Strategic Environmental Deception*

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Abstract

This study examines firms' strategic use of deceptive environmental disclosures to obscure their true environmental risks and secure capital market benefits. Utilizing a novel measure that captures deceptive linguistic cues, we find that firms with higher pollution levels tend to engage in more environmental deception. This tendency is especially pronounced among firms with stronger profitability and higher growth prospects, consistent with our theoretical framework. Empirical analysis shows that such deceptive disclosure strategies are associated with short-term increases in market returns, green fund inflows, and improved ESG ratings. However, these advantages tend to fade as investors acquire more accurate information over time.

Keywords: Deception, Environmental Disclosure, Environmental Risk, Short-term Benefits

JEL Classification Codes: G30, G23, M14, M40

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. A growing body of research demonstrates that firms' environmental performance—such as pollution levels and carbon emissions—has significant implications for investor decision-making and capital allocation (Bolton and Kacperczyk, 2021; Pástor, Stambaugh, and Taylor, 2022; Stroebel and Wurgler, 2021; Zhang, 2025). Investors are no longer merely responding to traditional financial indicators but are incorporating environmental metrics into valuation models and investment strategies (Barth, Cahan, Chen, and Venter, 2017; Grewal, Riedl, and Serafeim, 2019).

Despite this growing importance, environmental disclosure practices remain fragmented and inconsistently regulated, especially when compared to the more standardized landscape of financial reporting. The absence of a universally adopted reporting framework leaves room for subjectivity and inconsistency in how firms present their environmental performance. [1] 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.[2]

Yet, even with these regulatory advances, both academic research and real-world evidence have revealed a persistent prevalence of greenwashing and diversity washing in corporate disclosures. These practices raise serious concerns about the reliability of environmental information and highlight the need for investors to critically assess such disclosures (Kim and Lyon, 2015; Marquis, Toffel, and Zhou, 2016; Baker, Larcker, McClure, Saraph, and Watts, 2024; Fritsch, Zhang, and Zheng, 2025; Bailey, Glaeser, Omartian, and Raghunandan, 2022; Duchin, Gao, and Xu, 2025). In this context, understanding the incentives and mechanisms behind deceptive environmental

[1] 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.

[2] For further details on the SEC's regulation, see: www.sec.gov/newsroom/pressreleases/2024-31.

reporting becomes crucial.

To better understand how firms' exposure to environmental risks influences their disclosure behavior, this study investigates whether and how companies strategically manipulate the language of their environmental reports—particularly when experiencing higher levels of pollution. Theoretically, in classical disclosure models such as Verrecchia (1983) and Dye (1985), firms are assumed to choose between full disclosure and nondisclosure, voluntarily releasing favorable information while withholding unfavorable news. More recent theoretical work extends this framework by allowing for obfuscation, where managers use vague or ambiguous language to convey less informative disclosures(Aghamolla and Smith, 2023; Chen, 2023). These models suggest that such linguistic strategies can be deployed in ESG contexts to facilitate greenwashing. Building on these insights, we first propose a new model based on Stein (1996) and Baker, Stein, and Wurgler (2003) to show how environmental costs, such as pollutions affect corporate deceptive disclosure behaviors. Further, prior theoretical research suggests that firms with weaker financial performance are more inclined to engage in greenwashing—especially when financial and ESG projects are negatively correlated—often through the use of obfuscated language (Chen, 2023; Aghamolla and Smith, 2023). In contrast, our new model shows that firms with stronger financial performance are more likely to employ deceptive environmental language. These firms are better able to absorb the costs of being caught and are more easily trusted by external investors, making their deception more credible and less scrutinized.

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, Hollander, Van Lent, and Tahoun, 2019; Sautner, van Lent, Vilkov, and Zhang, 2023),[4] we construct a novel, continuous measure of

[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 in a qualitative and descriptive manner rather than through quantitative metrics. As

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 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 finding suggests that environmental risks, when high, motivate firms to obscure these realities through strategic linguistic manipulation, potentially distorting the perceptions of external stakeholders.[7] These results are robust across a wide range of sensitivity tests, including large language model (LLM) 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 an exogenous shock to establish causality between toxic emissions and environmental deception. Firms that reported new chemical releases following this expansion exhibited more deceptive environmental disclosure behaviors. 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

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.

[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.

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 in environmental deception. This evidence suggests that the primary motivation behind such deceptive behavior is to protect firm value (Cheng, Ioannou, and Serafeim, 2014), rather than to alleviate financing constraints (Li, 2008; Baker, Larcker, McClure, Saraph, and Watts, 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 finding suggests that managers strategically exploit information asymmetry, choosing to disclose deceptively when outsiders are least able to verify the credibility of their environmental claims. Next, we explore how capital market attention—particularly from institutional investors—influences firms' deceptive disclosure strategies. Increased attention from financial markets typically enhances monitoring and improves corporate governance. However, our results reveal a contrasting pattern: firms with a higher proportion of institutional ownership tend to engage in greater environmental deception. This suggests that firms may respond to heightened scrutiny not by improving transparency, but by intensifying efforts to manage perceptions and maintain reputation capital through deceptive disclosures.

In the final set of analyses, 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 deceptive disclosures are able to raise equity capital at a lower cost, attract greater inflows from 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 both capital markets and environmental rating agencies often fail to detect and unwind such deceptive practices in a timely manner. Interestingly, some of these benefits appear to reverse over time as more information becomes available and the market gains a clearer understanding of firms' actual environmental performance. This delayed market correction highlights the importance of transparency and information accessibility in mitigating the effectiveness and persistence of environmental deception. Our theoretical model also discusses both jump penalty and investor short-sightedness to support these findings.

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 highlights that although firms are affected by EPA regulations, the obfuscation we examine is a more active and strategic behavior aimed at securing potential benefits. Our first continuous measure more accurately captures the degree of deception and can be applied to full, partial, or non-disclosure contexts—unlike studies that rely on binary classifications, such as Fritsch, Zhang, and Zheng (2025) and Baker, Larcker, McClure, Saraph, and Watts (2024). Moreover, our analysis of deceptive language provides deeper insights into soft information, complementing the former study, and can also be extended to the social-washing context of the latter. 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, Glaeser, Omartian, and Raghunandan, 2022).

Second, we contribute to theoretical valuation literature 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, Lioui, Liu, and Tarelli, 2024; Goldstein, Kopytov, Shen, and Xiang, 2022). Our theoretical framework extends the concept of obfuscation to the ESG context (Aghamolla and Smith, 2023) and employs linguistic features to analyze greenwashing while accounting for financial performance (Chen, 2023). 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 trajectory, our paper suggests that environmental deception risk—captured through language—can temporarily enhance firm valuation in the short run.[9]

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, Hollander, Van Lent, and Tahoun, 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 large language model to receive both transparency as well as accuracy.

The remainder of the paper is organized as follows. **Section 2** discusses the related literature. **Section 3** develops a theory and proposes hypothesis. **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.

[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 likely to engage in diversity-washing to attract financing (Baker, Larcker, McClure, Saraph, and Watts, 2024).

2 Related Literature

Literature has provided evidence on firms' capital market incentives in deciding their disclosure strategies when experiencing negative earnings surprises. Studies have suggested that firms have greater incentives to withhold the negative information to avoid 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 the non-disclosures if opportunistic withholding is more likely to be detected (Lev, 1992; Skinner, 1994). Rather than treating 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 languages to obfuscate investors and reduce the information content in the disclosure, so that capital markets react less completely to the negative news information.

