent with a large body of empirical evidence showing that ESG is primarily perceived as a reputation risk or an asymmetric risk, one that is especially pronounced during downside cycles (Karpoff, Lott, and Wehrly, 2005; Fritsch, Zhang, and Zheng, 2025; Aobdia and Yoon, 2025) [12].

Hypothesis 2 (Financial Performance, Emissions, and Deception) *The association between*

[12] Databases such as RepRisk consider negative ESG events as the key drivers of their ESG indices. This also implies that the costs of ESG are given greater attention by stakeholders.

environmental pollution and ESG deceptive disclosures is more pronounced for firms with stronger financial performance and greater growth opportunities.

In the sequential game, financial performance affects the firm's best-response to pollution through its influence on both narrative benefits and expected detection losses. Let θ_H and θ_L denote strong and weak firms, respectively [13]. Our empirical tests correspond to the theoretical prediction that the marginal effect of emissions on deception is larger for strong firms:

$$\frac{\partial d^*(\theta_H, E)}{\partial E} > \frac{\partial d^*(\theta_L, E)}{\partial E},$$

or, equivalently, $\partial^2 d^*(\theta, E)/(\partial E\, \partial\theta) > 0$. This prediction is consistent with the interaction estimates documented in our empirical analysis.

Furthermore, it is supported by several strands of literature. Shapiro (1983) argues that high-quality firms enjoy reputation premiums from investors. In the context of earnings management, Strobl (2013) provides theoretical support, showing that firms have greater incentives to manipulate earnings during favorable economic conditions due to lower capital costs. Moreover, empirical studies have demonstrated that both greenwashing and environmental violations impose reputational costs on firms (Karpoff, Lott, and Wehrly, 2005; Akyildirim et al., 2023). These findings are consistent with the view that financially stronger firms face different marginal disclosure trade-offs, resulting in a steeper pollution–deception slope. This conclusion also aligns with a core premise in Aghamolla and Smith (2023), which finds that average investors respond most strongly to complex, informative disclosures and least to obfuscated ones—an effect that significantly influences model outcomes.

4 Measurements, Data, and Research Design

4.1 Measuring Deceptive Disclosure in Environmental Topics

To assess the degree to which a firm engages in deceptive environmental disclosures, we construct a measure of topic-specific deception. This measure consists of the set of topics T. In our specific

[13] In Case F, stronger firms may have greater short-term narrative benefits B_d or lower effective discounting of future penalties, leading to a steeper best-response of deception to pollution.

setting, we let T=E (environment). To account for variation in transcript length, we scale the count by the total number of words in the conference call transcript of firm i in quarter q, denoted $W_{i,q}$. We also have an indicator function (1[•]) to determine if one word in the call transcript is within a given set of topics.

Next, we adapt the methodology from Larcker and Zakolyukina (2012) to create a deception dictionary, D, compiled from three distinct sources: the Linguistic Inquiry and Word Count, synonyms from the lexical English database WordNet, and a word list created by Larcker and Zakolyukina (2012) specifically for firms' conference calls, focusing on general knowledge, shareholder value, and value creation, among other topics. Drawing on this dictionary, we identify linguistic patterns associated with deceptive communication, including the use of general or impersonal pronouns, vague or non-specific references to environmental initiatives, and linguistic features linked to obfuscation or uncertainty.

We then assign each keyword a value of -1 (+1) based on its hypothesized association with deception or truthfulness, respectively, according to Larcker and Zakolyukina (2012). Specifically, following Larcker and Zakolyukina (2012), we partition the dictionary D (see Appendix G) into two subsets. D_p, which means a collection of words in set D is positively correlated with deception, indicating a higher (lower) level of deception (truthfulness). D_n, which means a collection of words in set D is negatively correlated with deception, indicating a lower (higher) level of deception (truthfulness). Following this setting, our deception sentiment (weight) function, $DEC(w)$, is as follows:

$$DEC(w) = \begin{cases} 1 & \text{if } w \in D_p \\ -1 & \text{if } w \in D_n \\ 0 & \text{if } w \notin D \end{cases}$$

We calculate the total net count by subtracting the number of truthful keywords from deceptive words, considering a 10-word before- and after window, S, centralized by a target topic word (Hassan et al., 2019). Our study uses an environmental word dictionary (see in Internet Appendix E) created by (Henry, Jiang, and Rozario, 2024). The function that captures deception is as follows:

$$DECEPT_{i,q} = \frac{1}{W_{i,q}} \sum_{w=1}^{W_{i,q}} \left(\mathbb{1}[w \in E] \times \sum_{w}^{w \in S} DEC(w) \right)$$

Finally, the net count is scaled by the total number of words (in thousands). Then, we average all the quarterly level measures to an annual measure in a given year [14]. The framework is general and can be extended to other ESG-related topics by replacing E with alternative topic dictionaries (e.g., climate change). For instance, in our alternative measure tests, we replaced our environmental dictionary with a climate change dictionary, and the results hold.[15] Our final metric, $DECEPT$, represents the average net count of deceptive keywords in proximity to environmental keywords, scaled by the total number of words (in thousands) in the conference call across all conference calls for the firm during the year t.

The advantage of using conference call data is that it captures both prepared remarks and spontaneous Q&A interactions, where managers directly engage with investors on financial and sustainability matters. In contrast to 10-K reports, which are typically prepared and edited for consistency, conference calls may reflect more contemporaneous managerial communication. Although one may argue that narratives in conference calls can also be scripted, and it is possible that the list of participants can be controlled in a conference call setting (Mayew, 2008; Cohen, Lou, and Malloy, 2020), the spontaneity of the communications during conference calls is less planned and thus has greater authenticity in reflecting disclosers' feelings about the content.

4.2 Measuring Corporate Environmental Performance

We use the Toxic Release Inventory (TRI) data as a proxy for environmental performance. In 1986, Congress enacted the Emergency Planning and Community Right-to-Know Act (EPCRA) to improve emergency preparedness and provide the public with access to information regarding

[14] Larcker and Zakolyukina (2012) proposed expanding the list of hesitation keywords that are commonly used in firms' conference calls for keyword categories like "shareholder value" and "value creation" However, these words are used less frequently in conference calls regarding deception because executives may be concerned about future litigation associated with deception due to the inconsistency between their statements and their actual knowledge about the subject matter. They also categorize the extent of deception contained in managers' use of self-referencing words such as "I" or "me". They argue that the use of self-referencing words, such as first-person singular pronouns, emphasizes an individual's ownership of a statement; in contrast, liars try to dissociate themselves from their words by using fewer of, or even entirely omitting, these first-person pronouns, instead replacing them with group referencing words such as plural pronouns like "we" or "us" Due to the extremely high frequency of appearance of these self-referencing words and the ambiguous hypothesized signs of these words, we excluded this category of keywords from our main analyses.

[15] The reason we chose the environmental dictionary instead of the climate change dictionary in our main test is that we hoped to match the central words and deceptive words as both unigrams.

hazardous chemical releases in their communities. Section 313 of the EPCRA established the TRI program, which requires facilities to report annually to the Environmental Protection Agency (EPA) on their releases of toxic substances that pose long-term risks to human health and the environment.

Although TRI data are self-reported, reporting is subject to EPA oversight and potential penalties, enhancing credibility relative to many third-party ESG ratings [16]. Additionally, toxic releases are physically traceable and can be independently verified. Not all firms are subject to TRI reporting requirements. In general, the regulation applies to facilities in sectors such as manufacturing, metal mining, electric utilities, and commercial hazardous waste treatment [17].

We follow prior studies (Chatterji, Levine, and Toffel, 2009; Akey and Appel, 2021; Xu and Kim, 2022; Thomas et al., 2022) and use total toxic releases as the primary measure of corporate environmental performance. This variable captures the total volume of toxic chemicals released to land, water, and air at the plant-year level. According to the official statistics from the EPA website, the total volume of the TRI toxic chemical list contains 799 individually listed chemicals and 33 chemical categories in the year 2024 [18]. We aggregate these data to the firm-year level to construct the main independent variable and scale it by total sales, $TOXIC\_INTENSITY$, which serves as a firm-level intensity-based measure of corporate environmental performance (Zhang, 2025).

4.3 Data Overview

Overall, our sample starts with the universe of 469,851 conference call transcripts provided by Thomson Reuters StreetEvents over the period from Jan 1, 2002, to December 31, 2019. We map 48.7% (228,912/469,851) of these transcripts to 40,512 firm-years in the Compustat-CRSP merged database. We then retain the remaining 7,186 firm-years that have available TRI total emission information and financial variables for the analysis. To ensure comparability in disclosure inten-

[16] Many studies rely on ESG ratings to proxy for environmental performance; however, such ratings often suffer from issues such as rating disagreement and disclosure-based methodologies, which may reflect greenwashing rather than actual environmental outcomes.

[17] For further details, see: https://www.uscompliance.com/blog/toxic-release-inventory-reporting-process-and-considerations/

[18] See details in https://www.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals

sity, our final sample includes 5,730 firm-years that discuss environmental issues in at least one conference call within the year [19].

Table 1 provides the industry distribution of the sample. The manufacturing industry takes the largest share in the sample, followed by business equipment and the chemical and allied product industries, consistent with the greater environmental exposure of firms in these industries [20].

4.4 Research Design

We estimate the following baseline regression to examine firms' use of deceptive environmental disclosure:

$$\begin{aligned} DECEPT_{it} = \beta_0 + \beta_1\, TOXIC\_INTENSITY_{i,t-1} &+ \text{Control Variables} \\ &+ \text{Firm Fixed Effects} + \text{Year Fixed Effects} + \eta_{it} \end{aligned} \tag{16}$$

In the equation, the dependent variable is $DECEPT$, which measures the extent to which a firm deceives in its environmental disclosures during conference calls. The key independent variable is firm-level environmental performance, which is inherently multidimensional. We use the total amount of released toxic emissions, scaled by the total sales in that year, $TOXIC\_INTENSITY_{i,t}$, as our measure of a firm's environmental performance for its real environmental risk exposure (Zhang, 2025). This scaling controls for firm size and production scale. As Zhang (2025) show, while carbon emissions are positively correlated with corporate revenues, a higher value of $TOXIC\_INTENSITY$ in our setting does not necessarily indicate higher absolute pollution levels or superior financial performance. Rather, it reflects the relative environmental cost per unit of economic output.[21]

We also acknowledge that this measure captures only several dimensions of environmental performance, rather than a comprehensive environmental score. For example, toxic emissions

[19] This final data size is very similar to existing studies such as Thomas et al. (2022). The reason for ruling out 1,456 observations (7,186-5,730) is that these non-disclosure firms will have the same measurement ($DECEPT$=0) as those firms that disclose environmental information but do not use deceptive language or disclose biased, deceptive language. Because non-disclosure firms and non-deceptive disclosure firms have conceptually distinct interpretations of $DECEPT = 0$, we exclude the former to maintain the interpretability of the measure. The detailed sample distribution by year can be found in Appendix D.

[20] Our results are robust after excluding the firms in the manufacturing industry, which make up 31% of the sample.

[21] Although the relationship between financial performance and pollution is not mechanical in this context, a higher level of relative environmental cost still indicates poorer environmental performance. This interpretation does not undermine the other components of our paper.

differ in severity and environmental impact and do not reflect broader dimensions, such as resource use or biodiversity effects.

We include standard firm-level controls that may influence disclosure incentives (Ali, Klasa, and Yeung, 2014; Bushman et al., 2004; Li, 2008; Li et al., 2010; Miller, 2010; Dyer, Lang, and Stice-Lawrence, 2017). These variables include firm size ($SIZE$), financial leverage (LEV), growth (MTB), liquidity ($TURNOVER$), and profitability (ROA and $Loss$). We further control for capital market incentives related to disclosure behavior by including the number of analysts following (log_ANA) (Bozanic and Thevenot, 2015; Lehavy, Li, and Merkley, 2011) as well as whether a firm is incentivized to meet or beat consensus analyst forecasts (MBE) or to avoid restatements ($RESTATE$) (Thomas et al., 2022). We include other linguistic features of firms' disclosures that may correlate with deceptive disclosure features as additional control variables, including the vagueness and readability of disclosures based on the adapted Fog index (FOG) in the conference call settings (Li, 2008) and the net sentiment of management wording in conference calls ($SENTIMENT$) (Loughran and McDonald, 2011). All specifications include firm and year fixed effects to account for time-invariant firm characteristics and common shocks. All standard errors are clustered at the firm level to account for potential serial correlation and heteroskedasticity within firms over time.

