Decipher Market Responses to Climate TRACE Emission Data Release*

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Abstract

We study market reaction to the release of facility-level carbon emission information worldwide by the independent not-for-profit organization Climate TRACE. We find a significant negative market reaction of -0.9% – -2.8% to the data release, which intensifies with the degree of underreporting of carbon emissions. The degree of underreporting is positively associated with the inclusion of a carbon metric in executive compensation and institutional ownership, and negatively associated with the enforcement of environmental regulation. Additional analysis reveals that both lower expected cash flows and higher return volatility contribute to the negative market reaction. Existing environmental reporting policy mitigates, whereas the strength of formal and informal institutions, along with the enforcement of environmental regulation exacerbates the negative market reaction. Taken together, our study casts light on firms' strategic reporting behavior of environmental pollution and underscores the important role that reliable and accurate information from a third party plays in facilitating the capital market price discovery.

"It's pretty hard to hide from communities or regulators when someone is measuring your emissions from space."

— A Tumultuous Year in ESG and Sustainability, Harvard Business Review (2022)

1. Introduction

In recent years, the environmental, social, and governance (ESG) outcomes of firms have gained substantial attention from investors, regulators, and the public. This heightened focus has driven an escalating demand for reliable ESG information. Prior research underscores the importance that investors place on environmental performance metrics such as carbon emissions (Matsumura, Prakash, and Vera-Munoz 2014, Ceccarelli, Ramelli, and Wagner 2023). Yet, the majority of countries do not mandate the disclosure of environmental information (Krueger, Sautner, Tang, and Zhong 2024). Consequently, stakeholders – including investors, ESG rating agencies, and regulators like the Environment Protection Agency (EPA) – are often compelled to rely on unaudited environmental data voluntarily disclosed by firms.[1] At the same time, firms weigh the benefits and costs not only when deciding whether to voluntarily disclose environmental information but also when determining the precision of the information disclosed. This has fueled growing concerns among regulators, information intermediaries and the public about the accuracy and quality of the environmental information that companies release.[2]

Responding to this concern, Climate TRACE (hereafter CT), an independent non-profit organization, unveiled facility-level greenhouse gas (GHG) emission data in 2022. CT employs

[1] Anecdotal evidence suggests that many firms underreport to the EPA, and the EPA does not strictly monitor all cases (EPA 2011; Environmental Integrity Project 2022), which raises concerns about the credibility of EPA data.

[2] Anecdotal evidence of recent emissions restatements suggest that firms indeed may provide biased environmental information. For example, Marvell Technology Group and Unilever PLC restated GHG emissions in CDP questionnaires in 2023. Extant research indicates that firms have incentives to engage in greenwashing (Gibson et al., 2022; Kim and Yoon 2023; Liang, Sun and Teo 2022).

advanced technologies such as artificial intelligence (AI) and machine learning (ML) to process and aggregate data from more than 300 satellites, more than 11,000 on-site sensors, and an array of additional sources of emissions information from around the world. This comprehensive approach combined with the independent nature of CT enables the generation of emission estimates that are likely to be more accurate and unbiased.

In this study, we take the first step to investigate whether and how investors respond to emissions data released by independent sources like CT. We aim to achieve two objectives: first, to assess the value relevance of third-party data vendors (such as CT) to investors, and second, to uncover how this value relevance varies across various types of institutions at the country level.

The release of CT data has the potential to enhance the transparency and timeliness of carbon emissions information. If firms underreport their carbon emissions and investors perceive the CT data to be credible, we expect a negative market reaction to the release of CT data for three non-mutually exclusive reasons. First, prior literature documented that investors rely on public carbon emissions data for firm valuation (Bolton and Kacperczyk 2021, 2023). Therefore, if the CT data reveals underreporting, investors may revise the expectation of future cash flows downward in anticipation for a potential decline in consumer demand for the firms' product (Leonelli, Muhn, Rauter, and Sran 2024), potential regulatory penalties, and the need for cash outlay for carbon abatement technologies or purchase of carbon offsets (Kaplan, Ramanna, and Roston 2023). Second, investors with strong environmental preferences (such as Big 3 investors) might apply a higher risk premium to firms identified as underreporting. Moreover, underreporting by firms can lead to a higher discount rate due to increased uncertainty about firms' exposure to regulatory interventions, activism campaigns, institutional investors engagements, and changes of environmental regulations. Third, even for covered firms without clear evidence of underreporting, investors might still react negatively to the CT release due to the contagion effect. In other words, investors may infer the likelihood of underreporting by assuming that covered firms could operate facilities outside the scope of CT coverage.

To empirically test our predictions, we construct a sample of 1,850 (238) worldwide (U.S.) firms whose facilities are covered by the CT data (treatment group). We augment the treatment group with a set of control firms, which are not covered by the CT data but are from the same country and two-digit SIC industry with at least one treatment firm. Since large U.S. firms are mandated to report carbon emission data to the EPA, and this data is publicly available, it serves as a natural benchmark to compare with the CT emissions data,[3] and allows us to assess firms' strategic reporting behavior. Therefore, we conduct separate empirical analyses using both the international sample and the U.S. subsample.

We document a significant and negative market reaction of -0.8 percent to the CT data release among treatment firms for the international sample and -2.9 percent for the U.S. sample at the univariate level. Multiple regression analyses in which we compare treatment firms with control firms yield similar results. Next, taking advantage of facility-level carbon emission data reported to the EPA by U.S. firms, we probe whether underreporting is the culprit for the negative market response. The evidence confirms this prediction: we find the negative market reaction to CT data release intensifies with the extent of underreporting. Moreover, we find that the negative market reaction persists among covered firms that have not been implicated in underreporting by the CT data releases. This could be due to a contagion effect, where investors perceive these firms

[3] The EPA requires facilities to report their greenhouse gas emissions if they emit 25,000 metric tons or more of CO_2 equivalent per year. This threshold, established under the Greenhouse Gas Reporting Program (GHGRP), applies to the following industries: power plants, petroleum and natural gas systems, manufacturing, chemical production, refineries, mining and coal operations, waste management, industrial gas suppliers, transportation fuel suppliers, and other miscellaneous sectors.

as potentially associated with underreporting and anticipate higher regulatory costs from future regulations. In sum, our findings indicate that firms tend to underreport carbon emissions. By independently and objectively assessing the facility-level carbon emission information, Climate TRACE aids price discovery.

Next, we explore the determinants of underreporting. We find that facilities are more likely to underreport when the parent firm: (i) incorporates carbon metrics into executive compensation contracts; (ii) is extensively held by Big 3 institutional investors; or (iii) is covered by at least one ESG rating agency. Facilities are less likely to underreport in the year following enforcement actions by the environmental regulator, when the parent firm's headquarter is in a blue state (which typically have stricter environmental regulations), or when the facility is located in a state that has more stringent regulations mandating substantial real investments related to emission reduction. These results are broadly consistent with the findings of Zhang (2024).

The negative market reaction to the revelation of underreporting can reflect a downward revision in expected future cash flows (numerator effect), and/or upward revision of risk premium (denominator effect) discussed earlier. To test the numerator effect, we examine analysts' forecast revisions. We find that analysts revise EPS forecasts downward following CT data release, and the downward revision is more pronounced for the underreporting firms. However, we do not observe a similar effect on analysts' sales forecast revisions. Thus, the evidence suggests while investors revise the expectation of future cash flows downward upon the CT data release, this revision is unlikely to be due to the perceived decline in consumer demand. To shed further light on the numerator effect which might be attributable to the expected increase in expenses, we examine regulatory penalty and firms' environmental investments following the CT data release. The idea is that if environmental regulators take CT information into consideration when monitoring firms' carbon emissions, we would expect an increase in regulatory penalties for underreporting firms. Additionally, underreporting firms might increase their environmental investment in response to the heightened scrutiny by regulators. Our results confirm these predictions, suggesting that the numerator effect likely reflects investors' expectations of an increase in regulatory penalty and firms' environmental investments in the future.

To examine the denominator effect, we explore two aspects that could affect discount rate. On the one hand, we examine the changes in the uncertainty regarding firms' future operations. We find an increase in implied volatility following the CT data release, with the effect being more pronounced for firms that underreport emissions. On the other hand, we investigate the possibility that investors with environmental preferences demand a higher risk premium. We find that Big 3 investors vote with their feet by reducing their stake in covered firms following CT data releases, particularly in those firms that have been underreporting their carbon emissions. The results suggest the increases in investors' perceived uncertainty as well as investors' divestment might contribute to the negative market reactions to the CT data release.

Additionally, investors may find CT data valuable as it enhances the comparability of environmental information across firms (Gao, Jiang, and Zhang 2019). By consistently tracking carbon emissions worldwide using uniform technologies and methodologies across sectors, Climate TRACE can offer more comparable environmental information between different firms. This enhanced comparability reduces information asymmetry and predicts an increase in market liquidity. Our evidence supports this assertion: market liquidity increases for non-underreporting firms following CT releases, albeit the increase is attenuated for underreporting firms.

In our final set of analyses, we examine how various country-level institutions moderate the market reaction, as well as the numerator and denominator effect. We find a weaker market reaction for firms located in countries with existing environmental reporting mandates. Additionally, we observe a stronger market reaction for firms located in countries with stronger enforcement institutions. This is true for both formal institutions proxied by regulatory scrutiny (rule of law in general or environment stringency), and informal institutions (environmental performance index and institutional ownership). Taken together, our findings highlight the importance of third-party provision of environmental information, particularly in countries with less transparent reporting practices and strong environmental enforcement institutions.