With the rising demand for firms' environmental related information, many firms provide environmental disclosure to meet the information demand of regulatory authorities, communities, NGOs, and customers such that investors take a more holistic view of firms' financial and environmental performance (Al-Tuwaijri, Christensen, and Hughes Ii, 2004; Hughes, Anderson, and Golden, 2001; Patten, 2002). While transparency with firms' environmental information can bring a long list of potential business benefits to the presenting firms, including improving reputation and brand value, motivating employees and supporting the firm's control processes (Hahn and Kühnen, 2013), the absence of a broadly accepted theory on the objectives why firms should provide environmental disclosures result in diverse environmental disclosure practices driven by diverse incentives. For example, when firms perceive corporate environmental disclosure as a means to exhibit their social responsibility to fulfil their obligation for their 'social contract', they are more likely provide a higher level of disclosure on their environmental performance to meet the demands of stakeholder groups (Huang and Kung, 2010). Firms would also disclose more when experiencing poorer performance if their incentive for the disclosure is to enhance their operational legitimacy and to lessen the regulatory burden to reduce the constraints in executing corporate strategies. In contrast, when the disclosures are driven by firms' incentives to enhance their financial valuations, firms may be more proactive in disclosing aspects of their operations which meet or exceed stakeholder expectations of environmental performance and give the impression of doing good, but withholding poor performance on others (Clarkson, Li, Richardson, and Vasvari, 2008; Holder-Webb, Cohen, Nath, and Wood, 2009). They may also strategically choose to provide more technical (as opposed to more straightforward) terms and more defensive narratives to shift the blame onto external factors for negative outcomes away from themselves (Aerts, 1994; Freedman and Patten, 2004; Huang, Teoh, and Zhang, 2014; Brennan and Merkl-Davies, 2013).

When firms directly engage with the investment community to communicate and disseminate firm information, where non-disclosure is not an option, firms choose to be more strategic in their linguistics when communicating the negative news information to the investors in order to divert market attention away from the negative information. Such a disclosure strategy, helps impede investors' ability to comprehend and process the disclosure, and dampen capital market penalty associated with poorer environmental performance (Bloomfield, 2002; Cho, Roberts, and Patten, 2010; You and Zhang, 2009). In a related study, Cho, Roberts, and Patten (2010) propose and examine firms' opportunistic bias and concealment through the linguistics of the environmental disclosure in firms'10-K reports as the strategy to manage firms' environmental reputation. Different from Cho, Roberts, and Patten (2010), this study proposes that firms engage in opportunistic obfuscation and deceptive environmental disclosures when experiencing poorer environmental performance; such a disclosure strategy is interconnected with firms' financial conditions and financial disclosure.[10]

The obfuscated and deceptive linguistic features are built on the conceptual framework in linguistics, psychology, and deception detection research in Vrij (2008) that examines the linguistic composition of narratives to differentiate credible and truthful communication from obfuscated and deceptive ones by analyzing the extent to which firms've'rbal communications on environmental issues are obfuscated and deceptive.[11] According to Vrij (2008), deceivers are likely to experience negative emotions through their negative comments or affect, because of the guilt and

[10] In addition, our paper also differs from Cho, Roberts, and Patten (2010) in that we use environmental outcomes arising from firms' operational activities to measure firms' environmental performance rather than a rating based KLD score in Cho, Roberts, and Patten (2010), which could be endogenously affected by firms' disclosure policy.

[11] As in Larcker and Zakolyukina (2012), we assume that firm managers (CEOs and CFOs) have private information about the realization of firms' environmental performance, and thus their formal and spontaneous narratives provide cues to identify their deceitful (or lying) behaviors.

fear of being caught in a deceptive act.[12] These emotions make it likely that they use more general, non-specific, and fewer self-referencing language. As a result, their statements and verbal communications are often short, with little detail, indirect, and evasive, containing more irrelevant information as a substitute for the information that the deceivers do not want to provide. In contrast, truth-tellers use a reduced number of general claims but more specific statements with fewer hesitations.

3 Theoretical Framework and Hypothesis Development

This section develops a model-free 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 information structure or functional form. 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

Consider a firm that chooses the intensity of deceptive ESG language $d \geq 0$ 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,

[12] For example, Hobson, Mayew, and Venkatachalam (2012) and Burgoon, Bonito, Lowry, Humpherys, Moody, Gaskin, and Giboney (2016) focus on spoken language indicators of high-stakes deception and use utterances as distinct linguistic and vocalic features in financial disclosure. They find that firms using significantly more restatement-related utterances during conference calls are more likely to have misreported financial statements.

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. 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, we assume that for the listed firms in our sample, the marginal enforcement and reputation costs of ESG deception rise more slowly with emissions than the marginal benefits of continuing operations and maintaining a green image. 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, independently 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.

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.

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 by 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.

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).

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.

Case C: Cubic First-Order Condition. 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). Case D in the Internet Appendix uses the same specification with stronger curvature parameters to demonstrate robustness.

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, 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:

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

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 our setting, we assume that as emission intensity increases, firms' reliance on external finance declines and the marginal enforcement and reputational costs of ESG deception rise more slowly than the marginal benefits of continuing polluting operations while preserving a favorable ESG narrative. Under this condition, the camouflage channel dominates the disciplinary channel, 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.

Hypothesis 2 (Financial Performance, Emissions, and Deception) *The association between environmental pollution and ESG deceptive disclosures is more pronounced for firms with stronger financial performance and greater growth opportunities.*

In the model, financial performance affects the firm's optimal deception choice by shifting the parameters governing both the marginal benefits of maintaining a green image and the expected losses from detection. Firms with stronger financial performance rely less on external finance, face weaker capital market discipline, and are better able to absorb or offset reputational losses when ESG deception is uncovered.

Formally, let θ index firm financial strength. Then, for any given emission level E, the optimal deception choice satisfies:

$$d^*(\theta_H,E) > d^*(\theta_L,E),$$

where θ_H and θ_L denote financially strong and weak firms, respectively.

Moreover, because stronger firms face a lower effective marginal cost of deception, increases in emission intensity translate into larger adjustments in deceptive disclosure. As a result,

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

Thus, while higher emissions increase ESG deception for all firms as predicted by Hypothesis 1, this relationship is amplified for firms with stronger financial performance.

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 create a new measure for topic deception. This measure consists of the set of topics T. In our specific setting, we let T=E (environment). To account the call length, we scale the count by the number of words in the transcript, where w = 0, 1, ..., $W_{i,q}$ are the words in the conference call transcripts of firm i in quarter q. We also have an indicator function ($1[\bullet]$) to judge if one word in call transcript is within a set of given topic.

Next, we adapt the methodology from Larcker and Zakolyukina (2012) to create a deception dictionary, D, compiling from three distinct sources: the Linguistic Inquiry and Word Count, synonyms from lexical English database WordNet, and a word list created by Larcker and Zakolyukina (2012) specifically for firms' conference calls, with a focus on general knowledge, shareholder value, and value creation, among other topics. Drawing upon the word list, we classify narratives as deceptive if they (1) employ more first-person plural pronouns (we), third-person plural pronouns, or impersonal pronouns frequently associated with general statements (such as everybody, anybody, or nobody), (2) reference general knowledge but lack specific details about firms' environmental initiatives/engagements or action plans to address environmental issues; and (3) feature sentiments such as anger, anxiety, swear words, extreme negative emotions, negations, or tentative statements that suggest aversion toward a person or an opinion.

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, based on the findings in their paper, we could separate set D (see in Appendix G) into two parts. 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-words before- and after window, S, centralized by a target topic word (Hassan, Hollander, Van Lent, and Tahoun, 2019). Our study uses an environmental word dictionary (see in Internet Appendix E) created by (Henry, Jiang, and Rozario, 2024). Finally, the function captured 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, this net count is then 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.[13] If we replace E by another other topics within T such as climate change or society, our deception calculation can extend to other settings. For instance, in our alternative measure tests, we replaced our environmental dictionary with a climate change dictionary, and the results hold.[14] Our final metric,

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

[14]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.