Table 2 presents the descriptive statistics of the sample. The mean (median) values for $DECEPT$ are -0.055 (-0.015), suggesting that firms, on average, utilize less deceptive language in their environmental disclosure.

4.5 Deception Justification

Because the deception measure ($DECEPT$) is newly constructed, we conduct validation tests before proceeding with the baseline analysis. We evaluate the validity of $DECEPT$ along two dimensions: (1) whether linguistic deception is associated with disagreement in environmental ratings, and (2) whether the deception measure is correlated with environmental penalties imposed by the Environmental Protection Agency (EPA).

To capture the first dimension, we obtain environmental rating scores from three independent sources: *Bloomberg*, *Sustainalytics*, and *Asset4*. We use these three providers because they report environmental scores on a comparable 0–100 scale, facilitating the construction of a disagreement measure. Following the methodology of Berg, Kölbel, and Rigobon (2022), we calculate the standard deviation of the three environmental scores for each firm-year observation. The resulting measure, denoted as $E\_DISAGREE$, serves as a proxy for environmental rating disagreement. We then estimate simple one-to-one regressions of $E\_DISAGREE$ on $DECEPT$.

To examine the second dimension, we follow Yu (2022) and utilize the Violation Tracker database to validate our deception measure. The Violation Tracker database reports both total penalty amounts and federal-level penalty amounts for environmental violations. Using this information, we construct two variables: $PENALTY\_AMOUNT$ and $FEDERAL\_PENALTY$. These two measures are both scaled by 10^5. We then run one-to-one regressions of these penalty measures on $DECEPT$, including firm and year fixed effects [22].

Table 3 reports the validation results for our dependent variable. Columns (1) and (2) show a strong positive association between $DECEPT$ and ESG disagreement, significant at the 1% level, suggesting that deceptive language is associated with greater divergence in environmental ratings [23]. The difference in sample size between Columns (1) and (2) reflects the use of a large language model (LLM) to screen transcripts for environmental content, as well as the requirement that all three rating agencies cover the same firm-year observations. Columns (3) and (4) present the results for environmental penalties. We find positive and statistically significant associations between $DECEPT$ and both total and federal-level penalty amounts. As an additional validation, we restrict the sample to firm-years with nonzero penalties.

[22] We include firm and year fixed effects in the second validation test because firms do not incur environmental violation penalties every year. In contrast, for ESG disagreement, it is reasonable to expect relatively few sharp changes in environmental ratings within a small sample covering a limited number of firms. Therefore, we do not include fixed effects in the ESG disagreement regressions.

[23] One possible explanation is that ESG rating agencies rely on different information sets: some raters may incorporate private or proprietary information, leading their assessments to deviate from others that are more influenced by firms' observable—but potentially deceptive—disclosures.

5 Empirical Results

5.1 Baseline Results

After validating our deception measure, we examine the association between toxic emission intensity and environmental deceptive disclosures. Table 4 reports the main regression results. The coefficients on $TOXIC\_INTENSITY$ are 0.020, 0.018, and 0.019 in columns (1), (2), and (3), respectively, and are statistically significant at the 5% or 1% levels. These estimates are consistent with Hypothesis 1, indicating that firms with higher relative toxic emissions engage in more deceptive environmental disclosures.

In terms of economic magnitude, a one-standard-deviation increase in toxic releases—holding other variables at their sample means—is associated with approximately a 2% increase in the probability of deceptive environmental language (based on column (3)). Relative to the sample standard deviation of $DECEPT$ (0.227), this corresponds to an economically meaningful 11.2% increase.

Turning to control variables, the coefficient on ROA is positive and statistically significant, suggesting that firms with stronger financial performance are more likely to engage in deceptive environmental disclosures. Columns (2) and (3) additionally control for disclosure readability (FOG) following Li (2008) and sentiment ($SENTIMENT$) following Loughran and McDonald (2011). Both variables are measured at $t + 1$ to align with the timing of environmental disclosure. Consistent with prior linguistic evidence (Bushee, Gow, and Taylor, 2018), less readable and more negatively toned disclosures are associated with higher levels of environmental deception. Importantly, the coefficient on $TOXIC\_INTENSITY$ remains stable after including these controls, suggesting that the documented relationship is not driven by general disclosure opacity.

5.2 Robustness of Main Results

We conduct several additional tests to assess the robustness of the baseline findings. First, firms may employ different disclosure strategies across conference call contexts. We therefore reconstruct $DECEPT$ separately for earnings and non-earnings conference calls and further distinguish between narrative sessions and Q&A sessions. As shown in Table 5, the coefficient on $TOXIC\_INTENSITY$ remains positive and statistically significant across all specifications. These results indicate that the documented association is not driven by a specific disclosure setting [24].

Second, measurement noise may arise because $DECEPT$ captures environmental discussions beyond toxic emissions. To address this concern, we construct a climate-specific deception measure (CC_DECEPT) based on the top 200 climate-related keywords developed by Sautner et al. (2023). The keywords are listed in Appendix F. Our results in Table 6 confirm that the positive association between toxic intensity and deception persists under this narrower definition.

5.3 Refining Measurement via Large Language Models

Recent research suggests that dictionary-based text measures may contain measurement error (Fritsch, Zhang, and Zheng, 2025). To further validate our findings, we construct two large-language-model-based deception measures using Llama 3.2-3B. First, we restrict attention to 21-word windows surrounding environmental keywords and use the LLM to verify environmental relevance. Second, conditional on relevance, the LLM assigns a continuous deception score (0–100). We construct two transcript-level measures: one based on window-level aggregation ($DECEPT\_LLM\_W$), and one based on sentence-level scoring ($DECEPT\_LLM\_S$). The details are provided in Appendix I.

Table 7 reports results using these alternative measures. Across all specifications with controls and fixed effects, the coefficient on $TOXIC\_INTENSITY$ remains positive and statistically significant. We interpret these results as supportive robustness evidence. Given potential concerns regarding the opacity of LLM decision processes, our primary inference continues to rely on the baseline dictionary-based measure.

[24] A detailed distribution of conference call types is reported in Appendix D.

5.4 Endogeneity Concerns

To address potential endogeneity concerns, we conduct a series of identification strategies. Given that environmental deception is measured with a lag, reverse causality is less likely to drive the observed relationship. Therefore, our identification strategy primarily targets the issue of omitted variable bias.

First, we implement change specifications to mitigate concerns that unobserved, time-invariant firm characteristics—potentially correlated with both environmental performance and deceptive disclosure behavior—are confounding the results. As reported in Panel A of **Table 8**, the coefficient on $TOXIC\_INTENSITY$ remains positive and statistically significant, suggesting that the main findings are not solely driven by such omitted variables.

Second, we allow the effect of $TOXIC\_INTENSITY$ to vary across industries and years by interacting it with industry and year fixed effects in the main regression model. This approach controls for the possibility that certain industries in specific years exhibit systematically different relationships between environmental performance and deception. As a result, concerns about omitted variable bias arising from heterogeneous time trends are mitigated. The results, reported in **Table 8** Panel B, show that the main relationship remains quantitatively stable and statistically significant.

Third, we exploit an exogenous shock stemming from changes to the Toxic Release Inventory (TRI) reporting requirements, specifically the addition of new toxic chemicals to the TRI list by the EPA. These changes mechanically worsen affected firms' reported environmental performance, as firms are required to disclose additional toxic emissions, even if their actual production methods remain unchanged. This exogenous deterioration in reported performance provides an opportunity to examine how firms adjust their environmental disclosure language in response.

Conceptually, when firms are mandated to report newly listed toxic substances, their total reported toxic release inevitably increases—assuming other emissions remain constant—purely due to the expanded scope of disclosure. Importantly, this increase does not necessarily reflect a rise in actual pollution, nor does it affect firms' revenues, since the underlying chemical outputs are unchanged; the firm is simply being more transparent. However, investors may perceive this increase in reported emissions as a signal of deteriorating environmental performance, potentially triggering reputational or financial consequences. As a result, managers may have incentives to obfuscate such changes by adopting more deceptive or vague language in environmental disclosures. In more strategic cases, firms may even reallocate pollution toward unreported chemical categories, but nonetheless be compelled to reveal more authentic pollution data for the newly reportable substances due to EPA's expansion.[25]

Specifically, under the Emergency Planning and Community Right-to-Know Act, the EPA is authorized to periodically expand the TRI chemical list to improve public access to information on toxic exposures. Since the inception of the TRI program, the EPA has implemented multiple rounds of chemical additions, often informed by scientific advances in chemical toxicity and other regulatory overlaps. These additions did not require firms to collect new data, as many already monitored these substances for other compliance purposes. Thus, the resulting increase in reported toxic emissions is unlikely to reflect real changes in production processes or pollution levels, but rather a shift in reporting standards.

Notably, from 2000 to 2011, there were no TRI chemical additions, offering a stable pre-treatment period. Between 2011 and 2019, however, the EPA introduced several expansions across different categories of toxic releases.[26] Our empirical design leverages these expansions between 2011 and 2019. We hypothesize that firms more heavily affected by these regulatory changes—i.e., those required to disclose additional emissions due to newly listed chemicals—are more likely to use deceptive language in their environmental communications, in an attempt to mitigate investor reactions to perceived increases in environmental risk.

Specifically, we follow Gormley and Matsa (2011) and use a cohort-based matching approach such that the environmental performance of each treatment firm ($TREAT = 1$) is affected after the new chemical items are included in the expanded chemical list. We then match each treatment firm with a control firm operating in the same Fama-French 48 industries but whose environmental performance is not affected by the expanded chemical items list ($TREAT = 0$). We then keep

[25] This case closely resembles the findings of Duchin, Gao, and Xu (2025), who show that firms often reallocate rather than reduce pollution. Specifically, firms may shift emissions toward unregulated or non-reportable substances while reducing emissions of those that are subject to public disclosure.

[26] See details: https://www.epa.gov/toxics-release-inventory-tri-program/expansion-toxics-release-inventory-program

observations for the treatment and control firms five years before ($POST = 0$) and after ($POST = 1$) the expansion. Results in column 1 of **Table 8** panel C continue to show a positive and significant coefficient on $TREAT \times POST$. We also re-run the regression by adding the time dummy variables to show the parallel trend of the effect of changes in firms' environmental performance due to the expansion of the chemical lists and firms' deceptive environmental disclosures and present the related results in column 2. Our inferences remain unchanged.

5.5 Chemical Expansion Heteogeneity

As previously noted, our main independent variable, $TOXIC\_INTENSITY$, represents an aggregate measure of toxic releases. It is thus important to explore which specific types of toxic emissions drive the observed effects on environmental deception. The EPA's chemical inventory includes over 700 distinct toxic substances, and understanding the implications of each requires considerable technical expertise, both for managers and investors. To maintain clarity and relevance, this study focuses on two of the most commonly reported and policy-relevant emissions: nitrogen oxides (NOx) and sulfur oxides (SOx), such as nitrogen dioxide and sulfur dioxide.

To empirically investigate this heterogeneity, we obtain environmental performance data from the Asset4 database and use two specific indicators: "NOx Emissions to Revenues" ($TOXIC\_NOx$) and "SOx Emissions to Revenues" ($TOXIC\_SOx$). Both variables are scaled by firm revenue, ensuring consistency with the construction of our main independent variable. Carbon-based emissions are excluded from this analysis, as carbon dioxide is typically treated as a greenhouse gas rather than a toxic substance, and thus falls outside the scope of toxic release classifications.

Using a triple difference-in-differences specification, **Table 9** presents the results on chemical-specific heterogeneity. Column (1) shows that NOx emissions are positively associated with deceptive disclosure, although the effect is not significant. In contrast, column (2) reveals a statistically significant and economically larger effect of SOx emissions on environmental deception, with the coefficient roughly twice as large and significant at the 5% level. These findings suggest there is notable heterogeneity across different types of toxic emissions, implying that managers and investors may perceive and respond to them differently.

5.6 Empirical Results on Financial Performance

Guided by Hypothesis 2, we examine whether the pollution–deception association is stronger among firms with superior financial performance. To proxy for firm performance, we construct three measures: abnormal profitability (R_ROA), Tobin's Q ($Tobin\_Q$), and sales growth (Sal_Growth), following theoretical guidance by Zhang (2000). We partition the sample into high and low groups based on each measure and re-estimate the baseline regressions.

Tables 10 and 11 show that the positive association between $TOXIC\_INTENSITY$ and $DECEPT$ is significantly stronger among firms with higher profitability and growth opportunities. These findings are consistent with the theoretical prediction that firms with greater valuation exposure have stronger incentives to strategically manage environmental narratives.