Our study makes several contributions. First, the study adds to the literature on reliability of ESG data. There have been persistent concerns regarding the reliability of firms' ESG disclosures and the quality of estimates provided by ESG rating agencies, not to mention the significant disagreements among these agencies (e.g., Berg, Kölbel, and Rigobon 2022; Christensen, Serafeim, and Sikochi 2022). Our study is among the first to provide evidence on the usefulness and informativeness of third-party data in assessing environmental performance. A concurrent study by Zhang (2024) examines spatial CO2 concentration data provided by NASA and finds that firms underreport carbon emissions to the EPA. While related, there are a few key differences between the two studies. First, we focus on market reaction to the release of CT data whereas Zhang (2024) examines determinants of firms' underreporting behavior. Although we use different third-party data, our study and Zhang's (2024) reached comparable conclusions, reinforcing the notion that firms strategically underreport carbon emissions. Importantly, our study goes a step further not only demonstrating that investors negatively react to firm underreporting, thereby highlighting the market discipline imposed on firms' opportunistic reporting behavior, but also distinguishing the channels responsible for the negative market reaction. These findings further reveal investors' preferences and beliefs about carbon emissions. Second, Zhang (2024) focuses on U.S. firms, while our study extends the analysis to firms across 74 countries, enhancing our understanding of how the importance of reliable data to investors varies with a country's institutions.

Second, our findings contribute to the ongoing debate surrounding the mandate of environmental disclosure. Specifically, our evidence that the negative market reaction to the release of CT data is significantly weaker for firms from countries with an existing environmental reporting policy, and stronger for firms from countries with rigorous enforcement of environmental regulations, suggests that reporting transparency is central for investors to obtain credible information on carbon emissions. These findings shed further light on the potential benefits of regulators strengthening environmental reporting quality. Additionally, consistent with extant literature (Cohen, Kadach, Ormazabal 2023; Hartzmark and Sussman 2019), our results underscore that investors' taste plays an important role in their demand for carbon emission information.

Third, our study adds to the literature on alternative data and emerging technologies such as satellite data (Kang, Stice-Lawrence, Wong 2021) and artificial intelligence (Burke, Hoitash, Hoitash, Xiao 2023; Bernard, Blankespoor, Kok, Toynbee 2023). Industry has shown a growing demand for the implementation of emerging technologies in ESG practices (Ernst and Young 2022). Further, endowment managers have expressed concerns that existing carbon footprint metrics may be inaccurate and not yet reliable for practical use (ACSRI 2016). Our study offers preliminary evidence on whether alternative data based on emerging technologies such as satellite data, can provide a more accurate and unbiased signal on firms' carbon footprint, and assist capital market participants in evaluating corporate environmental performance.

2. Related Literature and Background

Our study is connected to three strands of literature.

2.1 Value relevance of corporate carbon emissions

Our study contributes to the bourgeoning literature dedicated to assessing the value relevance of environmental information. In seminal papers, Bolton and Kacperczyk (2021; 2023) estimate the market-based premium associated with carbon-transition risk. They find that investors demand a carbon risk premium as compensation for their exposure to carbon transition risk. This result holds in the cross-section of US listed firms and international firms.

In addition, the value relevance studies have focused on the impact of ESG factors on stock returns, particularly the role of uncertainty and disagreement in ESG ratings. Avramov et al. (2022) highlight that ESG ratings are negatively associated with future stock performance, particularly in cases where there is low uncertainty. However, the relationship between ESG ratings and stock returns becomes positive when there is significant uncertainty surrounding ESG ratings. This suggests that investor demand for green assets diminishes when there is uncertainty in the ratings, especially among institutional investors. In general, institutional investors show a tendency to invest more in stocks with low uncertainty, highlighting that the degree of uncertainty plays a crucial role in shaping ESG-related investment decisions (Stroebel and Wurgler 2021).

2.2 Measurement and reliability of environmental data

Our study adds to the literature on reliability of ESG data. There have been persistent concerns regarding the reliability of ESG information voluntarily reported by companies (Pinnuck et al. 2021), prepared in fulfilment of government disclosure mandates (Zhang 2024), or estimated by ESG information intermediaries – ESG rating agencies (Chatterji et al. 2016). Moreover, ESG rating agencies often have differing opinions on the ratings assigned to individual firms (Berg et al. 2022). Resulting ESG rating disagreement is associated with undesirable market consequences such as higher return volatility, larger price fluctuations, and lower external financing.

In voluntary disclosures, companies may intentionally overstate their environmental performance. Grimmer and Bingham (2013) document that consumers prefer to buy products from companies they perceive to have high environmental performance. When customers perceive firms as socially responsible, they may be more willing to buy the products from these firms at a higher price (Leonelli et al. 2024). Consequently, companies have strong incentives to portray themselves as socially responsible, which raises concerns about the credibility of their corporate ESG reporting.

In fact, several studies have raised doubts about the reliability of ESG disclosures (e.g., Cho, Roberts, and Patten 2010; Pinnuck et al. 2021). Pinnuck et al. (2021), for instance, found that 39% of the CSR reports in their sample had one or more line-item restatements. Similarly, Cho et al. (2010) discovered that companies with poor environmental performance were more likely to use optimistic and uncertain tones in their environmental disclosures. Zhang (2024) examines the quality of emissions information provided by companies to EPA. The author uses spatial CO_2 concentration data derived from satellite images of NASA and finds that firms underreport carbon emissions to the EPA. Further, it documents that firms tend to underreport their emissions more frequently when they have higher public visibility, face increased shareholder pressure to adopt environmentally friendly practices, and are subject to cap-and-trade programs. In contrast, they are less likely to underreport their emissions when they are subject to stricter board oversight and more impacted by environmental disclosure requirements.

Our study is among the first to provide evidence on the valuation impact of third-party data releases in evaluating corporate environmental performance. Specifically, to overcome the limitations of existing data, a non-profit organization, Climate TRACE, has recently released facility-level emissions data based on satellite observations, remote sensing techniques, and artificial intelligence. They aim to provide independent, accurate, and unbiased data to facilitate better decision-making among investors, policymakers, and activists. To achieve this, Climate TRACE uses artificial intelligence (AI) and machine learning (ML) to process and aggregate emission data from more than 300 satellites, 11,000 sensors, and various additional global sources, covering ten different sectors of the economy worldwide.[4]

2.3 Alternative data measurement using emerging technologies: satellite data

Our study also adds to the literature on alternative data and emerging technologies. Specifically, we rely on expanding grasp of satellite data that enabled the construction of alternative measures of important corporate metrics such as earnings forecasts (Kang et al. 2021) and carbon emissions. In addition, satellite-based measurements offer a consistent, manipulation-free method for monitoring pollution.[5]

Using satellite-based measurements researchers exposed opportunistic behaviours of local governments. For example, Zou (2021) shows that pollution is significantly worse on unmonitored

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[4] We provide a brief summary of Climate TRACE methodology in Appendix B. Detailed description of the Climate TRACE methodology is available at https://github.com/climatetracecoalition/methodology-documents/tree/main/2022.

[5] Recent advancements in research on alternative measurement methods using satellite data are driven by the development of the MODIS algorithm. NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm, which captures atmospheric aerosol concentrations by measuring how sunlight is scattered and absorbed by particles at different spectral wavelengths. This data is summarized in a dimensionless index known as Aerosol Optical Depth (AOD), which provides a measure of aerosol concentration in the atmosphere. The satellite captures this data over a wide area, with a spatial resolution of 10 km x 10 km, covering an entire atmospheric column from ground level to the satellite's viewpoint, approximately 700 km above the Earth. The satellite data differ from traditional ground-monitoring data, which measure particulate matter (PM2.5) at specific ground points. However, both methods target similar pollutants, and studies have shown a strong correlation between satellite-based and ground-based measurements, which makes it an effective tool for pollution estimation.

days due to strategic behavior by local governments and industries, who reduce emissions on monitored days to comply with federal standards under the Clean Air Act. Sullivan and Krupnick (2019) find that many counties classified as meeting air quality standards should be considered nonattainment based on satellite data. Yang et al. (2023) find that although automation of air quality monitoring led to a 3.2% decrease in pollution near monitoring stations, the local governments focused their efforts primarily on areas close to sensors, leading to uneven pollution control across cities. Mu and Rubin (2023) find evidence of strategic shutdowns of pollution monitoring stations by local governments around expected pollution spikes, particularly during air quality alerts.

Companies mandated to disclose their facility level emissions may opt for real actions to affect the reported numbers. Jiang (2023) finds that while pollution decreases around reporting facilities, it increases around non-reporting ones, highlighting potential pollution shifting behavior.

Researchers also employed satellite-based pollution data to investigate the adverse effects of pollution on students learning (Pham and Roach 2023), real-time cognitive function (Burton and Roach 2023), leisure activities (Sun 2023), safety (Burkhardt et al. 2019; Bondy, Roth, and Sager 2020), longevity (Gong et al. 2023), and labor productivity (He and Ji 2021).

Corporate world has shown a growing demand for the implementation of emerging technologies in ESG practices (Ernst and Young 2022). Further, endowment managers have expressed legitimate concerns about existing carbon footprint metrics, which may be imprecise and premature to use (ACSRI 2016). Our study offers evidence on whether alternative metrics, which integrate advanced technology combining satellite data, ground sensor data, and AI, can provide a more accurate and unbiased signal on firms' carbon footprint. This, in turn, may assist capital market participants in evaluating corporate environmental performance for price discovery.

3. Hypotheses Development

3.1 Whether and How Does the Market React to the CT Data Releases?

We begin by investigating whether the release of Climate TRACE (CT) carbon emissions data affects the capital market. Previous research indicates that investors value environmental information and react to companies' voluntary carbon disclosures (Matsumura et al. 2014), mandatory ESG disclosures (Krueger et al. 2024), and scores computed by ESG rating agencies (Jain, Jain, and Rezaee 2016). Therefore, it is reasonable to expect that investors will react to the CT carbon emissions data if it provides additional environmental insights.