$DECEPT$, 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 focuses on both the narratives and the spontaneous questions and answers sections (Q&As), where firms directly engage with the investment community to disseminate financial and sustainability information. In contrast to the often-criticized linguistics used in 10-K reports concerning environmental disclosure, which are typically composed and edited by investor relations personnel for consistency and effectiveness in communication, conference call scripts reflect managers' spontaneous reactions that are not available in 10-Ks and other disclosure and communication channels. Thus, examining firms' conference calls allows me to generalize firms' deceptive disclosure to a broader disclosure channel. 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 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 the TRI data are self-reported, the credibility of the information is reinforced by EPA oversight and the potential for penalties in cases of misreporting, making it more reliable than third-party environmental ratings.[15] Additionally, toxic releases are physically traceable and can

[15] 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.

be independently verified. It is important to note that 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.[16]

Following prior studies (Chatterji, Levine, and Toffel, 2009; Akey and Appel, 2021; Xu and Kim, 2022; Thomas, Yao, Zhang, and Zhu, 2022), we 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 EPA website, the total volume TRI toxic chemical list contains 799 individually listed chemicals and 33 chemical categories in year 2024[17]. We aggregate these data to the firm-year level to construct the main independent variable and scaled 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 Thompson Reuters StreetEvents over the period from Jan 1, 2002 to December 31, 2019. We map 48.7% (228,912/469,851) of these transcripts with 40,512 firm-years in the Compustat-CRSP merged database. We then keep the remaining 7,186 firm-years that have available TRI total emission information and financial variables in the analyses. To mitigate the potential selection bias related to firms' voluntary environmental disclosure decisions, our final sample includes 5,730 firm-years that have discussed environmental issues in any of the conference calls in the year.[18]

Table 1 provides the industry distribution of the sample. Not surprisingly, the manufacturing industry takes the largest share in the sample, followed by business equipment and the chemical

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

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

[18]This final data size is very similar to existing studies such as Thomas, Yao, Zhang, and Zhu (2022). The reason for ruling out 1,456 observations (7,186-5,730) is that these non-disclosure firms will share the same measurement ($DECEPT$=0) as those firms that disclose environmental information but do not use deceptive language or disclose a balanced deception language. However, the economic meaning is entirely different in those two settings, so we exclude those samples for a better scientific approach. The detailed sample distribution by year can be found in Appendix D.

and allied product industry, given the significance of environmental performance on the value implication of firms in these industries.[19]

[Table 1 about here.]

4.4 Research Design

We employ equation (1) below as our baseline regression model to examine the degree to which firms engage in deceptive environmental disclosures:

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

In the equation, the dependent variable is $DECEPT$, which measures the extent that a firm deceives in its environmental disclosures during conference calls. The independent variable is the firm's environmental performance, which is empirically difficult to measure due to its multi-dimensionality. 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). A higher value indicates worse environmental performance or less greenmium. One important reason we use this variable is because it is one of the few metrics that is quantifiable and has a common reporting framework and guideline governing the reporting process. The standardization of the measure makes the measure structured and consistent across time, and thus comparable across firms and industries.[20]

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

[20] We acknowledge the inherent limitation using this variable to measure their environmental performance. First, firms' environmental performance encompasses a wide range of environmental aspects, such as resource consumption, waste generation, and the impact on ecosystems and biodiversity. Focusing solely on toxic emissions provides an incomplete picture of the overall environmental performance of a firm. Second, the level of a firm's toxic emissions can vary greatly in terms of their environmental impact, toxicity, and persistence in the environment. The level of toxic emission may not accurately capture the differences in the severity of these various substances. This could lead to an over- or underestimation of the actual environmental impact of a firm's emissions. In addition, this measure does not provide information about the context in which these emissions occur. For example, emissions from a firm operating in a densely populated urban area may have a higher environmental and social impact compared to emissions from a similar firm operating in a remote, sparsely populated area. We thus caution readers to use a combination of indicators to assess firms' environmental performance, including measures of resource efficiency, waste management, environmental management systems, and stakeholder engagement.

We include a range of firm fundamentals as control variables, which are suggested to affect a firm's operational complexity and, hence its disclosure policy (Ali, Klasa, and Yeung, 2014; Bushman, Chen, Engel, and Smith, 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 also account for a firm's capital market incentives to deceive 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 to beat census analyst forecasts (MBE) or to avoid restatement ($RESTATE$) (Thomas, Yao, Zhang, and Zhu, 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 disclosure based on the adapted Fog index (FOG) in the conference call settings (Li, 2008), and net sentiment of management wording in conference calls ($SENTIMENT$) (Loughran and McDonald, 2011). Lastly, we include firm and year fixed effects to account for unobserved heterogeneity across firms and to control for time-specific shocks or trends that may bias the results. 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 more certain and less deceptive language in their environmental disclosure.

[Table 2 about here.]

4.5 Deception Justification

Since we develop the deception measure ($DECEPT$) using a unique methodology, we first establish its credibility before proceeding to the baseline regression 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*. An advantage of using these three providers—rather than alternatives such as KLD or RepRisk—is that they report environmental scores for U.S. public firms on a common 0–100 scale, which facilitates direct comparability and allows us to construct a measure of rating disagreement. Following the methodology of XXX, 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 XXX 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 $FEDERAL\_PENALTY$. We then run one-to-one regressions of these penalty measures on $DECEPT$, including firm and year fixed effects.[21]

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. 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. The difference in sample size between Columns (1) and (2) arises because we use a large language model (LLM) to screen one round of conference call transcripts for environmental-related content. Details of this procedure are provided in the Refinement Measure section. The reduction in sample size also reflects our 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 ($PENALTY\_AMOUNT$) and federal-level ($FEDERAL\_PENALTY$) penalty amounts. To further strengthen the validation of our measure, we restrict the sample to firm-year observations with nonzero monetary penal-

[21]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.

ties, excluding zero values.

[Table 3 about here.]

5 Empirical Results

5.1 Baseline Results

After validating our measure, we examine the relationship between toxic emission intensity and environmental deceptive disclosures. **Table 4** reports the 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% and 1% levels. These findings are consistent with the hypothesis that firms with poorer environmental performance are more likely to issue deceptive environmental disclosures. In terms of economic significance, a one-standard-deviation increase in toxic releases—while holding other variables at their sample means—is associated with a 2% increase in the likelihood of a firm using deceptive language in its environmental disclosures, based on the coefficient estimate of 0.019 in column (3). This increase corresponds to an 11.2% rise (0.026/0.227) relative to the standard deviation of $DECEPT$ in the sample, which is economically meaningful.

[Table 4 about here.]

Turning to the control variables, the coefficient on ROA is positive and statistically significant, indicating that firms with stronger financial performance are more prone to issue deceptive environmental disclosures. The key difference between columns (2) and (3) is the inclusion of additional controls such as disclosure readability (FOG) following Li (2008), and disclosure sentiment ($SENTIMENT$) based on Loughran and McDonald (2011), both measured at time $t + 1$. These variables help capture potential confounding characteristics shared with the dependent variable, environmental deception ($DECEPT$) (Bushee, Gow, and Taylor, 2018). The results are in line with expectations: firms that produce less readable and more ambiguous narratives, as well as convey negative sentiment in conference calls, are more likely to engage in environmental deception. This suggests a consistent disclosure strategy across different communication channels, aimed at obscuring the implications of poor environmental performance from investors.