An alternative explanation is that firms may engage in deceptive environmental disclosures not to dampen valuation penalties from poor environmental performance per se, but rather as a function of their financing needs. That is, financially constrained firms may place greater emphasis on preserving favorable capital market perceptions because they have a more urgent demand for external capital, especially equity financing (Baker and Wurgler, 2002; Faulkender and Petersen, 2006).

To disentangle this competing hypothesis, we further examine financial constraints using the Whited–Wu index (Whited and Wu, 2006). Table 12 shows that the positive pollution–deception relation is concentrated among less financially constrained firms ($CONSTN$ = low). A Chow test confirms that coefficient differences across constraint groups are statistically significant ($p < 0.05$). This pattern suggests that deceptive environmental disclosure is more closely linked to capital market valuation incentives than to financing necessity through ESG channel (Baker et al., 2024).

6 Additional Tests on Timing and Attention

6.1 Disclosure Timing on Environmental Deception

Prior literature emphasizes that disclosure timing affects the market impact of corporate information (Doyle and Magilke, 2009; Myers et al., 2018). In addition, managers may strategically allocate disclosures across communication channels to shape stakeholder perceptions (Jung et al., 2018). More recently, Foerderer and Schuetz (2022) document that firms time the release of negative ESG information to mitigate reputational costs. Motivated by this evidence, we examine whether the timing of environmental deception varies with the public availability of verifiable environmental data.

Under the Toxic Release Inventory (TRI) program administered by the U.S. Environmental Protection Agency (EPA), firms are required to report toxic emissions by July 1 of the following calendar year. Before TRI data are publicly released, firms possess private information regarding their emissions, whereas investors do not. This institutional feature creates a predictable window of information asymmetry within the calendar year.

To exploit this setting, we partition environmental disclosures into those made in the first half of the calendar year ($DECEPT\_E$) and those in the second half ($DECEPT\_L$). We then re-estimate the baseline regressions using these two measures. In addition, we conduct a contemporaneous specification to capture managerial responses within the same year but using FOG and $SENTIMENT$ measured at time t to mitigate potential look-ahead bias.

Table 13 reports the results. The coefficient on $TOXIC\_INTENSITY$ remains positive and statistically significant in the $DECEPT\_E$ specification (column 1), but becomes statistically insignificant in the $DECEPT\_L$ specification (column 2). Column (3) presents the contemporaneous specification, and the results show a similar pattern to that observed in the first half of the following year.

These findings are consistent with firms increasing deceptive environmental disclosures during periods when emissions data are not yet publicly observable and reducing such disclosures once verifiable information becomes available. The evidence suggests that the pollution–deception relation is concentrated in periods characterized by higher information asymmetry.

6.2 Institutional Attention and Strategic Environmental Deception

Prior research shows that capital market attention influences information dissemination and firm valuation (Antweiler and Frank, 2004; Tetlock, 2011; Peress, 2014). Institutional investors, in particular, both demand environmental information and serve as governance monitors (Chung and Zhang, 2011; Aggarwal et al., 2011; Cohen, Kadach, and Ormazabal, 2023; Ilhan et al., 2023). These dual roles imply competing predictions. On the one hand, greater institutional attention may increase firms' incentives to present favorable environmental narratives. On the other hand, enhanced monitoring could constrain opportunistic disclosure behavior.

To examine these competing mechanisms, we construct a measure of capital market attention, MKT_ATTN, based on institutional ownership from Form 13F filings. We define MKT_ATTN as an indicator equal to one if a firm's institutional ownership exceeds the sample median (including zero-ownership firms in the low-attention group). We then re-estimate the baseline regressions separately for high- and low-attention subsamples.

Table 14 shows that the coefficient on $TOXIC\_INTENSITY$ is positive and statistically significant at 99% in the high MKT_ATTN subsample, but statistically insignificant in the low-attention subsample. The difference in coefficients across subsamples is statistically significant. These results suggest that the pollution–deception association is stronger among firms subject to greater institutional attention.

Taken together, the evidence is more consistent with the interpretation that institutional attention amplifies valuation incentives related to environmental narratives rather than primarily functioning as a deterrent through monitoring.

7 Consequence Test

We next examine whether deceptive environmental disclosures are associated with capital market outcomes. These tests aim to assess whether the documented pollution–deception relation has economically meaningful implications for firms' financing conditions and valuation.

Prior literature shows that ESG-related information is incorporated into investor decisionmaking and reflected in asset prices (Flammer, 2013; Dimson, Karakaş, and Li, 2015; Grewal, Riedl, and Serafeim, 2019). Building on this evidence, we focus on two direct capital market outcomes: annual stock returns ($RETURN$) and the implied cost of equity capital (COE) (Gebhardt, Lee, and Swaminathan, 2001). To align with our timing analysis, we separately construct first-half-year and second-half-year measures, corresponding to periods when TRI information is not yet publicly released versus when it becomes observable.

Table 15 reports the results. We find that firms with both higher toxic emissions and higher levels of deceptive environmental disclosure exhibit significantly higher returns and lower implied costs of capital in the first half of the year. In contrast, these associations weaken or become statistically insignificant in the second half of the year. These patterns are consistent with capital markets initially pricing environmental narratives under conditions of greater information asymmetry, with adjustments occurring once more verifiable information becomes available [27].

We next examine whether deceptive environmental disclosures are associated with firms' access to external equity financing and capital from environmentally oriented investors. Specifically, we consider seasoned equity offerings (SEO) and green fund ownership ($GREENFUND$), consistent with prior studies on equity issuance and ESG-related capital flows (DeAngelo, DeAngelo, and Stulz, 2010; Kim and Purnanandam, 2014; Raghunandan and Rajgopal, 2022).

SEO is an indicator equal to one if a firm conducts a seasoned equity offering during the year. $GREENFUND$ follows Cohen, Gurun, and Nguyen (2020) and identifies ESG-oriented funds based on fund names containing "ESG" or "green". We further supplement this classification using data from the Forum for Sustainable and Responsible Investment (USSIF).

Table 16 shows that firms with higher toxic emissions and higher levels of deceptive environmental disclosure are more likely to issue seasoned equity (significant at the 99% level) and receive greater inflows from green funds (significant at the 90% level), particularly in the first half of the year. These findings are consistent with the interpretation that environmental narratives may affect firms' access to capital during periods of elevated information asymmetry.

Finally, we examine whether deceptive environmental disclosures are associated with firms'

[27] Because toxic emissions and environmental deception are jointly determined within firms, our analysis focuses on their interaction effects to capture conditional capital market responses.

environmental ratings. Prior research suggests that environmental ratings influence investor allocations and firm valuation (Chatterji, Levine, and Toffel, 2009; Serafeim and Yoon, 2022). If environmental narratives shape rating assessments, deception may attenuate the negative association between emissions and ratings.

Using annual environmental ratings from Refinitiv Asset4, Table 17 shows that the interaction between toxic emissions and deception is positive and statistically significant. This suggests that, conditional on pollution levels, firms engaging in more deceptive environmental disclosure experience a weaker negative association between emissions and environmental ratings.

To test this empirically, we use annual environmental ratings from Refinitiv's Asset4 database. As shown in **Table 17**, the positive and significant coefficient on the interaction term indicates that deception helps polluted firms mitigate the negative impact of poor environmental performance on their ratings. These results echo concerns raised by Hopwood (2009) that if underperforming firms can preserve their environmental reputation through disclosure alone, they may have reduced incentives to implement real improvements in environmental performance.

8 Conclusion

This study examines firms' use of deceptive environmental language during conference calls and its association with capital market outcomes. Building on prior research (Larcker and Zakolyukina, 2012), we develop a novel linguistic measure designed to quantify deceptive communication in corporate disclosures across topics. We apply this measure to firms' discussions of environmental performance during conference calls. Our empirical results indicate that firms with higher toxic emission intensity exhibit greater use of deceptive environmental language. This association is stronger among firms with superior financial performance, higher growth opportunities, and lower financial constraints—firms for which environmental narratives may have greater valuation relevance.

We further examine disclosure timing and find that the pollution–deception relation is concentrated in periods characterized by information asymmetry, namely when firms possess private information about their emissions before the public release of TRI data. During these periods, higher emissions combined with deceptive language are associated with higher contemporaneous returns, lower implied costs of equity, greater likelihood of seasoned equity issuance, increased green fund ownership, and more favorable environmental ratings. These associations attenuate once emissions data become publicly available. Our findings suggest that environmental narratives are priced by capital markets, particularly when verifiable environmental performance data are not yet observable.

Overall, this study contributes to the literature on ESG disclosure, capital market information processing, and green investment. By documenting systematic variation in environmental disclosure language and its conditional market associations, we provide evidence relevant to ongoing discussions about greenwashing, disclosure credibility, and the informational role of corporate communication. For real world implications, this study highlights the challenges investors and regulators face in detecting linguistic deception (Chisholm and Feehan, 1977; Spranca, Minsk, and Baron, 1991). By revealing how deceptive environmental disclosures can distort market perceptions, the research contributes to anti-greenwashing efforts and enhances stakeholders' ability to assess the reliability of firms' environmental claims.

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Table 1: Industry Distribution

This table reports the distribution of main observations based on Fama-French 12 Industries. The variable definitions can be found in Appendix A.

Fama-French 12 Industry Name	**# Firm-Years**	**% Firm-Years**
Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	1763	30.77%
Business Equipment – Computers, Software, and Electronic Equipment	858	14.97%
Chemicals and Allied Products	543	9.48%
Utilities	501	8.74%
Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	463	8.08%
Consumer Durables – Cars, TVs, Furniture, Household Appliances	366	6.39%
Healthcare, Medical Equipment, and Drugs	351	6.13%
Consumer Non-Durables – Food, Tobacco, Textiles, Apparel, Leather, Toys	346	6.04%
Oil, Gas, and Coal Extraction and Products	286	4.99%
Wholesale, Retail, and Some Services (Laundries, Repair Shops)	208	3.63%
Finance	34	0.59%
Telephone and Television Transmission	11	0.19%
Total	**5730**	**100%**

Table 2: Summary Statistics

This table reports the summary statistics of major variables between year 2002 and 2019. The variable definitions can be found in Appendix A.

Variable	N	Mean	Median	P25	P75	SD
$DECEPT_{it+1}$	5,730	-0.055	-0.015	-0.104	0.034	0.227
$TOXIC\_INTENSITY_{it}$	5,730	0.378	0.011	0.000	0.114	1.343
CC_DECEPT_{it+1}	5,730	-0.002	0.000	-0.001	0.000	0.009
$DECEPT\_LLM\_W_{it+1}$	3,145	36.261	35.000	20.000	54.250	21.626
$DECEPT\_LLM\_S_{it+1}$	3,145	33.385	30.909	15.000	51.250	22.431
$SIZE_{it}$	5,730	8.311	8.197	7.121	9.549	1.640
LEV_{it}	5,730	0.578	0.585	0.460	0.706	0.194
MTB_{it}	5,730	3.067	2.283	1.549	3.582	4.088
$TURNOVER_{it}$	5,730	1.053	0.932	0.634	1.293	0.639
ROA_{it}	5,730	0.045	0.049	0.022	0.083	0.078
$LOSS_{it}$	5,730	0.144	0.000	0.000	0.000	0.351
$\log(ANA_{it})$	5,730	2.238	2.303	1.792	2.833	0.690
MBE_{it}	5,730	0.678	1.000	0.000	1.000	0.467
$RESTATE_{it}$	5,730	0.136	0.000	0.000	0.000	0.342
FOG_{it}	5,730	94.965	94.829	89.924	99.733	7.512
$SENTIMENT_{it}$	5,730	8.599	8.518	4.929	11.975	5.350
$RETURN\_E_{it+1}$	5,699	0.093	0.033	-0.102	0.168	0.517
$RETURN\_L_{it+1}$	5,699	0.133	0.058	-0.099	0.220	0.662
SEO_E_{it+1}	5,730	0.040	0.000	0.000	0.000	0.197
SEO_L_{it+1}	5,730	0.036	0.000	0.000	0.000	0.187
$ENVSCORE_{it+1}$	3,877	0.416	0.422	0.174	0.634	0.274
$GREENFUND\_E_{it+1}$	5,730	0.550	1.000	0.000	1.000	0.497
$GREENFUND\_L_{it+1}$	5,730	0.559	1.000	0.000	1.000	0.497
$E\_DISAGREE_{it+1}$	1,414	14.217	14.375	10.667	17.632	5.204
$PENALTY\_AMOUNT_{it+1}$	300	3,201.255	5.000	2.000	17.850	29420.256
$FEDERAL\_PENALTY_{it+1}$	254	26.704	3.094	1.400	9.200	150.597