First, unlike company-provided disclosures of carbon emissions (e.g., to the EPA and CDP), CT data is generated by an independent third party, presumably without opportunistic incentives. Consequently, this data may be less downward-biased and more objective (Couture 2020; Climate TRACE 2020). By observing the underreporting of carbon emissions revealed by the CT data releases, investors might anticipate a decrease in future cash flows, as environmental regulators and activists can impose explicit and implicit fines or require firms to invest in environmental cleanup. Additionally, firms that previously underreported emissions might face greater uncertainty regarding their exposure to environmental policies. These lines of reasoning predict a negative market reaction to CT data releases, termed the “underreporting effect”.

Second, for covered firms without clear evidence of underreporting, investors might still react negatively to the CT release due to a contagion effect. Specifically, investors may perceive a potential risk of underreporting by covered firms with facilities that are currently outside the scope of CT coverage and may anticipate increased compliance costs from potential future regulations.

("contagion effect"[6]). Third, as discussed earlier, CT relies on advanced technologies to generate its data. Therefore, the data is potentially more precise and comprehensive. If this more precise information reduces investors' uncertainty about firms' carbon emissions and minimizes the information asymmetry between the market makers and informed traders, it warrants a lower discount rate and, consequently, a positive market response to CT data releases, termed the "precision effect."

Additionally, investors may find CT data valuable as it enhances the comparability of environmental information across firms. By consistently tracking carbon emissions worldwide using uniform technologies and methodologies across sectors, Climate TRACE can offer more comparable environmental information across different firms. This network effect can lower the costs of assessing firms' relative environmental performance, increase trading profitability, and attract more potential investors to the covered firms. This, in turn, can lead to heightened competition among investors and more informative stock prices (Gao, Jiang, and Zhang, 2019). Furthermore, the increased comparability may enhance investors' ability to make portfolio choices that align with their desired level of carbon emission exposure. The resulting improvements in price informativeness, market liquidity, and portfolio selection may lead to a reduction in discount rate in response to CT data releases (Baiman and Verrecchia, 1995, 1996), termed the "network effect."

However, the market may not react to the release of CT data if most investors are unaware of its availability or its superior attributes. Additionally, there may be no market response if the CT emissions data closely aligns with the company's disclosed data. CT data could also be

[6] Prior accounting studies have documented a contagion effect among peers of restating firms showing that these peers also experience negative cumulative abnormal returns at the time of the restatement announcement (Gleason, Jenkins, Johnson 2008; Xu, Najand, Ziegenfuss 2006).

uninformative if the technologies used to generate it have large inherent limitations such as the coverage and accuracy of satellites being constrained by natural factors like weather and visibility, resulting in a low signal-to-noise ratio.[7]

Although there are countervailing forces determining investors' reaction to CT data releases, we state our first hypothesis in the alternative form:

H1: *There is a negative market reaction to CT data releases.*

3.2 CT Data Releases and Firms' Fundamentals: Numerator Effect

Under the underreporting effect, if CT data releases uncover underreporting of carbon emissions, it may lead to a downward revision in expected future cash flows — the numerator effect. This revision could result from an anticipated decline in revenue and/or an expected rise in costs. For companies that deal directly with consumers (B2C), the exposure of underreporting may reduce customers' willingness to purchase from these companies (Grimmer and Bingham 2013) and diminish their willingness to pay premium prices for the companies' products (Leonelli et al. 2024).

In the context of supply-chain contracting (B2B), if the CT data reveals underreporting, a company may lose some of their corporate clients. Darendeli et al. (2022) found that suppliers with low CSR ratings experienced a decline in both contracts and customers, underscoring the importance of CSR performance in supplier selection.

Regarding the expected rise in costs, affected companies may face higher regulatory penalties, increased spending on carbon offsets and removals, and a greater need for investment in carbon abatement technologies. The premise is that if environmental regulators use CT data to monitor firms' carbon emissions, underreporting companies will likely face increased regulatory

[7] Appendix C summarizes our theoretical predictions.

penalties.[8] Subsequently, these firms may boost environmental investments in response to heightened regulatory scrutiny. We therefore state our second hypothesis as follows:

***H2**: The expected future cash flows in response to CT data releases will decrease.*

3.3 CT Data Releases and Firms' Perceived Risk: Denominator Effect

On one hand, under the underreporting effect, if the release of satellite-based emissions data reveals underreporting of carbon emissions, it may lead to an upward revision of the risk premium — known as the denominator effect. In other words, the value of affected companies may decline due to increased risk, resulting in a higher discount factor applied by market participants in their valuations (Bolton and Kacperczyk 2021, 2023). Rational investors may demand a higher risk premium because of heightened uncertainty regarding a firm's exposure to regulatory interventions, activist campaigns, and institutional investor engagement. Furthermore, increased uncertainty about firms' future operations and potential government regulations could contribute to negative market reactions following the release of satellite-based emissions data.

On the other hand, under the precision effect and network effect, CT data releases can lead to increased market liquidity and higher price informativeness, resulting in a lower discount rate, as discussed in the first hypothesis. Although the effect of CT data releases on the discount rate is ambiguous, we state our third hypothesis in the alternative form:

***H3**: Risk premium in response to CT data releases will increase.*

[8] Our discussion with the employee of CT indicates that regulators do reach out to CT for emission data.

4. Sample and Research Design

4.1 Sample Selection

We obtain facility-level greenhouse gas emission data released by Climate TRACE on two separate occasions: November 09, 2022 and December 03, 2023.[9,10] We then supplement the carbon emissions data from CT with various additional datasets: accounting data from Compustat and Worldscope, return data from CRSP, analyst forecast data from I/B/E/S, options data from OptionMetrics, institutional ownership data from Thomson Reuters and FactSet/LionShares database, ESG ratings from Refinitiv, Bloomberg, and Sustainalytics, facility-level carbon emissions from Facility Level Information on GreenHouse gases Tool (FLIGHT), and details of compensation contracts from ISS ECA database.

Our sample includes two types of firms: treatment firms, which are covered by the CT data releases, and control firms, which are not covered by CT but are from the same country and the same two-digit SIC industry as at least one treatment firm. We construct both an international sample and a U.S. sample. The U.S. sample is particularly useful because environmental regulator's data are available at the facility level for most of the firms, allowing us to compare the CT data with the regulator's data to assess firms' strategic reporting behavior.

Panel A of Table 1 presents sample selection process. We start with 99,705 firm-years in the Worldscope annual database for the years 2022 and 2023. From this initial dataset, we exclude observations from country-industry groups that do not contain any treated firms, as well as those missing essential information required for variable construction. This results in 36,876 firm-years

[9] Figure 1 presents Google Trends data for "Climate TRACE" around these two dates, highlighting increased search interest during this period.
[10] Climate TRACE research team conducted thorough investigations to identify the owners of each facility. They primarily focus on fossil fuel operations and manufacturing, as the carbon emissions of these sectors have been historically difficult to estimate (Gans et al. 2022).

for the international sample and 4,226 firm-years for the U.S. sample. Among these, there are 1,850 treatment firms in the international sample and 238 treatment firms in the U.S. sample. Sample size varies across different tests depending on the availability of data.

Panel B of Table 1 shows the composition of the sample by industry, categorized by one-digit SIC code. As disclosed by CT, we also find that firms in Manufacturing, Agriculture and Mining, Transportation and Communications, and Construction industries are more likely to be covered by CT.[11] Panel C of Table 1 presents the sample composition by geographic region, indicating that East Asia & Pacific, North America, and Europe & Central Asia are the three regions that have the highest representation in the sample of treatment firms.[12]

[Insert Table 1 here]

Table 2 presents descriptive statistics of the variables used in the analysis. We note that five percent of observations in our sample correspond to firms covered by Climate TRACE. In the U.S. sample, 2.6 percent of firms underreport their carbon emissions, while only 0.7 percent of firms have not underreported their facility level emissions in 2015-2022.[13] The average scope of documented underreporting is 37.5 percent of the carbon emissions levels revealed by CT.

In the U.S. sample, covered firms have an average Big 3 ownership of 11.2 percent, ownership by non-Big 3 PRI signatories of 12.2 percent, and ownership by the other institutions of 33.7 percent. Additionally, 9.2 percent of these firms incorporate specific GHG emission metrics in their executive compensation contracts, and 85.5 percent are rated by at least one ESG rating agency. Finally, 84 percent of firms in international sample come from countries with existing environmental reporting mandates.

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[11] See https://climatetrace.org/sectors?utm_source

[12] Figure 2 displays the global coverage of CT on a world map.

[13] The first Climate TRACE data release in 2022 covers the time period from 2015 to 2021, providing historical emissions data across various sectors and geographic regions.

[Insert Table 2 here]

4.2 Research Design

4.2.1 Market Reactions around CT Data Release (H1)

To test H1 of whether the market reacts to CT data releases, we estimate the following OLS regression model:

$$CAR_{it} = \beta_0 + \beta_1 COVERED_{it} + \beta_2 SIZE_{it} + \beta_3 MTB_{it} + \beta_4 ROA_{it} + \beta_5 LEVERAGE_{it} + \beta_6 CASH_{it} + \beta_7 TANGIBILITY_{it} + \beta_8\ R\&D\ INTENSITY_{it} + FEs + \varepsilon, \quad (1)$$

where *CAR* is the two-day [0,1] local-market adjusted cumulative abnormal returns following the data releases by Climate TRACE. We measure local-market adjusted index by value-weighting all the returns of individual stocks traded in the same country (Bartram and Grinblatt 2021). Our main test variable is *COVERED*, an indicator variable that equals to one if a firm is covered by Climate TRACE in year *t*, and zero otherwise. We include standard controls of firm characteristics such as firm size (*SIZE*), market-to-book ratio (*MTB*), profitability (*ROA*), leverage (*LEVERAGE*), cash holdings (*CASH*), asset tangibility (*TANGIBILITY*), and research and development expenditures (*R&D INTENSITY*) in the regression model. All variables are defined in Appendix A. We include year fixed effects to control for the variation in market conditions across the two events of data releases. We further include industry and country fixed effects to control for the effects of time-invariant industry and country characteristics. Standard errors are clustered at the country-industry level. The coefficient of interest in Equation (1) is β_1. A negative coefficient estimate for β_1 would be consistent with negative market reactions to the data releases by CT.