5.2 Robustness of Main Results

We conduct additional analyses to address concerns about the robustness check contained in our baseline results. First, firms may strategically provide deceptive environmental disclosure in different conference call contexts, for example, earnings conference calls, which are predominately about financial performance information, and other non-earnings conference call that may be specific to address environment issues. To address this concern, we reconstruct our $DECEPT$ measure based on linguistics used in earnings conference calls and non-earnings conference calls. Within conference calls, the deceptive environmental disclosure can also happen in different parts such as narrative sessions and Q&A sessions in conference calls, respectively. In **Table 5** both panel A and panel B, we examine the regression results by separating data into earnings calls and non-earnings calls as well as narrative sessions and Q&A sessions. The results show that the coefficients on $TOXIC\_INTENSITY$ remain positive and significant in both regressions, suggesting our results are robust across different contexts.[22]

[Table 5 about here.]

Second, one may concern about the noise contained in our $DECEPT$ measure because it includes firms' disclosure on various environmental issues other than toxic emissions. While we don't expect this measurement noise would systematically bias our main results, we address this concern by reconstructing our dependent variable by narrowly to define firms' deceptive disclosures on climate issues (see in Internet Appendix F) during conference calls (Sautner, van Lent, Vilkov, and Zhang, 2023), denoted as CC_DECEPT. It is the negative of the frequency that firms use the top 200 climate change keywords based on the dictionary developed in Sautner, van Lent, Vilkov, and Zhang (2023), scaled by the total number of words (in thousands) in the conference calls. Results presented in **Table 6** show that our baseline results remain robust.

[22] A detailed distribution of different types of conference calls can be found at Appendix D.

[Table 6 about here.]

5.3 Refining Measurement via Large Language Models

Unlike earlier discussions that distinguish deception from uncertainty, Fritsch, Zhang, and Zheng (2025) argue that dictionary-based methodologies may introduce measurement error. They suggest that combining traditional text-analysis approaches with emerging technologies such as large language models (LLMs) can improve measurement accuracy. To address this concern, we follow a procedure similar to that in Fritsch, Zhang, and Zheng (2025) and develop a continuous deception measure using large language models: Llama 3.2-3B.

Our approach consists of two key steps. First, because our analysis relies on central keywords to identify environmental information, we ensure that the surrounding context of these keywords is genuinely related to environmental discussions. Specifically, we query large language models to assess whether the context within 21-word windows is relevant to environmental topics. This step mitigates noise arising from keywords that may have different meanings in non-environmental contexts.

Second, we use large language models (Llama 3.2-3B) to assign a deception score to these validated contexts. The score ranges from 0 to 100 and is treated as a continuous variable. We implement this scoring procedure in two distinct ways, resulting in two LLM-based measures. The first measure assigns a single score to the collection of all 21-word windows within a given transcript ($DECEPT\_LLM\_W$), consistent with the methodology used in prior keyword-based dictionary studies. The second measure assigns a score to all sentences within a transcript that contain environmental keywords and are verified as relevant by the large language models ($DECEPT\_LLM\_S$). This sentence-level approach captures more coherent contextual information surrounding environmental disclosures.

In **Table 7**, we use these refined measures to examine the association between environmental emissions and corporate deceptive disclosures. The results remain positive and statistically significant across all six regressions with control variables and fixed effects. Nevertheless, these LLM-based measures may be subject to black-box concerns, as the internal decision-making process through which the models generate these scores is not fully transparent. Accordingly, we interpret the AI-based results as a robustness check rather than as the primary evidence in this paper.

[Table 7 about here.]

5.4 Endogeneity Concerns

To address potential endogeneity concerns and reinforce the validity of our baseline results, we conduct a series of robustness tests. 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.[23]

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.[24] 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

[23]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.

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

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 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.

[Table 8 about here.]

Finally, 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 only marginally significant at the 10% level. 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 two important implications. First, there is notable heterogeneity across different types of toxic emissions, implying that managers and investors may perceive and respond to them differently. Second, the stronger effect associated with SOx emissions indicates that managers may be more concerned about the reputational or regulatory consequences of SOx-related pollution, and thus have a greater incentive to obscure poor performance through deceptive environmental disclosures.

[Table 9 about here.]

5.5 Empirical Results on Financial Performance

Guided by the predictions of our theoretical framework, we hypothesize that firms with stronger financial performance have greater incentives to engage in deceptive environmental disclosures. The underlying mechanism is that such firms aim to obscure investors' ability to accurately assess their true environmental risks, thereby mitigating potential valuation penalties associated with poor environmental performance.

However, one alternative interpretation is that more heavily polluting firms use deceptive language in environmental contexts because their higher emissions reflect stronger growth opportunities and increased production. Under this view, the observed relationship simply reflects a mechanical correlation between pollution and financial performance. To address this concern, we emphasize that our main independent variable—toxic intensity—is defined as toxic releases scaled by sales, following Zhang (2025). This scaling controls for firm size and production scale.

Therefore, we caution against interpreting our findings as evidence that firms use toxic emissions to improve financial outcomes, which in turn drives deceptive disclosure. 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.[25]

To empirically test our hypothesis that firms with stronger financial performance have greater incentives to engage in deceptive environmental disclosures, we draw on insights from traditional accounting-based valuation theory (Zhang, 2000), and construct three proxies to capture firms' financial performance: abnormal profitability (R_ROA), Tobin's Q ($Tobin\_Q$), and sales growth (Sal_Growth).[26] These proxies effectively capture key dimensions of firm profitability and growth opportunities, making them well-suited for testing the theoretical predictions.

Specifically, we partition the full sample into high and low groups based on the distribution of each of these three variables and re-estimate the baseline regressions for each subgroup. The regression results, reported in **Table 10** and **Table 11**, are consistent with the theoretical prediction: firms with higher profitability and stronger growth prospects exhibit significantly greater use of deceptive environmental language. These findings suggest that firms with more to lose in terms of capital market valuation strategically adjust their disclosures to mask poor environmental performance, thereby avoiding immediate negative investor reactions.

[Table 10 about here.]

[Table 11 about here.]

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 and further validate the role of capital

[25] 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.

[26] In particular, Zhang (2000) suggests that the valuation impact of bad news is nonlinearly associated with a firm's growth options. Because profitability serves as a critical signal of growth potential, market penalties for adverse information are typically greater for firms with higher profitability and growth prospects than for their lower-performing counterparts. To empirically test this theory, the formula for abnormal profitability is defined as $R\_ROA_{i,t} = ROA_{i,t} - \overline{ROA}_{\text{industry},t}$. We use the Fama-French 12-industry classification as the benchmark for the industry average. Therefore, this abnormal profitability measure differs from the ROA used as a control variable in our analysis.

market valuation concerns, we conduct an additional analysis by stratifying the sample according to firms' financial constraint status, proxied by the Whited and Wu index (Whited and Wu, 2006).

Consistent with our primary hypothesis, the results presented in **Table 12** reveal that the coefficient on the key independent variable, $TOXIC\_INTENSITY$, remains positive and statistically significant only within the subsample of firms classified as less financially constrained ($CONSTN$ = low). In contrast, the effect diminishes and becomes statistically insignificant among firms facing higher financial constraints ($CONSTN$ = high). A Chow test further confirms that the difference in coefficients between the two groups is statistically significant at the 5% level ($p = 0.050$), providing robust evidence that deceptive environmental disclosure is primarily driven by the desire to mitigate capital market valuation penalties, rather than solely by the need for external financing under constraint from a different ESG channel (Baker, Larcker, McClure, Saraph, and Watts, 2024).

[Table 12 about here.]

6 Additional Tests on Timing and Attention

6.1 Disclosure Timing on Environmental Deception

Prior literature highlights the critical role of disclosure timing in shaping the impact of financial information, such as earnings announcements (Doyle and Magilke, 2009; Myers, Shipman, Swanquist, and Whited, 2018). Moreover, managers can strategically disseminate information across multiple platforms to influence stakeholder perceptions (Jung, Naughton, Tahoun, and Wang, 2018). More recently, Foerderer and Schuetz (2022) demonstrate that firms may strategically time the disclosure of negative ESG events to mitigate reputational damage. Building on this insight, it is pertinent to explore whether the timing of strategic environmental deception is also a key factor in our context.