Table 3: Justification: Environmental Deception and ESG Outcomes

This table provides justification evidence linking environmental deception to subsequent ESG outcomes and regulatory penalties. Columns (1) and (2) examine ESG rating outcomes, while Columns (3) and (4) examine monetary penalties. The sample used in column (2) is a sub-sample of column (1), which is screened by LLM for environmental topics. The difference between column (3) and column (4) is whether the penalty is conducted by a Federal Agency. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

VARIABLES	$E\_DISAGREE$	$E\_DISAGREE$	$PENALTY\_AMOUNT$	$FEDERAL\_PENALTY$
	(1)	(2)	(3)	(4)
$DECEPT$	2.264***	2.165***	7363.069*	42.027**
	(3.25)	(2.98)	(1.82)	(2.53)
Observations	1,414	896	300	254
Firm FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
R-squared	0.013	0.017	0.246	0.266

Table 4: Baseline Results

This table examines the relationship between toxic release ($TOXIC\_INTENSITY$) and environmental deception ($DECEPT$). All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$		
	(1)	(2)	(3)
$TOXIC\_INTENSITY_{i,t}$	0.020***	0.018**	0.019***
	(2.71)	(2.50)	(2.65)
$SIZE_{i,t}$		-0.018*	-0.018*
		(-1.68)	(-1.68)
$LEV_{i,t}$		-0.008	-0.008
		(-0.22)	(-0.22)
$MTB_{i,t}$		0.001	0.001
		(0.78)	(0.78)
$TURNOVER_{i,t}$		-0.016	-0.016
		(-1.27)	(-1.27)
$ROA_{i,t}$		0.124*	0.124*
		(1.69)	(1.69)
$LOSS_{i,t}$		-0.002	-0.002
		(-0.18)	(-0.18)
$\log(ANA_{i,t})$		-0.003	-0.003
		(-0.28)	(-0.28)
$MBE_{i,t}$		-0.010	-0.010
		(-1.51)	(-1.51)
$RESTATE_{i,t}$		-0.004	-0.004
		(-0.30)	(-0.30)
$FOG_{i,t+1}$			-0.003***
			(-3.17)
$SENTIMENT_{i,t+1}$			-0.006***
			(-5.89)
Observations	5,730	5,730	5,730
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.19	0.19	0.20

Table 5: Robustness Check on Different Contexts

This table examines the robustness of different conference call contexts. Panel A discusses earnings calls vs. non-earnings calls. Panel B discusses narrative parts and Q&A parts in the same conference calls. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Panel A: Earnings Conference Calls vs. Non-Earnings Conference Calls	Dependent Variable $DECEPT_{i,t+1}$	
	Earnings Calls (1)	Non-Earnings Calls (2)
$TOXIC\_INTENSITY_{i,t}$	0.019***	0.029**
	(2.65)	(2.46)
Controls	Yes	Yes
Observations	5,690	3,986
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.20	0.26

Panel B: Narratives and Q&A in Conference Calls	Dependent Variable $DECEPT_{i,t+1}$	
	Narratives (1)	Q&A (2)
$TOXIC\_INTENSITY_{i,t}$	0.037***	0.017**
	(2.91)	(2.09)
Controls	Yes	Yes
Observations	4,476	3,978
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.30	0.10

Table 6: Alternative Measures

This table examines the robustness of environmental deception by using a different climate change dictionary (CC_DECEPT). All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$CC\_DECEPT_{i,t+1}$
	(1)
$TOXIC\_INTENSITY_{it}$	0.001*
	(1.82)
Observations	5,730
Controls	Yes
Firm FE	Yes
Year FE	Yes
Adj_R2	0.20

Table 7: Large Language Model Measure Results

This table examines the relationship between toxic release ($TOXIC\_INTENSITY$) and environmental deception ($DECEPT$). The linguistic deception independent variable is reconstructed via large language models. Our deception score is either based on 21-word windows ($DECEPT\_LLM\_W$) or sentences ($DECEPT\_LLM\_S$) with central environmental words. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT\_LLM\_Wi, t+1$			$DECEPT\_LLM\_Si, t+1$		
	(1)	(2)	(3)	(4)	(5)	(6)
$TOXIC\_INTENSITY_{i,t}$	1.016*	2.152***	1.060**	1.137*	2.230***	1.016*
	(0.612)	(0.609)	(0.476)	(0.652)	(0.573)	(0.612)
$SIZE_{i,t}$		0.0888	-0.562		0.413	0.0670
		(0.669)	(1.205)		(0.681)	(1.272)
$LEV_{i,t}$		10.19**	1.970		12.55***	7.278
		(4.470)	(4.471)		(4.657)	(5.083)
$MTB_{i,t}$		-0.511***	-0.214**		-0.506***	-0.204**
		(0.132)	(0.0924)		(0.140)	(0.0969)
$TURNOVER_{i,t}$		-3.249***	-1.229		-3.467***	1.112
		(1.145)	(1.478)		(1.199)	(1.615)
$ROA_{i,t}$		-32.10***	13.35		-37.85***	3.171
		(12.18)	(8.173)		(13.45)	(9.900)
$LOSS_{i,t}$		-2.302	2.251		-4.753**	0.694
		(1.973)	(1.391)		(2.077)	(1.596)
$\log(ANA_{i,t})$		-2.629*	-0.239		-2.531*	1.348
		(1.367)	(1.119)		(1.436)	(1.335)
$MBE_{i,t}$		0.630	0.472		1.207	0.989
		(0.878)	(0.755)		(0.917)	(0.741)
$RESTATE_{i,t}$		0.200	1.170		-0.145	0.913
		(1.686)	(1.142)		(1.700)	(1.256)
$FOG_{i,t+1}$		0.0595	0.103		0.128	0.264***
		(0.0812)	(0.0678)		(0.0841)	(0.0777)
$SENTIMENT_{i,t+1}$		-0.217**	0.258**		-0.258**	0.201*
		(0.0986)	(0.105)		(0.104)	(0.108)
Observations	3,145	3,145	3,145	3,145	3,145	3,145
Firm FE	Yes	No	Yes	Yes	No	Yes
Year FE	Yes	No	Yes	Yes	No	Yes
Adj. R^2	0.56	0.08	0.58	0.55	0.09	0.56

Table 8: Endogeneity Concern Tests

This table addresses the endogeneity problem. Panel A is about change analysis. Panel B is about using $TOXIC\_INTENSITY$ interacted with industry fixed effect. Panel C is about the effect of changes in TRI disclosure requirements on the deceptive level of environmental disclosures. Treatment firms report new chemical releases after TRI expansions between 2011 and 2019, while control firms are in the same Fama-French 48 industry but do not report any new chemicals five years before and after each expansion. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Panel A: Change Analyses	**Dependent Variable** $\Delta DECEPT_{i,t+1}$	
$\Delta TOXIC\_INTENSITY_{i,t}$	0.041**	
	(2.48)	
Controls	Yes	
Observations	5,502	
Industry FE	Yes	
Year FE	Yes	
Adjusted R^2	0.01	
Panel B: Allowing the Coefficient of Toxic Release Intensity to Vary	**Dependent Variable** $DECEPT_{i,t+1}$	
$TOXIC\_INTENSITY_{i,t}$	0.016**	
	(2.22)	
Controls	Yes	
Observations	5,730	
Industry FE	Yes	
Year FE	Yes	
$TOXIC\_INTENSITY\times$ Industry FE	Yes	
$TOXIC\_INTENSITY\times$ Year FE	Yes	
Adjusted R^2	0.08	
Panel C: Expansion of TRI Chemical List and Deceptive Level	**Dependent Variable** $DECEPT_{i,t+1}$	
	(1)	(2)
$TREAT_i \times POST_t$	0.037**	
	(2.12)	
$TREAT_i \times YEAR(-4,-3)$		0.011
		(0.30)
$TREAT_i \times YEAR(-2,-1)$		-0.050
		(-1.18)
$TREAT_i \times YEAR(+1,+2)$		0.064**
		(2.08)
$TREAT_i \times YEAR(+3,+5)$		-0.013
		(-0.40)
Controls	Yes	Yes
Observations	2,765	2,765
Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Adjusted R^2	0.23	0.23

Table 9: Chemical Expansion Heterogeneity

This table examines the effect of changes in TRI disclosure requirements on the deceptive level of environmental disclosures. Treatment firms report new chemical releases after TRI expansions between 2011 and 2019, while control firms are in the same Fama-French 48 industry but do not report any new chemicals five years before and after each expansion. $TOXIC\_NOx$ is a continuous variable which measures the intensity of NOx emission intensity (scaled by revenue), while $TOXIC\_SOx$ is a continuous variable which measures the intensity of SOx emission intensity (scaled by revenue). All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$	
	(1)	(2)
$TREAT_i \times POST_t \times TOXIC\_NOx$	0.038	
	(1.70)	
$TREAT_i \times POST_t \times TOXIC\_SOx$		0.061**
		(2.36)
Controls	Yes	Yes
Observations	2,765	2,765
Firm FE	Yes	Yes
Cohort-Year FE	Yes	Yes
Adjusted R^2	0.23	0.24

Table 10: Financial Performance

This table examines how profitability (R_ROA) affects the relationship between toxic release and environmental deceptive languages for firms. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$	
	$R\_ROA = High$	$R\_ROA = Low$
	(1)	(2)
$TOXIC\_INTENSITY_{it}$	0.034***	0.012
	(2.61)	(1.16)
Controls	Yes	Yes
Observations	2,862	2,868
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.23	0.21

Table 11: Growth Opportunity

This table examines how growth option ($TobinsQ$ and Sal_Growth) affects the relationship between toxic release and environmental deceptive languages for firms. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$			
	Tobin's Q = High	Tobin's Q = Low	Sal_Growth = High	Sal_Growth = Low
	(1)	(2)	(3)	(4)
$TOXIC\_INTENSITY_{it}$	0.041**	0.006	0.028***	0.008
	(2.32)	(0.85)	(2.75)	(0.55)
Observations	2,862	2,868	2,865	2,865
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.27	0.19	0.18	0.21

Table 12: Financial Constraints

This table examines how financial constraints ($CONSTN$) affect the relationship between toxic release and environmental deceptive languages for firms. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$	
	CONSTN = Low	CONSTN = High
	(1)	(2)
$TOXIC\_INTENSITY_{it}$	0.028**	0.003
	(2.28)	(0.40)
Observations	2,877	2,853
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.24	0.16

Table 13: Disclosure Timing of Firms Deceptive Environmental Disclosure

This table examines firm toxic release and the disclosure timing of using environmental deceptive language. The timing is categorized at year t+1 for both the first half and the second half, and at year t for instant response. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$		$DECEPT_{i,t}$
	First Half	Second Half	Contemporary
	(1)	(2)	(3)
$TOXIC\_INTENSITY_{it}$	0.022***	0.002	0.013**
	(3.02)	(0.25)	(2.01)
Observations	5,688	5,389	5,678
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.13	0.12	0.18

Table 14: Capital Market Attention from Institutional Investors

This table examines how institutional ownership (MKT_ATTN) affects the relationship between toxic release and environmental deceptive language for firms. All continuous variables are winsorized at the 1% level. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent variable	$DECEPT_{i,t+1}$	
	MKT_ATTN = High	MKT_ATTN = Low
	(1)	(2)
$TOXIC\_INTENSITY_{it}$	0.027***	0.013
	(3.26)	(1.27)
Observations	2,865	2,865
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.20	0.21