To probe whether underreporting is responsible for any negative market response to CT data releases, we interact *COVERED* with *UNDERREPORTING*, an indicator variable capturing whether the CT data reveal underreporting behavior of the firm in the U.S. sample. We measure the intensity of underreporting of carbon emissions as the extent to which the level of firms' self-reported carbon emission deviates from that revealed by Climate TRACE. To do that we collect self-reported facility-level carbon emissions data from the EPA FLIGHT database. Since Climate TRACE's 2022 and 2023 data releases include facility-level carbon emissions data for years 2015 - 2022, we begin by computing the annual misreporting intensity at the facility level:

$$\%UNDERREPORTING\_FACILITY_{j,i,t} = \frac{CT\_CO2_{jit} - EPA\_CO2_{jit}}{CT\_CO2_{jit}},$$

where CT_CO2_{jit} is the level of carbon emission estimated by the CT for facility *j* of company *i* in year *t*; EPA_CO2_{jit} is the level of carbon emission at facility *j* reported by company *i* to the EPA in year *t*. Next, for each firm we average the facility level misreporting intensities across time and facilities, the result we denote as *%UNDERREPORTING*.

$$\%UNDERREPORTING_i = \frac{1}{8}\sum_{t=2015}^{2022}\frac{1}{J}\sum_{j} UNDERREPORTING\_FACILITY_{j,i,t}$$

We also create an indicator variable, *UNDERREPORTING*, that takes the value of one if *%UNDERREPORTING* is above zero, and zero otherwise.[14] A negative and significant coefficient on the interaction term, *COVERED*UNDERREPORTING*, would be consistent with the argument that underreporting is a primary driver of negative market reactions.

4.2.2 Determinants of Underreporting

To understand what motivates companies to underreport GHG emissions to the EPA, we estimate the following OLS regression model using the sample of facilities of U.S. firms that report to the EPA and are at the same time covered by CT:

$$\%UNDERREPORTING\_FACILITY_{j,i,t} = \beta_0 + \beta_1 CARBON\ METRIC_{i,t-1} + \beta_2 BIG\ 3_{i,t-1} + \beta_3 NON\text{-}BIG\ 3\ PRI_{i,t-1} + \beta_4 NON\text{-}PRI_{i,t-1} + \beta_5 RATED_{i,t-1}$$

[14] Under this definition, *UNDERREPORTING* takes the value of 0 for the following groups of firms: (1) firms not covered by CT (i.e., *COVERED* =0), (2) covered firms where facilities are exempt from disclosure to the EPA, and (3) covered firms where facility-level EPA data are available for the calculation of *%UNDERREPORTING* and where *%UNDERREPORTING* is lower than or equal to 0, i.e., the true non-underreporting firms. We create an indicator variable for the last group, *NON-UNDERREPORTING*, which takes the value of one if *%UNDERREPORTING* ⩽ 0. Notably, while the *NON-UNDERREPORTING* group does not have underreporting observed at facilities covered by CT, underreporting is still possible at non-covered facilities of these firms.

$$+ \beta_6 ENFORCEMENT\_HQ_{i,t-1} + \beta_7 ENFORCEMENT\_FACILITY_{j,t-1}$$
$$+ \beta_8 BLUE\ STATE\_HQ_{i,t-1} + \beta_9 BLUE\ STATE\_\ FACILITY_{j,t-1}$$
$$+ \beta_{10}\ NON\text{-}ATTAIN\_HQ_{i,t-1} + \beta_{11} NON\text{-}ATTAIN\_\ FACILITY_{j,t-1}$$
$$+ \beta_{12} SIZE_{i,t-1} + \beta_{13} MTB_{i,t-1} + \beta_{14} ROA_{i,t-1} + \beta_{15} LEVERAGE_{i,t-1} + \beta_{16} CASH\ _{i,t-1}$$
$$+ \beta_{17} TANGIBILITY\ _{i,t-1} + \beta_{18} R\&D\ INTENSITY_{i,t-1} + FEs + \varepsilon, \quad (2)$$

where *%UNDERREPORTING_FACILITY* is the intensity of underreporting of carbon emissions of facility *j* of company *i* in year *t* defined above. On the right-hand-side we include characteristics of the facilities and their parent firms in year *t-1*. To capture internal pressure to underreport carbon emissions, we include *CARBON METRIC*, an indicator variable that equals to one if a firm incorporates carbon metric to executive compensation contract in the previous year, and zero otherwise (Cohen et al. 2023). Prior literature finds that external parties such as climate-conscious institutions and ESG rating agencies demand information on firms' ESG practice (Azar et al. 2021; Christensen et al. 2022; Cohen et al. 2023). Thus, we control for *BIG 3*, the level of ownership by Big 3 institutional investors. Since all Big 3 institutional investors signed up for UN Principles for Responsible Investment (PRI) by November 2014, we also include *NON-BIG 3 PRI*, and *NON-PRI* to capture the level of ownership by non-Big 3 PRI signatories and non-PRI signatories. This enables us to disentangle the effects of Big 3 status and PRI signatory status on ESG misreporting. We control for external monitoring from ESG rating agencies by including *RATED*, an indicator variable that equals to one if the company is covered by at least one of the ESG rating agencies, and zero otherwise. We include *ENFORCEMENT_HQ* and *ENFORCEMENT_FACILITY* to account for the disciplining effect of previous enforcement actions by the EPA at both the parent firm and facility level.

We augment the model with *BLUE STATE_HQ*, *BLUE STATE_FACILITY*, *NON-ATTAIN_HQ*, *NON-ATTAIN_FACILITY* to account for the effect of local conditions on facility's reporting behavior. Specifically, *BLUE STATE_HQ* and *BLUE STATE_FACILITY* are proxies for whether the parent firm and facility locate in a "blue" state or not, respectively. In the same way, *NON-ATTAIN_HQ* and *NON-ATTAIN_FACILITY* are proxies for whether the parent firm and facility locate in a non-attainment county. In the U.S., counties are categorized as non-attainment by the EPA if they do not meet the National Ambient Air Quality Standards. Regulators in these counties thus face stronger incentives to improve air quality (Blundell, Gowrisankaran, and Langer 2020). We control for the non-attainment status of the county since facilities in non-attainment counties are required to adopt technologies that achieve the lowest possible emission rates, irrespective of the cost of doing so (Zou 2021). To the extent that facilities in non-attainment counties face higher level of regulatory monitoring, we would expect these facilities to engage in less underreporting behavior. Lastly, we include the same set of firm specific control variables as in Equation (1). We include industry and year fixed effects and cluster standard errors at three different levels, facility, firm, and industry.

5. Results

5.1 Market Reactions to CT Data Release (H1)

Panel A of Table 3 provides a univariate analysis of the market reaction to CT data releases. We find that the mean abnormal market reactions to CT data releases among treatment firms in both the international and U.S. samples are negative and significant, with returns of -0.8 percent and -2.9 percent, respectively. These results offer preliminary evidence that the market reacts negatively to CT data releases.

To strengthen and further verify this result in a multivariate setting, we estimate Equation (1), and the results of the multivariate regression analysis are presented in Panel B of Table 3. Specifically, the coefficients on *COVERED* are negative and significant in columns (1) and (2), suggesting that firms covered by CT experience significantly negative market reactions on the CT data release dates compared with control firms ($p<0.05$ and $p<0.01$). This negative association is not only statistically significant but also economically meaningful. Estimate from the full sample (column (1)) indicates that CT data releases are associated with a decrease in abnormal return by 40 basis points, or 9.5% (= 0.004/0.042) of its standard deviation.

In column (3) of Table 3, we document a negative and significant coefficient on the interaction term, *COVERED*UNDERREPORTING*, which supports the argument that underreporting of emissions is one of the drivers of negative market reactions on the CT data release dates. Additionally, the significantly negative coefficient on *COVERED* indicates that even treatment firms without any revealed underreporting behavior face negative market reactions following CT data releases, albeit to a lesser extent. This effect may potentially come from two types of firms: (1) covered firms where facilities are exempt from reporting to the EPA; (2) covered firms accurately reporting to the EPA data that aligns with the estimates released by CT. For the firms of the second type, we create an indicator variable, *NON-UNDERREPORTING*, that equals to one if *%UNDERREPORTING* is lower than or equal to 0.

To further explore the sources of negative market reactions following CT data releases among firms without revealed underreporting, we interact *COVERED* with *NON-UNDERREPORTING* in column (4) of Table 4. We find an insignificant coefficient on the interaction term, *COVERED*NON-UNDERREPORTING*, while the coefficients on *COVERED* as well as *COVERED* + *COVERED*NON-UNDERREPORTING,* are both negative and statistically significant. These results align with the contagion effect as the underlying cause of the negative market reactions observed in both types of firms on the releases of the CT data. Specifically, as a result of the CT data release, investors may anticipate higher regulatory and environmental compliance costs not only for underreporting firms, but also for non-underreporting firms and companies with facilities exempt from EPA reporting.

Results in Panel C of Table 3 corroborate and expand upon the interaction results in Panel B by clearly documenting a negative association between the market reaction (*CAR*) and the intensity of revealed underreporting (*%UNDERREPORTING*). This relationship holds regardless of whether the underreporting intensity is restricted to values greater than zero. Overall, these findings suggest that some firms tend to underreport carbon emissions, and Climate TRACE aids in price discovery by independently and objectively providing facility-level carbon emissions data that is valuable to the market.