Specifically, firms may hold conference calls throughout the fiscal year, and it is plausible that they engage in deceptive environmental disclosures during periods when investors and other information users have limited access to verifiable environmental performance data. Under the Toxic Release Inventory (TRI) program administered by the U.S. Environmental Protection Agency (EPA), firms are required to report their toxic emissions by July 1 of the following calendar year. This regulation ensures timely public access to environmental hazard information. However, prior to the release of this data, firms possess private information about their emissions, whereas investors do not. This temporal information asymmetry implies that, before TRI data becomes publicly available, investors face greater challenges in evaluating the credibility of environmental disclosures. Accordingly, firms may exploit this window of opacity to engage in more deceptive communication regarding their environmental performance.

To empirically test this hypothesis, we reconstruct the $DECEPT$ variable by separating environmental disclosures into two temporal categories: 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 regressions using these two measures to assess whether the timing of disclosures influences the extent of environmental deception. In addition, we conduct a contemporaneous test at time t to capture managerial responses within the same year, using FOG and $SENTIMENT$ measures also from time t, thereby avoiding potential look-ahead bias.

The results, presented in **Table 13**, show that the coefficient on $TOXIC\_INTENSITY$ remains positive and statistically significant in the $DECEPT\_E$ regression (column 1), but becomes insignificant in the $DECEPT\_L$ regression (column 2). This pattern is consistent with the hypothesis that firms strategically engage in more deceptive environmental disclosures during the first half of the year—before the TRI data is made publicly available by the EPA—when stakeholders have limited access to verifiable environmental performance information. By contrast, deception appears to diminish in the second half of the year, once the information asymmetry is reduced through public data release. Column (3) presents results from the contemporaneous test and reveals a similar pattern, indicating that managers respond to the information asymmetry within the same calendar year by increasing deceptive disclosures prior to the public availability of TRI data. These findings support the view that managers exploit their private information advantage and strategically time environmental disclosures to influence stakeholders' perceptions.

[Table 13 about here.]

6.2 Institutional Attention and Strategic Environmental Deception

Prior literature suggests that capital market attention plays a crucial role in shaping the dissemination of firm-specific information and ultimately affects firm valuation (Antweiler and Frank, 2004; Tetlock, 2011; Peress, 2014). For example, Antweiler and Frank (2004) show that the intensity of investor attention, as measured through activity on internet stock message boards, is positively associated with stock return volatility. More recently, studies highlight that institutional investors actively seek environmental information to inform their investment decisions, creating incentives for managers to disclose more favorable environmental narratives (Cohen, Kadach, and Ormazabal, 2023; Ilhan, Krueger, Sautner, and Starks, 2023). At the same time, institutional investors also serve as external monitors, helping to strengthen corporate governance mechanisms (Chung and Zhang, 2011; Aggarwal, Erel, Ferreira, and Matos, 2011). These dual roles suggest competing hypotheses: if institutional investors primarily rely on environmental disclosures for investment decision-making, firms may be incentivized to increase environmental deception to attract capital. Conversely, if institutional investors function mainly as monitors, greater institutional ownership may deter firms from engaging in deceptive environmental disclosures.[27]

To empirically investigate this mechanism, we construct a composite measure of capital market attention, denoted as MKT_ATTN, which captures the extent of institutional focus on firms' environmental performance. Specifically, we calculate institutional ownership using Form 13F filings and define MKT_ATTN as a binary variable equal to 1 if a firm's institutional ownership exceeds the sample median. This classification includes firms with zero institutional ownership in the lower attention group. The results, presented in **Table 14**, indicate that the coefficient on $TOXIC\_INTENSITY$ is positive and statistically significant in the high MKT_ATTN sub-

[27] Prior research suggests that media coverage plays a critical role in monitoring firms' environmental performance (e.g., (Core, Guay, and Larcker, 2008; Dyck and Zingales, 2002; Miller, 2006; Zingales, 2000)). Negative media exposure related to environmental issues can impose substantial reputational costs and legitimacy threats, leading to adverse market reactions and reduced firm valuation (Bartov, Marra, and Momenté, 2021; Clarkson, Li, and Richardson, 2004; Christensen, Floyd, Liu, and Maffett, 2017; Christensen, Hail, and Leuz, 2021). Accordingly, firms with poor environmental performance may have stronger incentives to engage in deceptive environmental disclosures when they are subject to heightened public media scrutiny. To test this hypothesis, we construct a variable, PUB_ATTN, which captures public media attention by measuring the number of negative news articles concerning a firm's environmental performance, as documented in the RepRisk database. Our findings indicate that firms under greater media scrutiny are more likely to engage in environmental deception.

group, suggesting that firms receiving greater institutional attention are more likely to engage in environmental deception. In contrast, the corresponding coefficients in the low MKT_ATTN subgroup are statistically insignificant. The differences in coefficients across the two subsamples are significant at conventional levels. These findings provide supporting evidence that firms strategically tailor their environmental disclosures in response to capital market attention, particularly from institutional investors, and that such deception may be driven by the perceived demand for favorable ESG information in investment decisions.

[Table 14 about here.]

7 Deception Consequence on Market Reaction, Financing, and ESG

Finally, we investigate the potential capital market benefits associated with firms' deceptive environmental disclosures. These tests aim to shed light on the underlying incentives for such disclosures—specifically, whether highly polluting firms strategically use deceptive language to obtain financial advantages. As a result, high-toxicity firms are able to convince investors by their environmental perceived risks rather than their real risks. Additionally, this analysis contributes to the understanding of whether capital market participants are capable of detecting such deception.

Prior literature has shown that ESG-related information is incorporated into investor decision-making and subsequently priced by the market (Flammer, 2013; Dimson, Karakaş, and Li, 2015; Grewal, Riedl, and Serafeim, 2019). Building on these findings, we focus on direct capital market responses, such as annual stock returns ($RETURN$) and implied cost of equity capital (COE) (Gebhardt, Lee, and Swaminathan, 2001). To capture the dynamics of market information processing, similar to the timing session, we construct both first half year and second half year measures, reflecting periods when investors have relatively limited versus greater access to firms' actual environmental performance information.

Furthermore, we also provide two important theoretical supports to explain this timing framework. Our theory considers both short-sighted investors and jump penalty. First, investors may value quick positive feedback and therefore choose to invest directly in firms without further monitoring, allocating greater weight to short-term capital returns.[28] Second, although investors may eventually infer the true environmental signal in the long run, it can still be optimal for them to follow this investment strategy if managers strategically disclose only a limited level of deceptive language that does not trigger severe penalties. This is because the overall benefits of such investments may outweigh the potential costs, and deceptive language is not equivalent to accounting fraud unless it is identified and sanctioned as an environmental fraud outcome.[29]

The results, presented in **Table 15**, support the hypothesis that deceptive firms benefit from misleading disclosures. Specifically, such firms (higher emissions and more deceptive languages) exhibit significantly higher returns and lower cost of capital, particularly in the first half of the year, when investors face greater information asymmetry.[30] These findings suggest that markets may initially reward firms for their deceptive environmental language before sufficient information becomes available to challenge its credibility.

[Table 15 about here.]