Table 15: Capital Market Consequence

This table reports the regression results examining the market consequence of capital market reaction by high-pollution firms using linguistic deception on environmental topics. The left panel reports effects on the annual stock return ($RETURN$), while the right panel focuses on the implied cost of capital (COE). Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent Variable	Stock Return		Implied Cost of Capital	
	(1) $RETURN\_E_{i,t+1}$	(2) $RETURN\_L_{i,t+1}$	(3) $COE\_E_{i,t+1}$	(4) $COE\_L_{i,t+1}$
$DECEPT\_HIGH_{i,t+1} \times TOXIC\_INTENSITY_{i,t}$	0.005***	0.000	-0.010**	-0.004
	(2.90)	(0.02)	(-2.01)	(-0.41)
$DECEPT\_HIGH_{i,t+1}$	-0.154	-0.134	0.002	0.002
	(-1.63)	(-1.63)	(0.38)	(0.39)
$TOXIC\_INTENSITY_{i,t}$	-0.000	0.005	0.009**	0.012**
	(-0.04)	(0.91)	(2.14)	(1.98)
$SIZE_{it}$	-0.069	0.001	-0.011**	-0.015***
	(-0.65)	(0.01)	(-2.19)	(-2.72)
LEV_{it}	1.244	0.646	0.015	0.015
	(1.35)	(1.31)	(0.52)	(0.48)
MTB_{it}	-0.030	-0.016	-0.002**	-0.001*
	(-1.48)	(-1.37)	(-2.51)	(-1.77)
$TURNOVER_{it}$	-0.091	-0.090	-0.033***	-0.034***
	(-1.06)	(-1.10)	(-2.59)	(-2.73)
ROA_{it}	1.642	0.920	-0.571***	-0.401***
	(1.38)	(1.08)	(-5.83)	(-3.69)
$LOSS_{it}$	0.153	0.083	0.081***	0.102***
	(1.25)	(0.81)	(5.32)	(5.78)
MBE_{it}	-0.010	0.062	-0.007	-0.005
	(-0.22)	(1.23)	(-0.92)	(-0.73)
$CAPEX_{it}$	2.930	1.262	0.413*	0.516**
	(0.90)	(0.56)	(1.89)	(2.46)
RD_{it}	3.096	3.341	0.068	0.063
	(1.32)	(1.11)	(0.36)	(0.38)
$ADVER_{it}$	6.414	8.244	0.147	0.287
	(0.90)	(1.04)	(0.77)	(1.35)
SGA_{it}	-0.405	-0.099	0.100	0.093
	(-0.69)	(-0.19)	(1.47)	(1.52)
OCF_{it}	-1.163	-1.680	-0.029	-0.241***
	(-1.21)	(-1.26)	(-0.36)	(-2.85)
$\log(ANA_{it})$	0.036	-0.053	-0.000	-0.000
	(0.28)	(-0.64)	(-0.01)	(-0.03)
$RESTATE_{it}$	-0.019	0.064	0.017*	0.016*
	(-0.21)	(0.87)	(1.80)	(1.68)
FOG_{it}	0.005	0.006	0.001*	0.000
	(0.66)	(0.99)	(1.74)	(0.56)
$SENTI_{it}$	0.021	0.007	-0.003***	-0.004***
	(0.90)	(0.43)	(-3.22)	(-4.47)
Observations	5,143	5,143	4,151	4,648
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.07	0.14	0.32	0.31

Table 16: Seasonal Equity Offering and Green Fund Investment Finance Consequence

This table reports the regression results examining the market consequence of financing by highly polluted firms using linguistic deception on environmental topics. The left panel reports effects on the likelihood of seasoned equity offerings (*SEO*), while the right panel focuses on green fund holdings (*GREENFUND*). Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent Variable	Seasoned Equity Offering		Green Fund Holdings	
	(1)	(2)	(3)	(4)
	$SEO\_E_{i,t+1}$	$SEO\_L_{i,t+1}$	$GREENFUND\_E_{i,t+1}$	$GREENFUND\_L_{i,t+1}$
$DECEPT\_HIGH_{i,t+1} \times TOXIC\_INTENSITY_{i,t}$	0.001***	-0.001*	0.008*	-0.002
	(2.66)	(-1.76)	(1.67)	(-0.34)
$DECEPT\_HIGH_{i,t+1}$	-0.010*	-0.002	-0.005	0.015
	(-1.89)	(-0.40)	(-0.43)	(1.07)
$TOXIC\_INTENSITY_{i,t}$	-0.000***	0.001	-0.015*	-0.014*
	(-3.59)	(1.13)	(-1.76)	(-1.81)
$SIZE_{it}$	-0.014***	-0.013***	0.053***	0.039***
	(-3.40)	(-3.97)	(3.73)	(2.63)
LEV_{it}	0.072***	0.068***	-0.034	-0.083
	(2.92)	(3.62)	(-0.49)	(-1.06)
MTB_{it}	0.001	0.000	0.005**	0.003
	(0.65)	(0.56)	(2.50)	(1.00)
$TURNOVER_{it}$	-0.004	-0.019**	0.028	-0.020
	(-0.42)	(-2.14)	(0.78)	(-0.74)
ROA_{it}	-0.236**	-0.188**	0.216	0.023
	(-2.43)	(-2.45)	(1.44)	(0.13)
$LOSS_{it}$	-0.009	-0.003	-0.004	-0.010
	(-0.65)	(-0.25)	(-0.17)	(-0.29)
MBE_{it}	0.017**	0.017***	-0.006	0.031**
	(2.19)	(2.65)	(-0.46)	(2.16)
$CAPEX_{it}$	0.185	0.354***	-0.013	-0.422
	(1.50)	(3.11)	(-0.04)	(-1.30)
RD_{it}	0.187	0.096	0.073	-0.379
	(1.59)	(0.55)	(0.28)	(-1.30)
$ADVER_{it}$	-0.047	-0.087	0.344	-1.399*
	(-0.35)	(-0.57)	(0.46)	(-1.67)
SGA_{it}	-0.032	0.012	0.146	0.749***
	(-0.76)	(0.24)	(0.81)	(5.11)
OCF_{it}	-0.144**	-0.062	0.458***	0.549***
	(-2.20)	(-0.90)	(3.04)	(3.26)
$\log(ANA_{it})$	0.016**	0.004	0.190***	0.199***
	(2.15)	(0.70)	(8.35)	(7.79)
$RESTATE_{it}$	-0.015**	0.004	0.028	0.043*
	(-1.98)	(0.46)	(1.21)	(1.77)
FOG_{it}	0.000	0.001**	-0.002	-0.001
	(0.63)	(2.10)	(-1.38)	(-0.78)
$SENTI_{it}$	-0.000	-0.000	0.002	0.006***
	(-0.15)	(-0.56)	(1.04)	(2.82)
Observations	5,172	5,172	5,172	5,172
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.07	0.06	0.43	0.22

Table 17: Impact of Environmental Deception on Ratings

This table reports the regression results examining the market consequence of ESG ratings ($ENVSCORE$) by high-pollution firms using linguistic deception on environmental topics. Robust t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The variable definitions can be found in Appendix A.

Dependent Variable	ENVSCORE	
$DECEPT\_HIGH_{i,t+1} \times TOXIC\_INTENSITY_{i,t}$		0.001**
		(2.12)
$DECEPT\_HIGH_{i,t+1}$	-0.005	-0.006
	(-0.68)	(-0.83)
$TOXIC\_INTENSITY_{i,t}$	-0.001*	-0.002**
	(-1.68)	(-2.28)
$SIZE_{it}$	0.119***	0.118***
	(13.91)	(13.93)
LEV_{it}	-0.022	-0.022
	(-0.48)	(-0.47)
MTB_{it}	-0.001	-0.001
	(-0.66)	(-0.66)
$TURNOVER_{it}$	-0.033	-0.033
	(-1.60)	(-1.61)
ROA_{it}	0.193**	0.189**
	(1.99)	(1.97)
$LOSS_{it}$	-0.023	-0.024
	(-1.42)	(-1.48)
MBE_{it}	-0.006	-0.006
	(-0.86)	(-0.82)
$CAPEX_{it}$	-0.060	-0.049
	(-0.23)	(-0.19)
RD_{it}	0.075	0.078
	(0.42)	(0.43)
$ADVER_{it}$	-0.395	-0.388
	(-0.64)	(-0.63)
SGA_{it}	0.416***	0.412***
	(3.09)	(3.07)
OCF_{it}	-0.126	-0.128
	(-1.18)	(-1.21)
$\log(ANA_{it})$	0.063***	0.063***
	(4.12)	(4.11)
$RESTATE_{it}$	0.011	0.011
	(0.70)	(0.70)
FOG_{it}	0.001	0.001
	(1.62)	(1.60)
$SENTI_{it}$	0.002*	0.002*
	(1.69)	(1.71)
Observations	3,400	3,400
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adj_R2	0.67	0.67

Online Appendix for "Strategic Environmental Deception"

A Variable Definitions

Table A1: Variable Definitions

Variable	Definition
Deception Variables	
$\text{DECEPT}_{i,t+1}$	The measure captures the degree of deceptive environmental language in the management disclosure after netting out negation terms and scaled by the total number of words. DECEPT is measured using conference call transcripts in year t+1. (Source: Thomson Reuters, Larcker and Zakolyukina (2012), Henry, Jiang, and Rozario (2024))
$\text{DECEPT\_E}_{i,t+1}$	Deception measure constructed using the transcripts in the first half of year $t + 1$. (Source: Thomson Reuters, Larcker and Zakolyukina (2012), Henry, Jiang, and Rozario (2024))
$\text{DECEPT\_L}_{i,t+1}$	Deception measure constructed using the transcripts in the second half of year $t + 1$. (Source: Thomson Reuters, Larcker and Zakolyukina (2012), Henry, Jiang, and Rozario (2024))
$\text{DECEPT}_{i,t}$	Deception measure constructed using transcripts in year t. (Source: Thomson Reuters, Larcker and Zakolyukina (2012), Henry, Jiang, and Rozario (2024))
$\text{CC\_DECEPT}_{i,t+1}$	Deceptive environmental language that appears in the neighborhood of top 200 climate-related words. (Source: Thomson Reuters, Larcker and Zakolyukina (2012), Sautner, van Lent, Vilkov, and Zhang (2023))

Table A1 (continued)

Variable	**Definition**
DECEPT_LLM_W$_{i,t+1}$	The measure captures the degree of deceptive environmental language in the management disclosure via large language model on a 0-100 range. The scored contexts are based on 21 environmental keyword windows in a given transcript. The keyword is within environmental list and the context is verified by large language model for a environment discussion. DECEPT is measured using conference call transcripts in year $t + 1$. (Source: Thomson Reuters)
DECEPT_LLM_Si, $t + 1$	The measure captures the degree of deceptive environmental language in the management disclosure via large language model on a 0-100 range. The scored contexts are based on environmental keyword sentences in a given transcript. The keyword is within environmental list and the context is verified by large language model for a environment discussion. DECEPT is measured using conference call transcripts in year $t + 1$. (Source: Thomson Reuters)
Capital Market Consequences	
SEO_E$_{it+1}$	An indicator variable equals to 1 if a firm conducts SEO in the first half of year $t + 1$, and 0 otherwise. (Source: SDC)
SEO_L$_{it+1}$	An indicator variable equals to 1 if a firm conducts SEO in the second half of year $t + 1$, and 0 otherwise. (Source: SDC)
GREENFUND_E$_{it+1}$	An indicator variable equals to 1 if a firm is held by green funds in the first half of year $t+1$, and 0 otherwise. (Source: USSIF, Cohen, Gurun, and Nguyen (2020))
GREENFUND_L$_{it+1}$	An indicator variable equals to 1 if a firm is held by green funds in the second half of year $t + 1$, and 0 otherwise. (Source: USSIF, Cohen, Gurun, and Nguyen (2020))
RETURN_E$_{it+1}$	The raw buy-and-hold stock returns in the first half of year $t+1$. (Source: Compustat)
RETURN_L$_{it+1}$	The raw buy-and-hold stock returns in the second half of year $t + 1$. (Source: Compustat)

Table A1 (continued)

Variable	Definition
COE_E_{it+1}	The implied cost of equity based on Gebhardt, Lee, and Swaminathan (2001) in the first half of year $t+1$. (Source: IBES, Compustat)
COE_L_{it+1}	The implied cost of equity based on Gebhardt, Lee, and Swaminathan (2001) in the second half of year $t+1$. (Source: IBES, Compustat)
$ENVSCORE_{t+1}$	The rating score of environmental pillar in Refinitiv. We multiply by minus one so that higher values represent worse environmental performance. (Source: Asset 4)
Explanatory Variables	
$TOXIC\_INTENSITY_{i,t}$	The total amount of toxic emissions scaled by sales revenue in year t. (Source: EPA, Compustat)
$MBE_{i,t}$	An indicator variable equals to 1 if the firm meets or beats analyst forecast at t-1, and 0 otherwise. (Source: IBES)
$SIZE_{it}$	Logarithm of total assets. (Source: Compustat)
LEV_{it}	Total liabilities divided by total assets. (Source: Compustat)
MTB_{it}	Market-to-book ratio. (Source: Compustat)
$TURNOVER_{it}$	Sales divided by total assets. (Source: Compustat)
$ROA_{i,t}$	Net income divided by total assets. (Source: Compustat)
$LOSS_{it}$	An indicator variable equals to 1 if the firm reports a loss, and 0 otherwise. (Source: Compustat)
$Log(ANA)_{it}$	Logarithm of number of analysts following. (Source: IBES)
$RESTATE_{it}$	An indicator variable equals to 1 if the firm restates financial statements, and 0 otherwise. (Source: Compustat)
Additional Variables	
TOXIC_NOx	The total amount of NOx emissions scaled by sales revenue. (Source: Asset 4)
TOXIC_SOx	The total amount of SOx emissions scaled by sales revenue. (Source: Asset 4)
R_ROA	An indicator variable equals to 1 if the firm's ROA is above the sample median, and 0 otherwise. (Source: CRSP, Compustat)