[Insert Table 3 here]

5.2 Determinants of Underreporting

To investigate the factors driving companies' emissions underreporting behavior, we estimate Equation (2). The results of these estimations are presented in Table 4. We find that the intensity of facility-level underreporting increases when the firm includes environmental metrics in its executive compensation contract, has greater ownership by Big 3 institutional investors, and is rated by at least one ESG rating agency. [15] All these factors may induce pressure on firms to report lower levels of carbon emissions. Conversely, we observe negative and significant coefficient on *ENFORCEMENT_HQ*, suggesting that the intensity of underreporting decreases following enforcement actions by the EPA. Similarly, we document negative and significant coefficients on *BLUE STATE_HQ* and *NON-ATTAIN_FACILITY*. These results suggest that

[15] The positive coefficients on *BIG 3*, along with the negative coefficients on *NON-BIG 3 PRI* and *NON-PRI*, suggests the following. First, Big 3 are distinct from the rest of institutional investors in terms of their positive influence on firms' incentives to underreport CO_2 emissions. Such evidence helps substantiate our investigation of the moderating effects of Big 3 ownership in the cross-sectional analyses part. Second, in general PRI signatories do not appear to have a clear directional influence on firms' incentives to underreport, consistent with recent literature's finding that PRI signatories do not exhibit superior ESG scores of funds or their portfolio companies (e.g., Gibson et al., 2022; Kim and Yoon, 2022; Liang et al., 2022).

underreporting is less pronounced when a firm is headquartered in a "blue" state, where environmental regulations are typically stricter, and when a facility is located in a non-attainment country, where stringent regulations mandate substantial real investments in emission-reduction plans (Blundell, Gowrisankaran, and Langer 2020).

Lastly, we find that larger firms, R&D intensive firms, and firms with more tangible assets are more likely to underreport their emissions. In contrast, more profitable firms and more leveraged firms tend to underreport their emissions to a lesser extent. Overall, our results are broadly consistent with the findings of Zhang (2024).

[Insert Table 4 here]

5.3 Numerator vs. Denominator Effects (H2 and H3)

After documenting significant negative market reactions to CT data releases, we next explore whether these reactions are due to the market adjusting its expectations of future cash flows (the numerator effect) and/or discount rates (the denominator effect).

Table 5 presents the results of regressions estimating the numerator effect. We use equity analysts' forecasts revisions to capture changes in investors' expectations regarding future cash flows. We compute the dependent variable, *EPSREV*, as follows:

$$EPSREV = 100 * \frac{EPS\_forecast\_Post - EPS\_forecast\_Prior}{Price},$$

where *EPS_forecast_Post* is the median analysts' consensus of one-year ahead EPS forecast within four months after CT data release, *EPS_forecast_Prior* the median analysts' consensus of one-year ahead EPS forecast within four months before CT data release, and *Price* is the firm's stock price at the beginning of the year.[16]

[16] Results are robust to the use of alternative time frames, such as a three-month window, to calculate forecast revisions.

Columns (1) and (3) model the changes in analysts' earnings forecasts following the CT data releases for the international and U.S. samples, respectively. We find a negative and significant coefficient on *COVERED* in both samples, indicating that analysts revised their expected future cash flows downwards following the CT data releases. This result is not only statistically significant but also economically meaningful. Estimate from the international sample (column (1)) indicates that CT data releases are associated with a decrease in *EPSREV* of 13.3 percent (= 0.041 in columns (1)/0.042) of the standard deviation. For the U.S. sample in column (4), we find a negative and significant coefficient for the interaction term, *COVERED*UNDERREPORTING*, suggesting that analysts factor in the underreporting revealed by CT data releases when revising earnings forecasts downward.

Next, we examine how CT data releases affect sales forecast revisions to pinpoint the specific components leading up to the downward earnings forecast revisions. We compute the dependent variable, *SALEREV*, as follows:

$$SALEREV = 100 * \frac{Sales\_forecast\_Post \text{ - } Sales\_forecast\_Prior}{MarketCap.},$$

where *Sales_forecast_Post* is the median analysts' consensus of one-year ahead sales forecast within four months after CT data release, *Sales_forecast_Prior* the median analysts' consensus of one-year ahead sales forecast within four months before CT data release, and *MarketCap* is the firm's market capitalization at the beginning of the year. We do not observe significant effect of CT data releases on *SALEREV* in either sample. Taken together, these results suggest that analysts lower their expectations for future cash flows following CT data release, and these downward revisions are unlikely to be driven by an expected decline in sales.

[Insert Table 5 here]

Table 6 Panel A presents the results of regressions estimating the denominator effect related to investors' perceived uncertainty. To proxy for the component of the discount rate related to uncertainty we use abnormal implied volatility, ABNIMPVOL, which is computed as follows:

$$ABNIMPVOL=\frac{IMPVOL_t+IMPVOL_{t+1}}{2}-\frac{IMPVOL_{t-2}+IMPVOL_{t-1}}{2}$$

where $IMPVOL_t$ is an implied volatility over date t (i.e., CT data release date) of standardized options with a time to maturity of 30 calendar days. Column (1) uses the international sample and presents a positive and significant coefficient on *COVERED*, suggesting an increase in implied volatility for treatment firms compared to control firms following CT data releases. This finding supports the conjecture that investors' perceived uncertainty increases following the CT data releases. Economically, the incremental abnormal implied volatility observed in treatment firms relative to control firms correspond to a 13.4 percent (0.021/0.157) increase of the standard deviation of *ABNIMPVOL*. In column (2), we find that a significant and positive coefficient on the interaction term, *COVERED*UNDERREPORTING*, which suggests that the increase in implied volatility is more pronounced for underreporting firms.

To investigate whether the network effect and precision effect also play a role, we supplement the implied volatility tests with tests of how CT releases affect firms' market liquidity based on measures of trading volume and bid-ask spread. Specifically, we calculate *ABNVOLUME1W* (*ABNVOLUME1M*) as the mean value of log trading volume in the week (month) after CT release minus that in the week (month) before CT release. *ABNSPREAD1W (ABNSPREAD1M)* is calculated as the mean value of bid-ask spread as a percentage of mid-price in the week (month) after CT release minus that in the week (month) before CT release. We present the trading volume test results in columns (3) to (6) of Table 6 Panel A, which show that the coefficient on *COVERED* is positive and significant in three out of four columns, and the coefficient on *COVERED*UNDERREPORTING* is negative and significant in columns (4) and (6) using the U.S. sample. The bid-ask spread results in columns (7) to (10) are generally consistent with the volume results. Combined, these findings suggest an increase in market liquidity for non-underreporting firms upon CT releases, whereas the increase is attenuated for underreporting firms, supporting both the network effect and precision effect of CT. Using column (4) result to interpret the economic significance of the effect of CT data release on market liquidity, we find the incremental liquidity observed in non-underreporting treatment firms relative to control firms correspond to a 10.1 percent (0.085/0.836) increase of the standard deviation of *ABNVOLUME1W*.

Aside from increased uncertainties, investors' preferences can also explain the increase in the discount rate if these investors apply substantial discounts for firms with higher carbon emissions. To capture changes in the risk premium of investors with environmental preferences, we examine changes in holdings by Big 3 investors (i.e., BlackRock, State Street, and Vanguard) since prior studies suggest these investors are large and influential investors who care about environmental issues when investing (Cohen et al. 2023). Thus, we expect Big 3, compared with Non-Big 3 investors, to "vote with their feet" when the CT data exposes underreporting firms.

Table 6 Panel B presents the regression results estimating how Big 3 respond to CT data releases. The first two columns use the international sample and show a negative and significant coefficient on *COVERED* when we use *ΔBIG3 OWNERSHIP* as the dependent variable to capture the change in holdings by Big 3 institutional investors. In contrast, when we use *ΔNON-BIG3 OWNERSHIP* as the dependent variable, the coefficient on *COVERED* is not statistically significant. Additionally, the negative effect of *COVERED* on ownership by Big 3 investors is more pronounced for underreporting firms (column (2)). These results suggest that large and influential investors “vote with their feet” by divesting from firms covered by CT, particularly from those firms that have been underreporting carbon emissions.

[Insert Table 6 here]

Taken together, results in Table 5 and Table 6 suggest that both the lower expected cash flows (the numerator effect) and higher risk premium (the denominator effect) contribute to negative market reactions experienced by firms covered by the CT data releases. These results are consistent with our predictions formulated in H2 and H3.

5.4 Cross-sectional Variation in Country Institutions

In this section, we assess the potential of various country-level institutions to moderate the market impact of CT data releases. We focus on three aspects of country-level institutions: i) mandatory environmental reporting, ii) strength of formal institutions, and iii) strength of informal institutions.

We obtain information on ESG regulations across the world from Krueger et al. (2024). *E-REPORTING MANDATE* is an indicator variable that equals one if a firm is located in a country that mandates environmental reporting regulations in year t, and zero otherwise. In panel A of Table 7, we find a positive coefficient on the interaction term *COVERED* * *E-REPORTING MANDATE* when the dependent variables are *CAR* (column (1)) and *EPSREV* (column (2)). In other words, in countries with mandated environmental reporting, the market reaction to CT data releases is less pronounced, implying that investors rely less on third-party data when firms are already required by law to disclose environmental information. This result sheds light on the association between mandated environmental disclosure regulations and third-party environmental information provision.[17]

We use two measures of quality of country's formal institutions. First, following La Porta et al. (2006), Srinivasan et al. (2015), and Krueger et al. (2024), we use the Rule of Law index from the World Bank to capture the overall strength of a country's formal institutions. The Rule of Law index, *RULE OF LAW*, reflects perceptions of the extent to which agents in a country have confidence in and abide by the rules of society regarding the contract enforcement, property rights protection, the law enforcement. This measure also captures the quality of the judiciary system and the prevalence of crime and violence.[18] Second, we use the Environmental Policy Stringency Index, *ENV. STRINGENCY INDEX*, from OECD to capture the enforcement strength of environmental laws specifically (Botta and Koźluk 2014; Kim et al. 2021). This index measures the degree to which environmental policies impose an explicit or implicit price on polluting or environmentally harmful behavior.