Second, we examine whether deceptive environmental disclosures facilitate firms' access to equity financing and enhance their appeal to environmentally conscious investors. Specifically, we focus on two key channels: firms' ability to raise capital through seasoned equity offerings (SEO) and their capacity to attract investment from ESG-oriented funds ($GREENFUND$), consistent with prior research highlighting the significance of these financing mechanisms (DeAngelo, DeAngelo, and Stulz, 2010; Kim and Purnanandam, 2014; Raghunandan and Rajgopal, 2022). The variable, SEO, is a binary indicator equal to one if a firm conducts a seasoned equity offering during the year. For green fund ($GREENFUND$), we adopt the methodology of Cohen, Gurun, and Nguyen (2020), identifying ESG-focused funds based on fund names containing terms such

[28] See the math formulas in Internet Appendix **??**.

[29] See the math formulas in Internet Appendix H.

[30] Building on the significantly positive relationship between toxic releases and environmental deception found in our main regression, we further investigate the capital market implications by considering their conditional dependence. Specifically, toxic releases and environmental deception tend to co-occur among comparable firms, suggesting a non-independent structure that warrants a joint analysis.

as "ESG" or "green". We further supplement this list by manually collecting green fund data from The Forum for Sustainable and Responsible Investment (USSIF).

As reported in **Table 16**, high toxic emission firms that engage in more deceptive environmental disclosures are significantly more likely to issue seasoned equity and receive greater inflows from green funds. These effects are especially pronounced in the first half of the year, consistent with the timing-based information asymmetry mechanism. The estimates are statistically significant at the 1% level for *SEO* and the 10% level for *GREENFUND*, reinforcing the notion that firms strategically exploit deception to secure equity financing and appeal to ESG-focused capital sources.

[Table 16 about here.]

Finally, prior studies suggest that capital market participants rely on environmental ratings to guide investment decisions, and that firms with higher ratings attract more socially responsible investors (Chatterji, Levine, and Toffel, 2009; Serafeim and Yoon, 2022). It is therefore plausible that firms engage in deceptive environmental disclosures to maintain favorable environmental ratings, thereby continuing to benefit from green capital inflows.

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.

[Table 17 about here.]

8 Conclusion

This study examines firms' strategic use of deceptive environmental disclosures during conference calls to influence capital market valuations. Building on prior research (Larcker and Zakolyukina, 2012), we develop a novel measure to quantify the level of deception in corporate communications, applicable across a range of topics. Specifically, we focus on linguistic deception employed by firms when discussing environmental performance during conference calls. The findings reveal that firms with poorer environmental performance tend to use more deceptive language in their environmental disclosures. This tendency is especially pronounced among firms more susceptible to valuation penalties for poor environmental outcomes—namely, those that are more profitable, exhibit higher growth opportunities, and face fewer financial constraints.

We further investigate the timing of deceptive environmental disclosures and find that the effects are most significant when there is an information asymmetry: the public remains unaware of a firm's true environmental performance while managers possess inside information. This asymmetry enables firms to achieve several strategic objectives: they obtain higher market valuations, raise equity capital at a lower cost, attract increased inflows from green funds, and temporarily improve their environmental ratings. However, these advantages tend to dissipate over time as investors become better informed through mandatory environmental performance disclosures.

Overall, these findings underscore the importance of linguistic analysis in evaluating the credibility of corporate environmental disclosures, offering valuable implications for green investment decisions. Moreover, 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

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%**

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

Table 2: Summary Statistics

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

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

Table 3: Justification: Environmental Deception and ESG Outcomes

VARIABLES	*E_DISAGREE*	*E_DISAGREE*	*PENALTY_AMOUNT*	*FEDERAL_PENALTY*
	(1)	(2)	(3)	(4)
DECEPT	2.264***	2.165***	7.363e+07*	420,273**
	(0.697)	(0.725)	(4.038e+07)	(166,352)
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

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 that whether the penalty is conducted by 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.

Table 4: Baseline Results

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

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.

Table 5: Robustness Check on Different Contexts

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

This table examines the robustness of different conference call contexts. Panel A discusses earnings call 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.

Table 6: Alternative Measures

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

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.

Table 7: Large Language Model Measure Results

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

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 words 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.

Table 8: Endogeneity Concern Tests

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

This table addresses the endogeneity problem. The panel A is about change analysis. The panel B is about using $TOXIC\_INTENSITY$ interacted 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.

Table 9: Chemical Expansion Heterogeneity

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

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.

Table 10: Financial Performance

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

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.

Table 11: Growth Opportunity

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

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.

Table 12: Financial Constraints

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

This table examines how financial constraints ($CONSTN$) 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.

Table 13: Disclosure timing of firms deceptive environmental disclosure

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

This table examines firm toxic release and the disclosure timing of using environmental deceptive languages. The timing is categorized at year t+1 for both first half and 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.

Table 14: Capital Market Attention from Institutional Investors

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

This table examines how institutional ownership (MKT_ATTN) 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.

Table 15: Capital Market Consequence

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

This table reports the regression results examining the market consequence of capital market reaction by high polluted firms using linguistic deception on environmental topics. The left panel reports effects on the annual stock return ($RETURN$), while the right panel focuses on 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.

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

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

This table reports the regression results examining the market consequence of financing by high 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.

Table 17: Impact of Environmental Deception on Ratings

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

This table reports the regression results examining the market consequence of ESG ratings ($ENVSCORE$) by high polluted 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.

A Variable Definitions

Table 18: 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 total number of words. DECEPT is measured using conference call transcripts in year $t+1$. (Source: Thomson Reuters)
$\text{DECEPT\_E}_{i,t+1}$	Deception measure constructed using the transcripts in the first half of year $t+1$.
$\text{DECEPT\_L}_{i,t+1}$	Deception measure constructed using the transcripts in the second half of year $t+1$.
$\text{DECEPT}_{i,t}$	Deception measure constructed using transcripts in year t.
$\text{CC\_DECEPT}_{i,t+1}$	Deceptive environmental language that appears in the neighborhood of top 200 climate-related words. (Source: Thomson Reuters)
$\text{DECEPT\_LLM\_W}_{i,t+1}$	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	

Table 18 (continued)

Variable	Definition
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)
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)

Table 18 (continued)

Variable	Definition
$TURNOVER_{it}$	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)
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.

B Internet Appendix: Excerpts as examples of more deceptive discussions on environmental issues

Darling Ingredients Inc, 2009Q1

Randall Stuewe, Chairman and CEO:

> "...... Under the proposed rule, in order 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 in order 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 Internet Appendix: Excerpts as examples of less deceptive discussions on environmental issues

VWR Corp, 2016Q2

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 Internet Appendix: Distribution of conference calls and TRI Firms

This table shows the distribution of the types of conference calls that can be matched to Compustat firms.

Table 19: Sample Distribution by Different Types of Calls

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	

This table shows the overall distribution of conference calls. The majority conference calls are earnings calls (over 60%).

Table 20: Sample Distribution by Year

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%**	–

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

E Internet Appendix: 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 Internet Appendix: 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, guangdong 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 Internet Appendix: 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 Internet Appendix: Difference between Deception and Linguistic Uncertainty

Table 21: 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 22: 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 Internet Appendix: Deception Measure Distribution

In this section, we present the distributions of our environmental obfuscation measures. We consider both a textual dictionary–based measure and LLM-based measures constructed using different scoring methods. 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 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 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

J Internet Appendix: 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 (d) of Figure 4 show numerical policy functions for four cases 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 only to produce smooth, monotonic policy functions and are not estimated from the data.

J.1 Numerical policy functions

Figure 4 plots optimal deception $d^*_\theta(E)$ against emission intensity E for two firm types, $\theta = \alpha$ (strong) and $\theta = \beta$ (weak), under four specifications.

[Figure 4 about here.]

Case A (Panel 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 (Panel 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:

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

which preserve the qualitative properties of an upward-sloping relation, with the strong type lying above the weak type.