Table A1 (continued)

Variable	Definition
Tobins Q	An indicator variable equals to 1 if the firm's Tobins Q is above the sample median, and 0 otherwise. (Source: CRSP, Compustat)
Sal_Growth	An indicator variable equals to 1 if the firm's sales growth is above the sample median, and 0 otherwise. (Source: Compustat)
CONSTN	An indicator variable equals to 1 if the firm's financial constraint indicator is above the sample median, and 0 otherwise. (Source: Compustat, Whited and Wu (2006))
MKT_ATTN	An indicator variable equals to 1 if the firm's institutional ownership is above the sample median, and 0 otherwise. (Source: Thomson Reuters 13F)
Post	An indicator variable equals to 1 if the year is after the EPA added new chemicals to the TRI list.
Treat	An indicator variable equals to 1 if the firm is more likely to be affected by the EPA's inclusion of new chemicals into the TRI list.
E_DISAGREE	It is the standard deviation of the three environmental scores (range from 0-100) for each firm-year. (Source: Bloomberg, Sustainalytics, and Asset 4, Berg, Kölbel, and Rigobon (2022))
PENALTY_AMOUNT (10^5)	A continuous variable represents the total amount of penalty value for environmental violations made by the US government. (Source: Violation Tracker)
FEDERAL_PENALTY (10^5)	A continuous variable represents the amount of penalty value for environmental violations made by the US Federal government. (Source: Violation Tracker)

B Excerpts as examples of more deceptive discussions on environmental issues

Darling Ingredients Inc, 2009 Q1

Randall Stuewe, Chairman and CEO:

> "...... Under the proposed rule, to meet the **renewable** fuels standard or the RFS, required usage of biodiesel and **renewable** diesel for the 2009-2010 period, the use of animal fats and cooking oil *most likely* will be required to achieve these objectives. ...
>
> Now we would like to take a minute to give you an update on Darlings involvement in **alternative fuels**. Throughout 2008, we discussed *potential* opportunities that exist for Darling in **renewable** energy, and we are continuing to make progress on this front......"

C Excerpts as examples of less deceptive discussions on environmental issues

VWR Corp, 2016 Q2

Manuel Brocke-Benz, CEO:

> "......our customers ... was a recipient of the 2016 outstanding vendor and **sustainability** award. This was for efforts in helping ... toward its goal of zero waste ...**reusable** pallet program.
>
> We would note that we are the first ever scientific Company to be the recipient of this *award*. Other **sustainability** *awards* include Intel Corporations Preferred Quality Supplier *Award*, Agensys, **Green** Supplier Challenge *Award*, the Kimberly Clark Greenovation Champion *Award* and the Johnson & Johnson, Supplier **Sustainability** *Award*. These *awards* reflect our effort to be a *true* partner to the lab specialty distribution market in driving **sustainability** and by extension, in driving *value* for our customers.......”

D Distribution of Conference Calls and TRI Firms

Table D1: Sample Distribution by Different Types of Calls

This table shows the distribution of the types of conference calls that can be matched to Compustat firms. The majority of conference calls are earnings calls (over 60%).

Conference call types	**#**	**%**	**Cum%**
Earnings conference calls	145,744	63.67	63.67
Other conference calls			
Conference Presentation	61,947	27.06	90.73
Corporate Conference Call/Presentation	7,356	3.21	93.94
Analyst Meeting	4,494	1.96	95.9
Shareholder Meeting	3,285	1.44	97.34
M&A Conference Call/Presentation	2,980	1.30	98.64
Sales Conference Call/Presentation	2,033	0.89	99.53
Guidance Conference Call/Presentation	572	0.25	99.78
Other Corporate Conference Event	422	0.18	99.96
Analyst Conference Call	37	0.02	99.98
Syndicated Roadshow	29	0.01	99.99
Conference	1	0.00	99.99
Earning Release	11	0.00	99.99
Other Brokerage Event	1	0.00	100.00
Total	228,912	100.00	

Table D2: Sample Distribution by Year

This table shows the distribution of the main sample across years from 2002 to 2019.

Year	Frequency	Percent	Cumulative
2002	191	3.33%	3.33%
2003	224	3.91%	7.24%
2004	236	4.12%	11.36%
2005	257	4.49%	15.85%
2006	290	5.06%	20.91%
2007	315	5.50%	26.40%
2008	316	5.51%	31.92%
2009	321	5.60%	37.52%
2010	338	5.90%	43.42%
2011	347	6.06%	49.48%
2012	350	6.11%	55.58%
2013	348	6.07%	61.66%
2014	362	6.32%	67.98%
2015	358	6.25%	74.22%
2016	392	6.84%	81.06%
2017	382	6.67%	87.73%
2018	370	6.46%	94.19%
2019	333	5.81%	100.00%
Total	**5,730**	**100.00%**	–

E Word Dictionary for Environmental Discussions

Based on Henry, Jiang, and Rozario (2024)

The following is the word dictionary used to identify environmental discussions in firm disclosures:

alternative energies, energy efficiency, polluted, alternative energy, energy efficient, polluting, alternatives renewable, environmental, epa, recoverable, biofuels, environmentally, recyclable, biomass, euro 6, recycle, biopower, euro 7, recycled, bioprocessing, global warming, recycling, bioproduct, green development, reduce carbon, bioproducts, green electricity, reduces carbon, carbon, green energy, reduces ethylene, carbon credits, green innovation, reducing flaring, carbon emissions, green transformation, reforestation, carbon footprint, greenhouse gas, renewable, carbon intensity, greenhouse gases, renewables, carbon management, hydrocarbons, reusable, carbon price, hydropower, scope 3, carbon-neutral, iso 14000, solar, circular economy, iso26000, spills, clean energy, landfill, substantially green, clean gas, low carbon, superfund, clean technology, low-carbon, superfund sites, cleanup, lower carbon, sustainability, climate action, lower-carbon, sustainable agricultural practices, climate change, methane reduction, sustainable development goals, climate goals, national energy strategy, sustainable packaging, climate reporting, ozone-depleting, sustainable products, co2, Paris agreement, sustainably managed, co2-neutral, Paris climate change, waste, conservation, Paris climate goals, waste-free, decarbonization, Paris goals, wind business, decarbonize energy, planet, wind capacity, eco ideas, pollutant, wind energy, eco solutions, pollutants, wind power, emission, pollute, WLTP certification, emissions, pollutes, zero-carbon.

F Keywords for Climate Change

Based on Sautner, van Lent, Vilkov, and Zhang (2023)

The following is the word dictionary used to identify climate change-related discussions in firm disclosures:

renewable energy, electric vehicle, clean energy, new energy, wind power, wind energy, energy efficient, climate change, greenhouse gas, solar energy, clean air, air quality, reduce emission, water resource, energy need, carbon emission, carbon dioxide, carbon footprint, gas emission, energy environment, wind resource, air pollution, reduce carbon, president obama, battery power, clean power, energy regulatory, plug hybrid, obama administration, build power, world population, heat power, light bulb, carbon capture, renewable resource, carbon tax, carbon price, power generator, indoor outdoor, solar farm, coastal area, energy star, scale solar, major design, transmission grid, energy plant, global warm, motor control, battery electric, clean water, combine heat, need energy, future energy, use water, environmental concern, include megawatt, build owner, electric grid, energy team, world energy, energy application, wind capacity, transmission infrastructure, population center, energy reform, charge station, wind park, produce power, environmental footprint, source power, pass house, gas vehicle, plant power, energy program, unit megawatt, environmental standard, exist power, new clean, increase renewable, help state, snow ice, electrical energy, electric hybrid, solar installation, connect grid, driver assistance, reach gigawatt, provide clean, reinvestment act, invest energy, green build, sector energy, california department, plant use, friendly product, energy initiative, issue rfp, transmission capacity, close megawatt, market solar, business air, construction megawatt, rooftop solar, application power, forest land, grid power, advance driver, northern pass, nox emission, wind facility, energy component, vehicle application, emission trade, industry energy, environmental upgrade, deliver energy, social environmental, new battery, dioxide emission, use coal, green technology, recovery reinvestment, thermal energy, solar generation, lot clean, market wind, utility state, state land, come renewable, efficient light, thing energy, energy standard, energy intensive, power cool, vehicle company, vehicle commercial, sustainable energy, vehicle charge, energy requirement, nearly megawatt, generation resource, water recycle, lng truck, epa regulation, state power, coal capacity, area florida, diesel vehicle, energy category, environmental quality, sea level, provide water, come wind, home energy, nickel metal, inner mongolia, guang-

dong province, joaquin valley, energy world, compliance plan, president elect, eletricity grid, regional transmission, resource board, facilitate development, water pipeline, efficiency power, variable speed, quality monitor, use state, burn fuel, energy independence, carbon intensity, vehicle europe, generate energy, mercury control, portfolio energy, flue gas, power component, ontario power, control power, example energy, hybrid car, issue request, report china, improve environmental, market air, term renewable, carbon reduction, lng fuel, step advance, increase gigawatt, bush administration, energy opportunity, wind wind, clean burn, build wind, loy yang, charge infrastructure, energy legislation.

G Keywords for Deceptive Language

Keywords Associated with More Deceptive Statements (D_p)

LIWC Category: Anger abuse, abusi, aggravat, aggress, aggressive, aggressively, aggressor, agitat, anger, angrier, angry, annoy, annoyed, annoying, antagoni, argu, assault, asshole, attack, bastard, battl, beaten, bitch, bitter, blam, bother, brutal, cheat, confront, contempt, contradic, crap, crappy, critical, cruel, cruelty, cunt, cynic, damn, despis, destroy, destruct, destruction, distrust, dumb, dumbass, dummy, enemie, enrag, envie, envy, feroc, feud, fight, foe, frustrat, fuck, fucked, fucker, furious, fury, goddam, greed, grouch, grudg, harass, hate, hated, hateful, hatred, heartless, hell, hostil, ...

LIWC Category: Anxiety afraid, alarm, anxiety, anxious, anxiously, anxiousness, apprehens, asham, aversi, avoid, awkward, confuse, confused, confusedly, confusing, desperat, discomfort, distraught, distress, disturb, doubt, dread, embarrass, fear, feared, fearful, fears, fright, guilt, guilty, horrible, horrid, horror, humiliat, nervously, overwhelm, panic, paranoi, repress, restless, scare, scared, ...

LIWC Category: Negate aint, arent, cant, cannot, couldnt, didnt, doesnt, dont, hadnt, hasnt, havent, idk, isnt, mustnt, nah, neednt, ...

LIWC Category: Swear af, ass, asshole, badass, bastard, bitch, bloody, bs, bullshit, cock, crap, crappy, cunt, damn, dick, dickhead, douche, dumbass, dumbfuck, effin, fuck, fucker, fucked, fucking, hell, shit, shitty, ...

LIWC Category: Tentative almost, ambiguous, appear, apparently, approximate, assum, barely, bet, chance, confuse, could, depend, doubt, feasible, generally, guess, hope, hypothetic, if, indecisive, kind of, likely, may, maybe, might, mostly, nearly, opinion, perhaps, possible, probably, uncertain, unsure, ...

Self-constructed Category: Extreme Negative Emotions abominable, absurd, advers, aggressive, atrocious, awful, brutal, careless, coercive, crazy, cruel, cunning, dangerous, daunting, depress, despair, despicable, devastat, difficult, disastrous, dread, fail, fatal, fear, fearful, fright, frustrated, griev, harmful, heartbreaking, hideous, hopeless, horr, humiliat, hurt, idiot, implausible, impossible, insecure, insane, intimidat, jerk, laughable, ludicrous, mad, menace, messy, miser, mortifying, nasty, overwhelming, painf, panic, pathetic, precarious, problem, resent, ridiculous, ruin, ...

Keywords Associated with Less Deceptive Statements (D_n)

LIWC Category: Assent absolutely, agree, alright, aok, awesome, cool, indeed, mhm, ok, okay, okey, ...

LIWC Category: Certainty absolute, absolutely, always, apparent, assured, certain, clear, clearly, committed, complete, confidence, confident, correct, definite, definitely, entire, evident, exact, explicit, fact, facts, frankly, fundamental, ...