We use two measures of quality of country's informal institutions. First, following Starks (2023) and Krueger et al. (2024), we construct the country-level Environmental Performance Index, *ENV. PERF. INDEX*. This index measures societal outcomes related to environmental health and ecosystem vitality and captures the strength of environmental performance. It reflects the extent of public belief in the importance of environmental issues in a given country-year. Second, we calculate country-year level of Big 3 institutional ownership, *BIG 3 OWNERSHIP_COUNTRY*, as the value weighed ownership ratio by Big 3 institutional investors in the previous year. This metric

[17] While the insignificant coefficients on the interaction term when the dependent variable is *ABNIMPVOL* in Table 7 could suggest lack of results, they could be attributable to lack of power or variation in the moderating variable since options data is only available for the U.S. and Europe.
[18] Our results are robust to use of alternative formal institution measures, such as Government Effectiveness Index, from Krueger et al. (2024).

reflects the influence of large, environmentally conscious investors on corporate behavior in a specific country-year.

The coefficients on the interaction terms in Panels B to E are negative and significant, suggesting a stronger market reaction to CT data releases for firms located in countries with stronger institutions, whether formal or informal. These results may indicate that in countries with strong institutions companies may face more severe consequences if underreporting is revealed by the release of the third-party data. Moreover, the release of such data may induce substantial changes in environmental regulations that will affect all companies.

[Insert Table 7 here]

5.5 Economic Consequences

In the final section, we investigate the economic consequences for covered firms following the release of CT data. Specifically, we examine whether CT data release is associated with a decline in future cash flows due to higher regulatory penalties and environmental abatement activities of treatment firms. To the extent that EPA takes CT information into consideration when monitoring firms' carbon emissions, we expect an increase in regulatory penalties for underreporting firms. If there is indeed heightened scrutiny by regulators, we would also expect firms to respond by increasing their investments in carbon abatement initiatives.

We calculate *LOG(PENALTY)* as the natural logarithm of one plus the EPA penalty amount. To capture firms' investments in environmental issues (i.e., abatement initiatives), we follow Naaraayanan, Sachdeva, and Sharma, (2020) and use reductions in toxic releases, *LOG(TOXIC RELEASES)*, which is computed as the natural logarithm of one plus the amount of toxic releases (in pounds). To test our conjectures, we create an indicator variable, *POST*, which takes the value of one for 2023, and zero for 2020 and 2021. A positive (negative) coefficient on the interaction between *COVERED* and *POST* when the dependent variable is *LOG(PENALTY)* (*LOG(TOXIC RELEASES)*) would be consistent with higher regulatory cost and environmental investment following CT's coverage.

Table 8 presents results of the estimating how CT data releases affect the EPA penalty and environmental investments. In column (1), the coefficient on the interaction between *COVERED* and *POST* is positive and significant, indicating an increase in regulatory penalties for treatment firms. This result is consistent with the EPA integrating CT information into their enforcement decisions. In column (2), we find a negative and significant coefficient on the interaction term, suggesting that treatment firms increase the level of environmental investments which led to the reduction in the amount of toxic releases. Taken together, these results suggest CT releases lead to increases in both regulatory penalties and environmental investments for treatment firms, corroborating the numerator mechanism for the market impact of CT releases.

[Insert Table 8 here]

6. Conclusion

This study examines market reactions worldwide to emissions data releases by Climate TRACE. We find negative market reactions of 40 BP in the two days around the events. The negative market reactions are primarily due to the underreporting of carbon emissions. Various facility and firm-specific factors are shown to be associated with underreporting decisions, including the use of carbon metric in executive compensation, Big 3 ownership, and the political leaning of the firm's headquarters location. Additional analysis reveals that investors expect a decline in future cash flows, possibly due to increased regulatory penalties and additional investments in cleanup, rather than declining sales to consumers and corporate clients. We also observe a significant increase in uncertainties and thus a discount rate, as evidenced by higher implied volatilities of the options. Additionally, there is an improvement in market liquidity, although this is less pronounced for underreporting firms. This evidence is consistent with the enhanced comparability and information precision due to CT releases. Cross-sectionally, a country's existing environmental reporting mandates mitigate negative market reactions, whereas a country's formal and informal institutions in environmental enforcement exacerbate negative market reactions.

Overall, our study is pioneering in providing empirical evidence on market reactions to third-party data releases on pollution. Our findings offer critical insights for policymakers, illuminating how capital market values transparency on pollution data and how market perceptions are influenced by a country's institutional framework. Our evidence is also informative to corporations, helping them understand whether and how shareholders react to increased transparency in pollution data. By understanding shareholder reactions, firms can better navigate their environmental reporting and compliance strategies. Finally, our findings contribute to academic research by highlighting the importance of objective data on emissions for price discovery. This underscores the role of accurate and transparent environmental data in shaping market behavior and informing investment decisions.

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Appendix A. Variable Definitions

Variables	Definitions
Dependent Variables	
CAR	Two-day local market adjusted cumulative abnormal return after the data release date of Climate TRACE.
EPSREV	Difference between median consensus of one-year ahead EPS forecast within four months following the data release date and that within four months before the data release date, scaled by beginning-of-year stock price, multiplied by 100.
SALEREV	Difference between median consensus of one-year ahead sales forecast within four months following the data release date and that within four months before the data release date, scaled by beginning-of-year market capitalization, multiplied by 100.
ABNIMPVOL	Mean value of implied volatility of standardized options from OptionMetrics over date t and t+1 minus mean value of implied volatility over date t-2 and t-1 among standardized options with a time to maturity of 30 calendar days.
ABNVOLUME1W	Mean value of log trading volume over next week minus mean value of log trading volume over the prior week.
ABNVOLUME1M	Mean value of log trading volume over next month minus mean value of log trading volume over the prior month.
ABNSPREAD1W	Mean value of bid-ask spread as a percentage of mid-price over next week minus mean value of bid-ask spread as a percentage of mid-price over the prior week.
ABNSPREAD1M	Mean value of bid-ask spread as a percentage of mid-price over next month minus mean value of bid-ask spread as a percentage of mid-price over the prior month.
ΔBIG 3 OWNERSHIP	Change in big 3 ownership from three months prior to CT data release to three months post release.
ΔNON-BIG 3 OWNERSHIP	Change in non-big 3 ownership from three months prior to CT data release to three months post release.
LOG(PENALTY)	Natural logarithm of one plus the EPA penalty amount.
LOG(TOXIC RELEASES)	Natural logarithm of one plus the amount of toxic releases (in pounds).
Test Variables	
COVERED	Indicator variable that equals one if a firm is covered by Climate TRACE at date *t*, and zero otherwise.
UNDERREPORTING	Indicator variable that equals one if *%UNDERREPORTING* is above zero, and zero otherwise. *%UNDERREPORTING* is defined below.
NON-UNDERREPORTING	Indicator variable that equals one if *%UNDERREPORTING* less than or equal to zero, and zero otherwise. *%UNDERREPORTING* is defined below.
%UNDERREPORTING	Firm-level underreporting intensity, calculated as the average of facility-year level underreporting intensity across reporting years (i.e., 2015 to 2022) and facilities of each firm, where facility-year level underreporting intensity , *%UNDERREPORTING_FACILITY*, is defined below.
%UNDERREPORTING_FACILITY	Facility-year level underreporting intensity, calculated as (CT CO2 emissions - EPA CO2 emissions)/CT CO2 emissions, the difference between facility-level CO_2 emissions from Climate TRACE for year *YYYY* and that from EPA FLIGHT database for year *YYYY*, scaled by CO_2 emissions from Climate TRACE.
Control Variables	
SIZE	Natural logarithm of one plus the market capitalization.
MTB	Market value of equity scaled by book value of equity.
ROA	Prior-year net income scaled by lagged assets.
LEVERAGE	Total debt scaled by lagged assets.
CASH	Cash and cash equivalents scaled by assets.
TANGIBILITY	Property, plant, and equipment scaled by assets.
R&D INTENSITY	Research & Development expense scaled by assets.
Variables for Facility-level Determinant Analysis	
CARBON METRIC	Indicator variable that equals one if firm incorporates carbon metric to compensation contract in the previous year, and zero otherwise.
BIG 3	Ratio of ownership by Big Three institutional investors in the previous year.
NON-BIG 3 PRI	Ratio of ownership by non-Big Three PRI signatories in the previous year.
NON-PRI	Ratio of ownership by non-PRI signatories in the previous year.

RATED	Indicator variable that equals one if a firm is rated by ESG rating agencies in the previous year, and zero otherwise.
ENFORCEMENT_HQ	Indicator variable that equals one if the firm has at least one enforcement case from the EPA during the previous year, and zero otherwise.
ENFORCEMENT_FACILITY	Indicator variable that equals one if the facility has at least one enforcement case from the EPA during the previous year, and zero otherwise.
BLUE STATE_HQ	Indicator variable that equals one if the firm's headquarters is in a blue state, and zero otherwise.
BLUE STATE_FACILITY	Indicator variable that equals one if a facility is in a blue state, and zero otherwise.
NON-ATTAIN_HQ	Indicator variable that equals one if the firm's headquarters is in a non-attainment country in previous year (categorized by the EPA based on monitoring results), and zero otherwise.
NON-ATTAIN_FACILITY	Indicator variable that equals one if the facility is in a non-attainment country in a previous year (categorized by the EPA based on monitoring results), and zero otherwise.
Cross-sectional Variables	
E-REPORTING MANDATE	Indicator variable that equals one if a firm is located in a country that mandates E-reporting, and zero otherwise.
RULE OF LAW	Country-level Rule of Law (source: World Bank) in the previous year. This index captures perceptions of the extent to which agents in a country have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.
ENV. STRINGENCY INDEX	Country-level OECD Environmental Policy Stringency Index (source: OECD) in the previous year. This index captures the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior.
ENV. PERF. INDEX	Country-level Environmental Performance Index (EPI) (source: Yale Center for Environmental Law) in the previous year. This index measures societal outcomes related to environmental health and ecosystem vitality and captures the strength of environmental performance and, in turn, strength of common belief in the importance of environmental issues in a country-year.
BIG 3 OWNERSHIP_COUNTRY	Country-level value weighed ownership ratio by big 3 institutional investors across firms in the previous year.