Case C (Panel c). For the cubic first-order condition example, we set

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

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 (Panel d). Case D uses the same functional form as Case C but with a stronger curvature:

$$\kappa_\alpha = -0.8, \quad \kappa_\beta = -0.5, \quad c_\alpha = c_\beta = 1.4,$$

which increases the nonlinearity of the policy functions while preserving their upward slope in E.

The figure is generated by the Python script `AllCases_FourPanel.py`, which evaluates the policy functions on a grid of $E \in [0, 1.1]$ and saves the resulting four-panel figure.

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

$$L(\theta, E) = k_\theta(E)\,\lambda(E), \tag{14}$$

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 (**??**). 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

$$U(d;\theta,E) = B(d;\theta,E) - C(d;\theta,E) - \phi\beta\, p(E,d)L(\theta). \tag{15}$$

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 deception level 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.

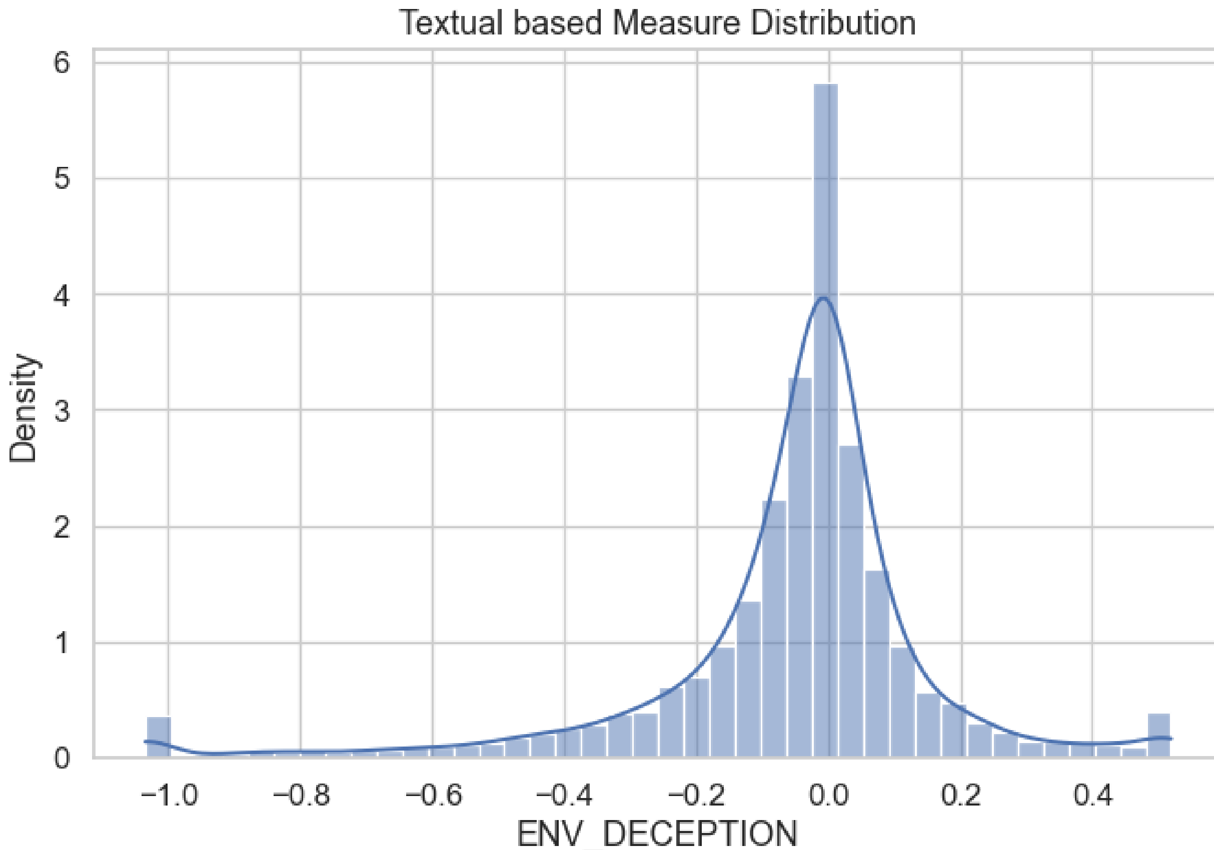

Figure 1: Distribution of ENV_DECEPTION

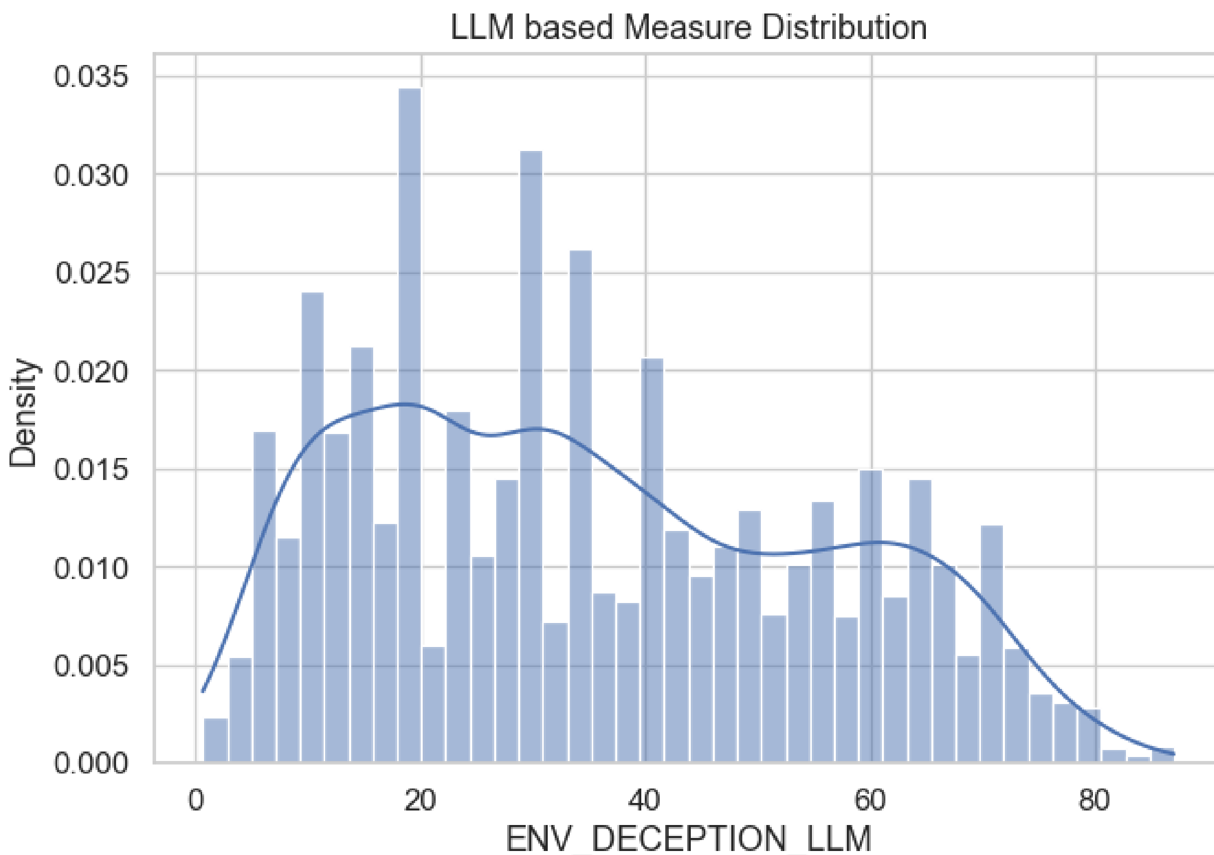

Figure 2: Distribution of ENV_DECEPTION_LLM_W

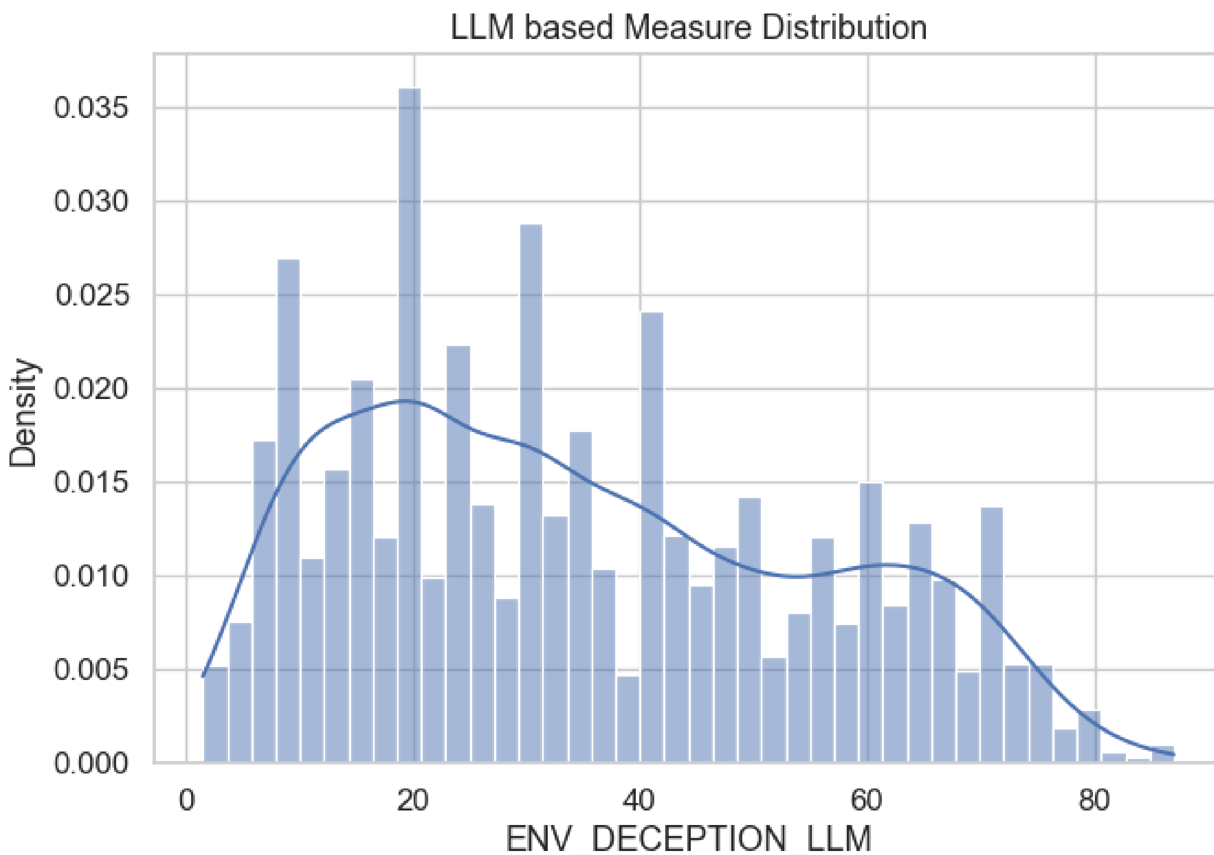

Figure 3: Distribution of ENV_DECEPTION_LLM_S

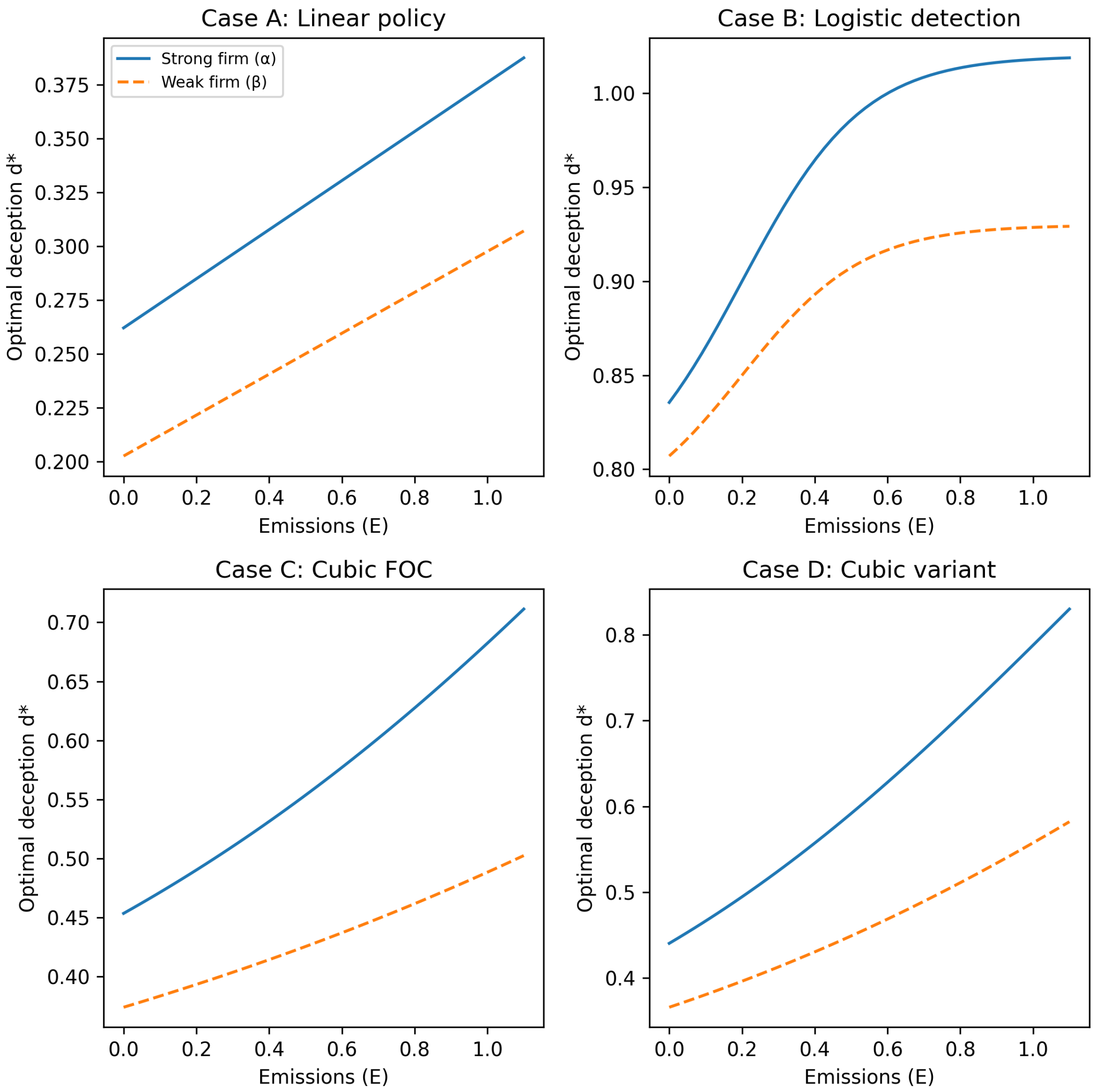

Figure 4: Numerical policy functions under four specifications. Panel (a) shows Case A (linear policy with affine detection); Panel (b) shows Case B (logistic detection); Panel (c) shows Case C (cubic first-order condition); Panel (d) shows Case D (cubic variant with stronger curvature). In each panel, the solid line corresponds to the strong firm (α) and the dashed line to the weak firm (β). Parameter values are reported in the text.