Self-constructed Category: Extreme Positive Emotions amazing, awesome, best, bless, brilliant, cherish, confidence, confident, definitely, delicious, delight, dynamite, eager, enormous, excel, excited, fabulous, fantastic, flawless, genuine, glorious, gorgeous, grand, ...

H Difference between Deception and Linguistic Uncertainty

Table D3: Conceptual Differences Between Deception and Linguistic Uncertainty

Aspect	**Deception**	**Linguistic Uncertainty**
Definition	Intentional manipulation to mislead	Lack of clarity due to ambiguity or complexity
Speakers Goal	Mislead or obscure truth	Signal doubt or incomplete information
Source of Ambiguity	Strategic	Epistemic (knowledge-based)
Tone or Confidence	Overconfident, exaggerated	Cautious, hesitant
Common Contexts	ESG-washing, fraud, overstatements	Risk disclosures, forward-looking statements

Table D4: Linguistic Markers in Deception vs. Uncertainty

Linguistic Feature	**Appears in Both?**	**Interpretation Depends On...**
Passive Voice	Yes	Can indicate both deception and uncertainty
Hedges (e.g., might, could)	Yes	Uncertainty: genuine doubt; Deception: strategic ambiguity
Lack of Specifics	Yes	Uncertainty: complexity; Deception: concealment
Negations or Emotion Words	No (mostly deception)	Guilt or avoidance in deceptive context

I LLM Deception Methodology and Distribution

To accurately capture the overall sentiment score of specific text segments within a given topic using large language models (LLMs), this paper adopts a dual-verification approach that combines keyword identification with the judgment capabilities of LLMs. It extracts the necessary fields from the original text and reassembles them into standardized segments for subsequent sentiment scoring. This method is crucial for two reasons: firstly, existing keywords may not be precise enough to identify relevant expressions across different linguistic contexts; secondly, the creation of these keywords can be influenced by variations in researchers' sample selections, thereby compromising the method's long-term effectiveness.

Therefore, we developed a simple yet efficient method to accurately locate the target content and perform direct scoring. The process consists of two steps: (1) identifying potentially relevant sentences using keywords, further filtering and merging them into new text segments using the Llama-3.2-3B model; (2) directly scoring these segments using the Llama-3.2-3B model based on given prompts for further cross-validation with other variables.

To establish this process, we faced three main tasks: firstly, we needed to organize the original text into standardized fields, preserving punctuation as well, since the conference data was not in the desired format, and preprocessing was required. Secondly, relying solely on LLMs to generate long text segments could lead to inaccuracies due to model instability; thus, we devised a system that separated the processes of evaluation and text organization. Lastly, due to the unpredictability of LLM responses, we needed to create precise prompts to ensure accurate responses while standardizing output formats.

To address the aforementioned issues, we designed a corresponding text cleaning process and utilized a small set of samples to create a set of prompts with clear instructions. We also developed code for processing responses based on these prompts. Specifically, we split the original conference call transcripts into individual words, converted them to lowercase, and filtered out those files that were not suitable for further processing. When using LLMs to determine whether a sentence belonged to a specific category, we only returned "Yes/No" labels for each sentence, which were then used for subsequent filtering and concatenation of sentences. To standardize responses, we adopted a "zero-shot" approach to ensure that the returned answers included the required scores. We also added code to filter out unnecessary information, simplifying the responses into the numerical form we needed. As a result, we obtained a stable list of scores ranging from 0 to 100 as mentioned in the main text. Compared to the original scoring method without LLM assistance, these improved metrics can serve as a control group in regression analysis, providing more comprehensive data support.

As shown in the figures, the textual measure exhibits a distribution that is closer to normality, whereas the LLM-based measures display a nearly uniform distribution over environmental deception. The distributional patterns remain similar when the textual context is segmented using different window definitions, such as central keywords or sentence-level windows. These results surprisingly provide strong evidence that traditional text-based measures remain highly informative, even though AI-based methods possess strong capabilities in generating and processing disclosure content.