Appendix B: Climate TRACE Methodology

We briefly summarize how Climate TRACE estimates emissions for each sector.

Power

The power sector is divided into electricity generation and other energy use. In the electricity generation sector, Climate TRACE combines satellite data with existing country- and region-level data, ground-truth generation data, and machine learning models to generate a comprehensive data set on emissions estimates, covering 41 countries throughout the period between 2015 and 2021. They identify global fossil power plants employing a set of datasets including U.S. Energy Information Administration, World Resources Institute, etc. Regarding satellite data, they use remote sensing imagery from the PlanetScope constellation, Sentinel-2A/B, and Landsat-8 satellites to identify emitted water and smoke plumes and infer firms' operational status. Climate TRACE processes the satellite data using a machine-learning approach that predicts the activity of a power plant from a single satellite image. They use region-, fuel-, and prime-mover-specific average carbon intensities to convert asset-level generation estimates to emissions estimates.

In the other energy use subsector, where it is geographically and temporally difficult to track emissions using satellites, Climate TRACE employs an implicit estimation technique by imputing figures derived from a set of datasets, including the Emissions Database for Global Atmospheric Research and Food and Agriculture Organization of the United Nations (FAO).

Manufacturing

The manufacturing sector comprises four main subsectors: steel, cement, chemical and pulp and paper, and aluminum. In steel subsector, Climate TRACE uses satellite-derived production estimates for each plant (in tons of crude steel per plant) and applies emissions factor (tons of CO_2 per ton of crude steel produced), covering facilities across 78 countries. All satellite images were sourced and processed using Google Earth Engine.

In cement subsector, Climate TRACE calculates emissions as a product of satellite-based production levels (in tons of clinker) and emission factor (tons of CO_2 per one of clinker produced), covering cement plants across 36 countries. Production estimates are produced whenever satellite captures enough heat (more than 1,400°C) for the clinkerization to occur.

In chemical and pulp and paper subsector, Climate TRACE estimates the production levels (e.g., in tons of ammonia) for each plant and applies calculated emissions factor (tons of CO_2 per ton of ammonia) to generate emission estimates. They combine datasets, including asset inventory data from Industrial Info Resources, production data from FAO and United Nations Industrial Development Organization, emission factors from International Fertiliser Society, Intergovernmental Panel on Climate Change (IPCC), etc.

In aluminum subsector, Climate TRACE employs multiple data sources to estimate aluminum production, including International Aluminum Institute statistics, United Nations Framework on Climate Change, etc., and systematically applies emission factors to infer emissions.

Fossil Fuel

Fossil fuel operations mainly consist of two subsectors: oil and gas production and transport oil and gas refining, and coal mining. In the oil and gas production, Climate TRACE analyzes remote sensing data and ground truth data to generate Oil Production Greenhouse Emissions Estimator (OPGEE) and The Petroleum Refinery Life-Cycle Inventory Model (PRELIM) to quantify emissions from the production and refining portions of petroleum cycle, respectively. These two models have been peer-reviewed and used globally by policymakers and consider a host of emission sources including flaring, venting, on-site fuel usage, super-emitter events, etc.

In the coal mining subsector, Climate TRACE identifies the 500 highest-producing mines in Google Earth imagery. They combine multiple datasets including UEPG Mineral Publication to acquire historical data on minerals production, Global Energy Monitor Coal Mine Tracker to retrieve information about coal mine production as well as methane emission factors, etc. They apply emission factors to reported production values to estimate emissions derived from mining and quarrying.

Agriculture

The agriculture sector is divided into four main categories: enteric fermentation and manure management, cropland fires, rice cultivation, and synthetic fertilizer application. In enteric fermentation and manure management, Climate TRACE develops a method that uses an artificial intelligence tool called Rapid Automated Image Characterization and satellite imagery to identify beef and dairy feedlot facilities in California and Texas, U.S., and portions of Argentina.

In cropland fires subsector, Climate TRACE uses remote sensing data to detect burned areas and active fires, which enables them to identify global fire emissions inventories. Bottom-up inventories use satellite data to estimate the biomass fuel quantity burned using detections of the burned area along with other observed and modeled factors. Top-down inventories, on the other hand, use satellite observations of fire radiative power as the basis for estimating emissions.

In rice cultivation, Climate TRACE uses Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery data, which provides temporal resolution and spectral measurements to estimate emissions, encompassing 23 countries. They also use Paddy Watch approach in the Google Earth Engine platform, to estimate methane emissions from rice cultivation by identifying where rice was planted, grown, and harvested.

In synthetic fertilizer, Climate TRACE uses a modeling approach to estimate nitrous oxide emissions from synthetic fertilizer applications in the agricultural sector. They combine Tier 1, Tier 2, and Tier 3 methods suggested by the IPCC, with direct N2O emission data reported by countries and crop yield and area data based on national census data from the FAO.

Appendix C: Theoretical Prediction

$$R = \Delta P = \frac{\Delta\left(\sum_{t=1}^{N} CF_t\right)}{\Delta d} \quad \begin{cases} \text{Revenue} \downarrow \\ \text{Expenses/Environmental Investments} \uparrow \end{cases} \quad \begin{cases} \text{Precision effect} \downarrow \\ \text{Network effect} \downarrow \\ \text{Uncertainty} \uparrow \end{cases}$$

Figure 1. Google Trend on "Climate TRACE"

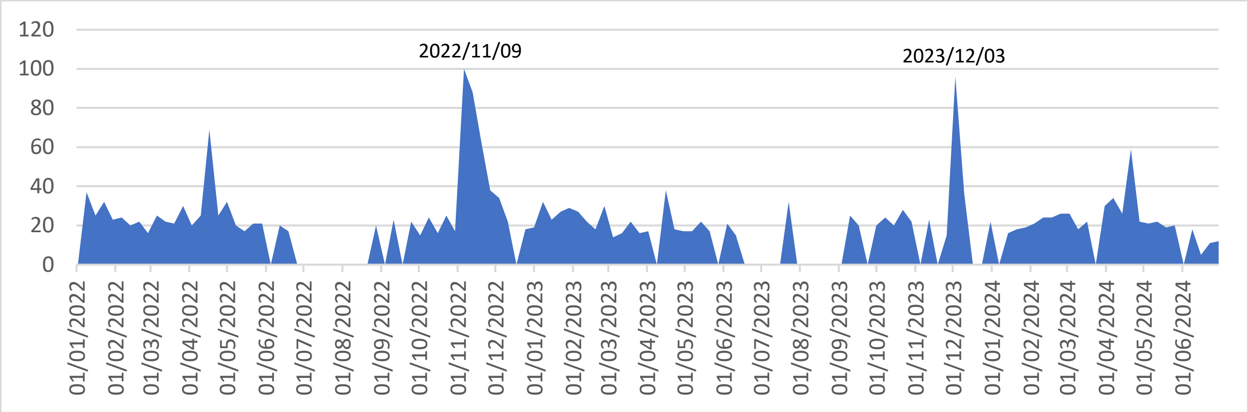

Figure 2. Facilities Covered in Our Sample

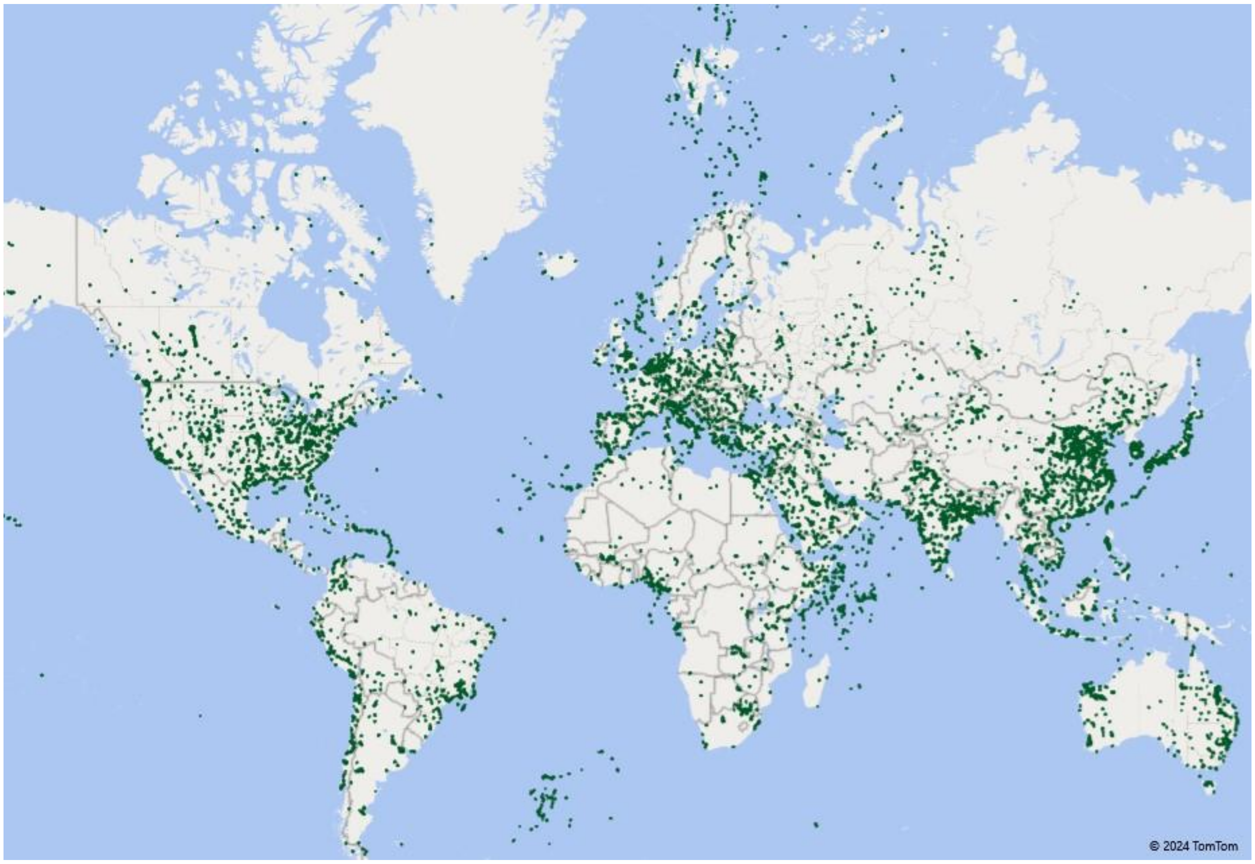

Table 1. Sample Selection and Distribution

This table presents the sample composition across all firms vs. firms covered by Climate TRACE. Panel A presents the sample selection process. Panel B presents sample composition based on SIC one-digit industry. Panel C presents sample composition based on country region (source: World Bank).