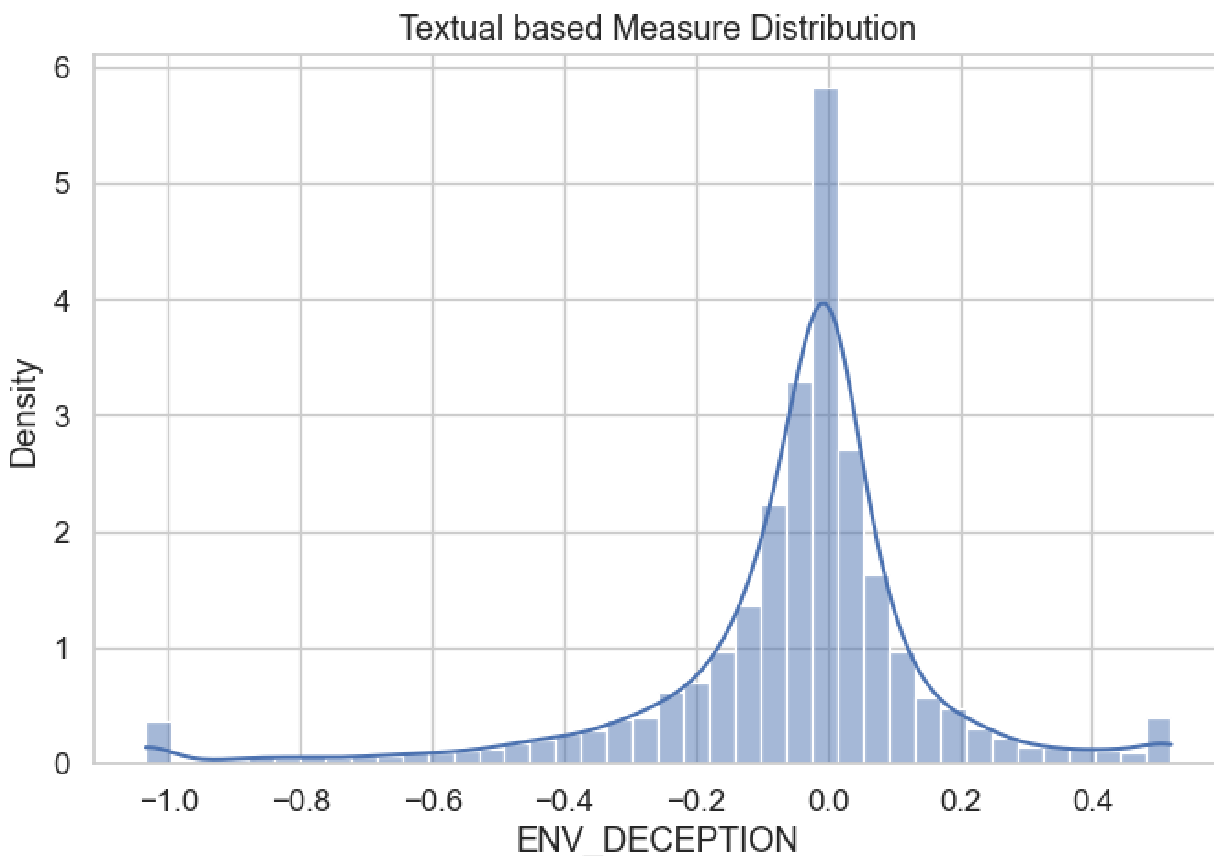

Figure I1: Distribution of ENV_DECEPTION

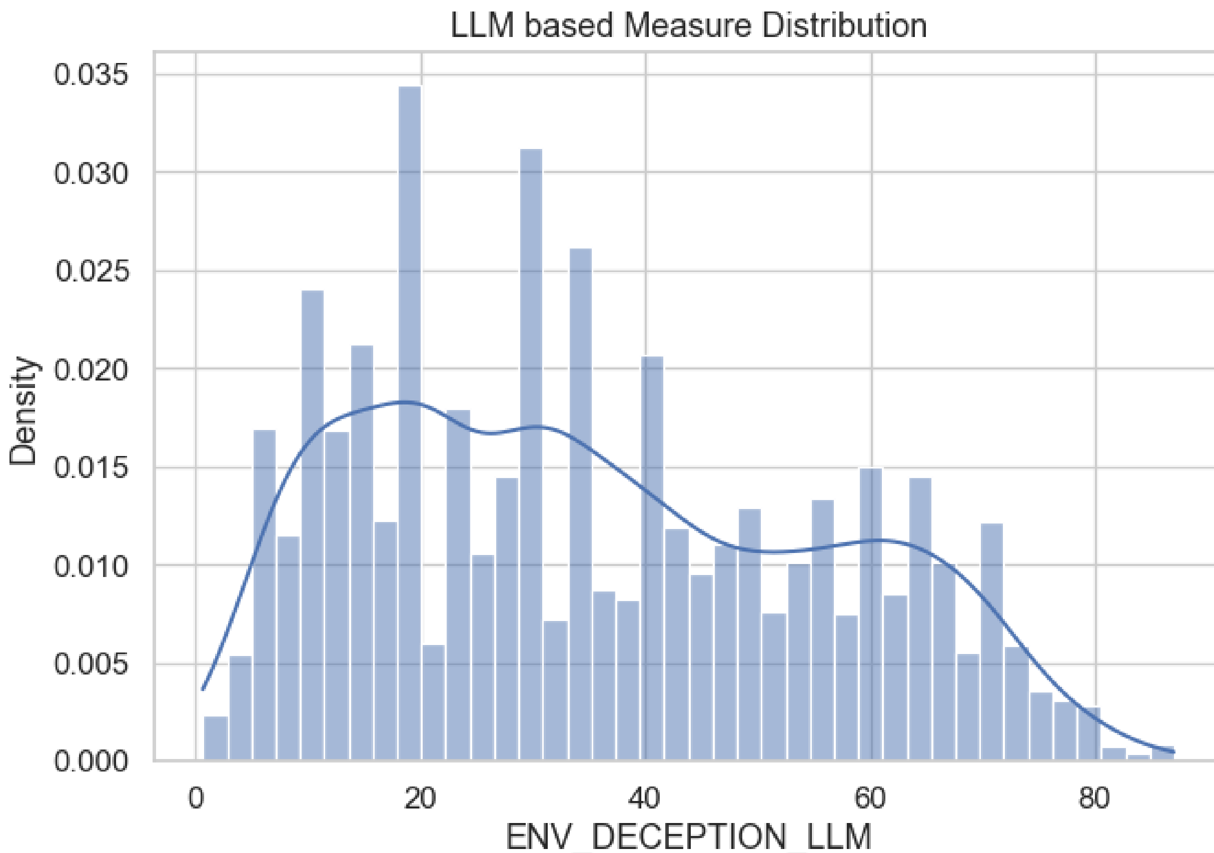

Figure I2: Distribution of ENV_DECEPTION_LLM_W

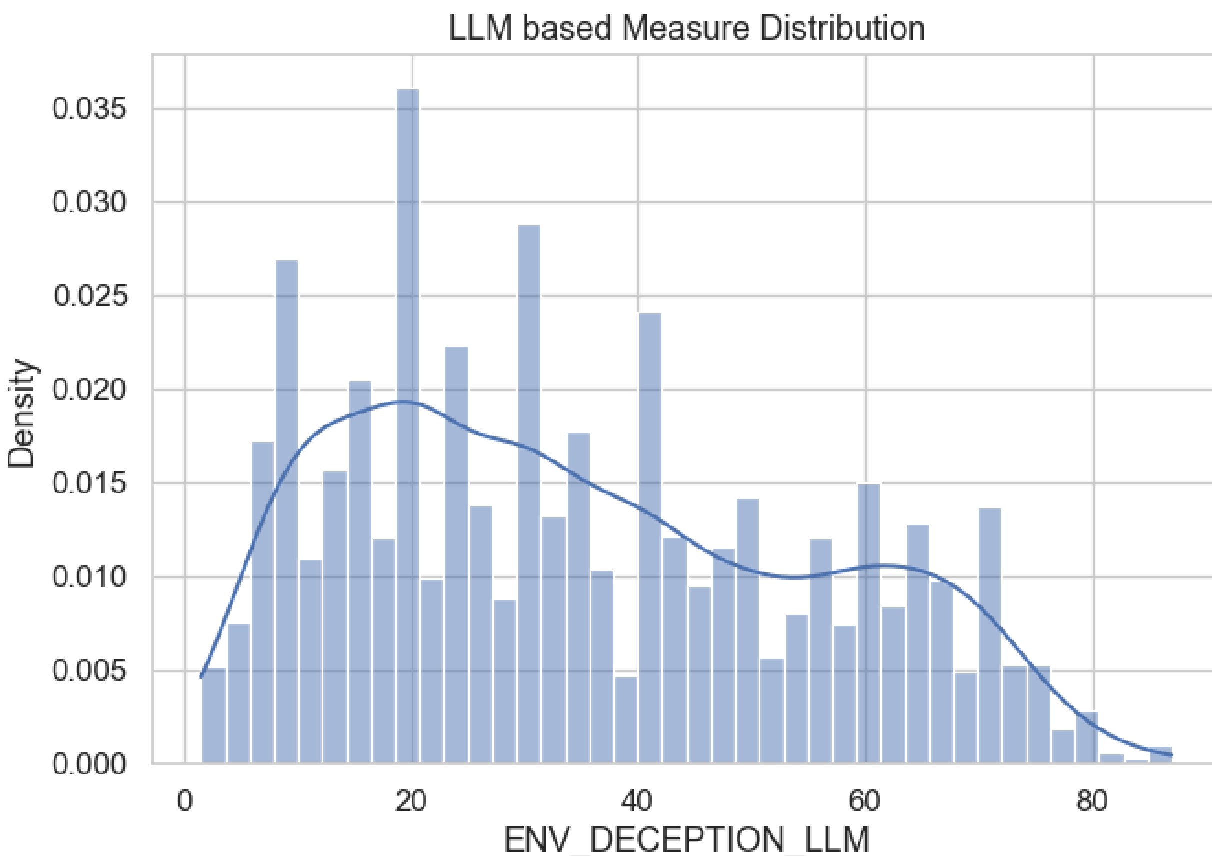

Figure I3: Distribution of ENV_DECEPTION_LLM_S

J Illustrative Specifications and Extensions

This appendix provides additional details on the illustrative specifications of the general framework in Section 3 and two optional extensions. Panels (a) to (f) of Figure I4 show numerical policy functions for Cases A to F discussed in Section 3.2.2. All examples are consistent with the model-free first-order condition in Equation (2). The numerical values are chosen solely to produce smooth, monotonic policy functions and are not estimated from the data.

J.1 Numerical Policy functions

Figure I4 plots optimal deception $d^*_\theta(E)$ against emission intensity E for two firm types, $\theta = \alpha$ (strong) and $\theta = \beta$ (weak), under six specifications.

Case A. For type $\theta \in \{\alpha, \beta\}$, we set

$$U_\theta(d; E) = a_\theta d - \tfrac{1}{2} b_\theta d^2 - \beta L_\theta\big(p_{d,\theta} d + p_{Ed,\theta} E d\big),$$

with parameters

$$a_\alpha = 1.2, \quad a_\beta = 1.0, \quad b_\alpha = b_\beta = 4.0, \quad L_\alpha = 0.8, \quad L_\beta = 1.0, \quad p_{d,\theta} = 0.2, \quad p_{Ed,\alpha} = -0.6, \quad p_{Ed,\beta} = -0.4,$$

and the discount factor $\beta = 0.95$. These values imply upward-sloping policy functions and $d^*_\alpha(E) > d^*_\beta(E)$ for all E.

Case B. Case B uses logistic detection technology and quadratic benefits and costs, as described in Section 3.2.2. For simplicity, the panel plots smooth nonlinear approximations of the resulting policy functions:

$$d^*_\alpha(E) \approx 0.90 + 0.12 \tanh(3(E - 0.2)), \qquad d^*_\beta(E) \approx 0.85 + 0.08 \tanh(3(E - 0.2)).$$

Case C. For the cubic first-order condition example, we set

$$U_\theta(d; E) = a_\theta d - \tfrac{1}{2} b_\theta (1 + \kappa_\theta E) d^2 - \tfrac{1}{4} c_\theta d^4,$$

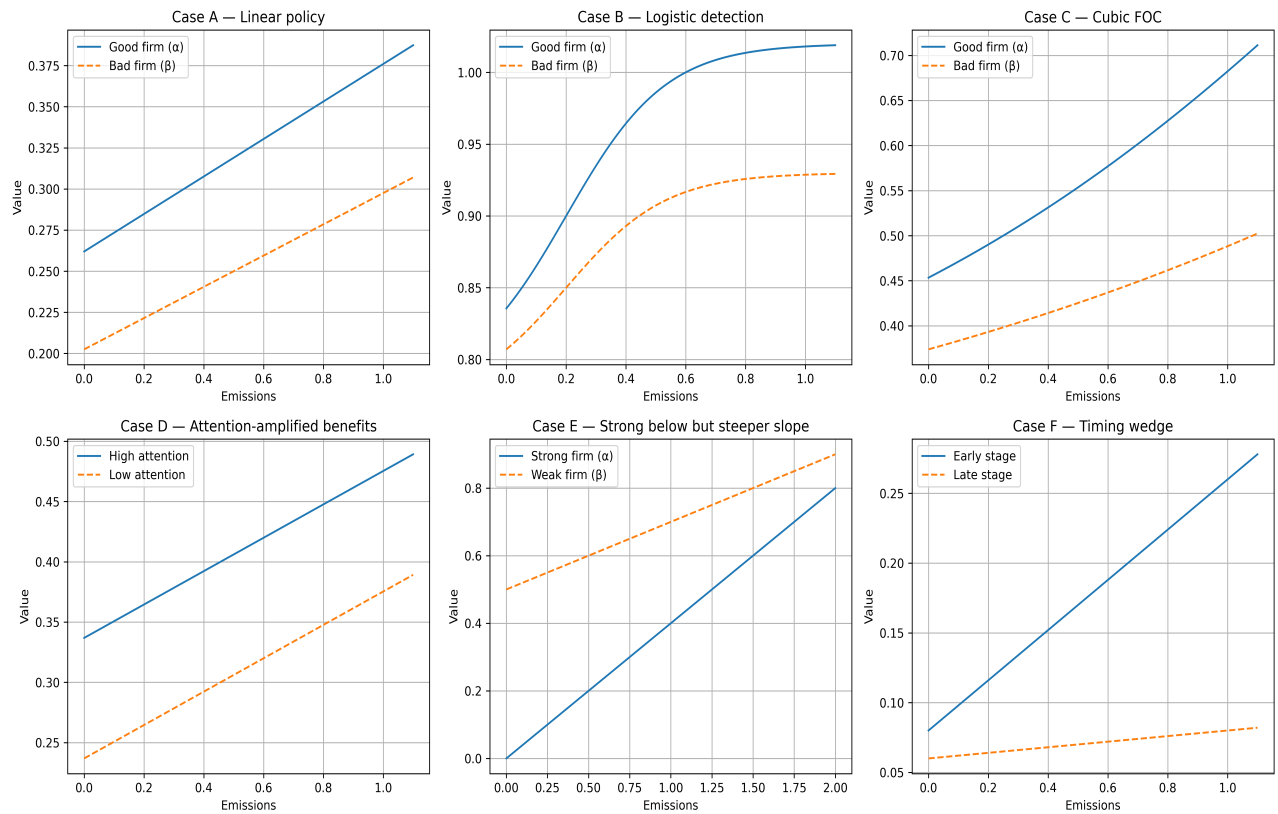

Figure I4: Optimal deception and emissions across six numerical specifications

.

In this figure, Cases A to C display optimal deception policies for three baseline cases: (a) linear policy, (b) logistic detection, and (c) a cubic first-order condition. Case D captures *market attention* (institutional attention) as an amplification of short-run narrative benefits, consistent with Table 14. Case E shows that financially stronger firms choose lower deception levels at each emission level but exhibit a steeper pollution–deception slope. Case F illustrates a timing wedge: short-run market benefits associated with deceptive narratives attenuate once delayed regulatory information is incorporated, consistent with Table 13. Parameter values are illustrative and not estimated.

with parameters

$$a_\alpha = 1.0, \quad a_\beta = 0.8, \quad b_\alpha = b_\beta = 2.0, \quad \kappa_\alpha = -0.5, \quad \kappa_\beta = -0.3, \quad c_\alpha = c_\beta = 1.0.$$

For each type and emission level, the optimal deception level is the unique positive root of $a_\theta - b_\theta(1 + \kappa_\theta E)d - c_\theta d^3 = 0$.

Case D. In this revised Case D, we treat institutional attention as *market attention* that amplifies the short-run valuation impact of environmental narratives. A convenient reduced-form specification is

$$U(d; E, A) = (a + \gamma A + s_E E)d - \tfrac{1}{2} b\, d^2 - \beta L\,(p_d + p_{Ed} E)\, d,$$

where A is an indicator of close attention. This yields a closed-form best response

$$d^*(E, A) = \frac{a + \gamma A + s_E E - \beta L(p_d + p_{Ed} E)}{b}.$$

with parameters

$$a = 1, \quad b = 3.5, \quad \gamma = 0.35, \quad s_E = 0.10, \quad L = 0.9, \quad P_d = 0.2, \quad p_{Ed} = 0.45, \quad \beta = 0.95, \quad A \in (0, 1)$$

Because $\gamma > 0$, high-attention firms exhibit a steeper pollution–deception relation, consistent with the stronger slope documented for high-attention firms in Table 14.

Case E. To visualize the comparative statics in Case E, we consider the parameterization $a = 1.0$, $b = 1.0$, $\beta = 1.0$, $p_0 = 0.5$, $p_E = -0.2$, $L(\alpha) = 2.0$, and $L(\beta) = 1.0$. Emission intensity E ranges from 0 to 2. The resulting optimal deception policies are

$$d^*_\theta(E) = \frac{a - \beta L(\theta)(p_0 + p_E E)}{b},$$

so that $\partial d^*_\theta(E)/\partial E = -\beta L(\theta) p_E / b > 0$ for both types and $\partial d^*_\alpha(E)/\partial E > \partial d^*_\beta(E)/\partial E$. Strong firms ($\alpha$) always choose *less* deception at a given emission level, but their deception responds more strongly to increases in emissions, leading to a steeper pollution–deception slope.

Case F. Case F illustrates a staggered-information timing wedge consistent with Table 13. Let deceptive narratives generate short-run market benefits that depend on emissions, but that attenuate once delayed regulatory information is incorporated. Panel (f) plots a simple proxy in which the early-stage benefit increases with emissions while the late-stage benefit is substantially attenuated. This numerical illustration is intended to capture the timing of information revelation (not to map calendar time one-to-one) and is not structurally estimated.

J.2 Extension: State-Dependent Detection Penalty

This subsection presents a simple state-dependent penalty function that is compatible with the model-free framework. Suppose that detection leads to a loss $L(\theta, E)$ that increases with both firm fundamentals and emission intensity. One convenient specification is

$$L(\theta, E) = k_\theta(E)\, \lambda(E), \tag{I1}$$

where $k_\theta(E)$ captures how stakeholders scale reputational losses for type θ as a function of emissions, and $\lambda(E)$ captures the overall sensitivity of markets and regulators to environmental events. For example, $k_\theta(E)$ may be larger for firms that are already under scrutiny, and $\lambda(E)$ may increase with E, but at a rate that is slower than the growth of operational benefits. Under this specification, the general FOC is given by,

$$B_d(d^*; \theta, E) - C_d(d^*; \theta, E) - \beta\, p_d(E, d^*) L(\theta, E) = 0,$$

still holds. The sign of $\partial d^* / \partial E$ is governed by the same comparative static in Equation (4). Hypothesis 1 corresponds to the condition that the emission-induced increase in $B_d - C_d$ dominates the emission-induced increase in $\beta p_d L(\theta, E)$ for the relevant range of E.

J.3 Extension: Investor Short-Sightedness

As a second extension, we briefly incorporate investor short-sightedness into the framework. Suppose that investors place a weight $\phi \in (0, 1]$ on future losses from detection relative to the benchmark discount factor β. The firms objective becomes

$$U(d; \theta, E) = B(d; \theta, E) - C(d; \theta, E) - \phi\beta\, p(E, d) L(\theta). \tag{I2}$$

The FOC is identical to Equation (2) with β replaced by $\phi\beta$. A lower value of ϕ effectively reduces the marginal expected cost of deception and, therefore, increases the optimal level of deception and its sensitivity to emissions. In particular, for $\phi < \phi$, we have $d^*(\theta, E; \phi) \geq d^*(\theta, E; \phi)$ and $\partial d^*(\theta, E; \phi)/\partial E \geq \partial d^*(\theta, E; \phi)/\partial E$. This extension is consistent with evidence that ESG risks are often perceived as reputational or asymmetric risks that are especially pronounced during downside cycles.