Panel A: Sample Selection

	Observations
Total firm-years from 2022 to 2023 in Worldscope annual database	99,705
Excluding observations not meeting the following criteria:	
SIC two-digit industry-country with at least one firm covered by Climate TRACE	(51,742)
Non-missing control variables	(9,405)
Non-missing main dependent variable (*CAR*)	(1,592)
Final Sample for International Sample	**36,876**
Less Non-US firms	(32,650)
Final Sample for US Sample	**4,226**

Panel B: Sample Distribution by Industry

SIC1	Description	# of All Firms	# of Treatment Firms
1	Agriculture and Mining	6414	477
2	Construction	8067	337
3	Manufacturing	10482	530
4	Transportation, Communications	2687	377
5	Wholesale Trade	2139	69
6	Retail Trade	1953	34
7	Finance, Insurance, and Real Estate	4400	15
8	Services	734	11
Total		36876	1850

Panel C: Sample Distribution by Region

Region	# of All Firms	# of Treatment Firms
North America	6558	369
Latin America & Caribbean	462	95
Europe & Central Asia	2486	286
East Asia & Pacific	20928	701
South Asia	5097	224
Middle East & North Africa	575	112
Sub-Saharan Africa	770	63
Total	36876	1850

Table 2. Descriptive Statistics

This table provides descriptive statistics of the variables used in the analyses. All variables are defined in Appendix A. All continuous variables are winsorized at the top and bottom one percent.

Variables	#Obs.	Mean	S.D.	p25	Median	p75
Dependent Variables						
CAR	36876	-0.001	0.042	-0.019	-0.001	0.015
EPSREV	13194	-0.007	0.309	-0.084	-0.002	0.055
SALEREV	13194	-0.021	9.109	-2.611	0.000	1.937
ABNIMPVOL	1854	0.023	0.157	-0.021	-0.004	0.017
ABNVOLUME1W	34074	0.116	0.836	-0.287	0.060	0.453
ABNVOLUME1M	34074	0.088	0.748	-0.309	0.025	0.432
ABNSPREAD1W	34074	-0.037	2.422	-0.073	-0.001	0.058
ABNSPREAD1M	34074	-0.100	2.310	-0.085	-0.006	0.026
ΔBIG 3 OWNERSHIP	24694	0.030	0.140	0.000	0.000	0.008
ΔNON-BIG 3 OWNERSHIP	24694	-0.001	0.013	-0.003	0.000	0.002
LOG(PENALTY)	6912	0.045	0.691	0.000	0.000	0.000
LOG(TOXIC RELEASES)	6912	1.479	3.935	0.000	0.000	0.000
Test Variables						
COVERED	36876	0.050	0.218	0.000	0.000	0.000
UNDERREPORTING	4226	0.026	0.132	0.000	0.000	0.000
NON-UNDERREPORTING	4226	0.007	0.083	0.000	0.000	0.000
%UNDERREPORTING	144	0.375	0.561	0.000	0.337	0.982
Control Variables						
SIZE	36876	5.217	2.330	3.457	5.337	6.852
MTB	36876	2.547	4.990	0.772	1.535	2.943
ROA	36876	-0.129	0.995	-0.024	0.031	0.081
LEVERAGE	36876	0.235	0.323	0.028	0.164	0.335
CASH	36876	0.223	0.214	0.061	0.153	0.319
TANGIBILITY	36876	0.289	0.248	0.082	0.231	0.436
R&D INTENSITY	36876	2.042	4.927	0.000	0.045	2.003
Variables for Facility-level Analysis						
CARBON METRIC	2195	0.092	0.289	0.000	0.000	0.000
BIG 3	2195	0.112	0.076	0.032	0.135	0.171
NON-BIG 3 PRI	2195	0.122	0.117	0.030	0.123	0.193
NON-PRI	2195	0.337	0.239	0.122	0.402	0.476
RATED	2195	0.855	0.353	1.000	1.000	1.000
ENFORCEMENT_HQ	2195	0.087	0.282	0.000	0.000	0.000
ENFORCEMENT_FACILITY	2195	0.015	0.122	0.000	0.000	0.000
BLUE STATE_HQ	2195	0.194	0.396	0.000	0.000	0.000
BLUE STATE_FACILITY	2195	0.419	0.493	0.000	0.000	1.000
NON-ATTAIN_HQ	2195	0.494	0.500	0.000	0.000	1.000
NON-ATTAIN_FACILITY	2195	0.357	0.479	0.000	0.000	1.000
Cross-sectional Variables						
E-REPORTING MANDATE	36876	0.840	0.366	1.000	1.000	1.000
RULE OF LAW	36876	0.736	0.755	0.011	1.096	1.510
ENV. STRINGENCY INDEX	36876	1.729	1.537	0.000	1.450	3.000
ENV. PERF. INDEX	36876	46.010	24.786	28.400	46.900	71.000
BIG 3 OWNERSHIP_COUNTRY	36876	0.039	0.040	0.005	0.030	0.045

Table 3. Short-window Market Return around Data Release

This table presents the cumulative abnormal return around the date of a CT data release. Panel A provides the univariate statistics for *CAR* among the treatment firms. Panel B presents the market reactions to CT data releases for treatment firms compared to control firms, along with the moderating effect of underreporting intensity on these market reactions. *CAR* is the two-day local market adjusted cumulative abnormal return after the CT data release date. Panel C presents the association of aggregated underreporting intensity and market reactions to CT data releases in the subsample of treatment firms. *COVERED* equals one for firms covered by Climate TRACE at date *t*, and zero otherwise. *UNDERREPORTING* is an indicator variable that equals one if *%UNDERREPORTING* is above zero, and zero otherwise. *NON-UNDERREPORTING* is an indicator variable that equals one if *%UNDERREPORTING* is less than or equal to zero, and zero otherwise. *%UNDERREPORTING* is the firm-level underreporting intensity, calculated as the average underreporting intensity at the facility-year level across all reporting years (2015 to 2022) and facilities for each firm. Facility-year level underreporting intensity is the difference between facility-level CO_2 emissions from Climate TRACE for year *t* and the corresponding amounts from EPA FLIGHT database, scaled by CO_2 emissions from Climate TRACE. Standard errors are clustered at the country-industry level. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

Panel A: Univariate Results

	N	Mean	t-stat.
CAR (International Sample)	1,850	-0.008***	-10.88
CAR (US Sample)	238	-0.029***	-13.58

Panel B: Multivariate Regression Results

Sample	International Sample	US Sample		
		Dependent Variable: *CAR*		
Variable	(1)	(2)	(3)	(4)
COVERED	-0.004**	-0.013***	-0.011***	-0.011***
	(-2.09)	(-3.96)	(-3.84)	(-4.23)
*COVERED*UNDERREPORTING*			-0.004*	-0.005**
			(-1.70)	(-2.02)
*COVERED*NON-UNDERREPORTING*				0.002
				(0.75)
SIZE	0.001*	0.002***	0.002***	0.002***
	(1.86)	(6.25)	(6.35)	(6.50)
MTB	0.000	-0.000	-0.000	-0.000
	(0.97)	(-0.33)	(-0.36)	(-0.37)
ROA	0.001**	0.001***	0.001***	0.001***
	(2.21)	(2.73)	(2.72)	(2.80)
LEVERAGE	-0.000	0.001	0.001	0.001
	(-0.18)	(0.56)	(0.55)	(0.56)
CASH	-0.006***	-0.002	-0.002	-0.002
	(-3.16)	(-0.53)	(-0.53)	(-0.48)
TANGIBILITY	-0.004***	0.003	0.003	0.003
	(-2.62)	(0.64)	(0.64)	(0.70)
R&D INTENSITY	-0.000	0.000**	0.000**	0.000**
	(-0.08)	(2.31)	(2.31)	(2.22)
*COVERED + COVERED*NON-UNDERREPORTING*				-0.009
F-statistic (p-value)				*9.74 (0.002)*
N	36876	4226	4226	4226
Adj. R^2	0.044	0.099	0.099	0.099
Industry FE	Y	Y	Y	Y
Country FE	Y	N	N	N
Year FE	Y	Y	Y	Y

Panel C: Cumulative Facility Underreporting Intensity Across Reporting Years (US Sample)

Sample	**Full Sample**	***UNDERREPORTING > 0***
	Dependent Variable: *CAR*	
Variable	**(1)**	**(2)**
Sample	**Full Sample**	***UNDERREPORTING > 0***
%UNDERREPORTING	-0.013**	-0.028**
	(-2.89)	(-2.35)
N	144	108
Adj. R^2	0.457	0.442
Controls	Y	Y
Industry FE	Y	Y
Year FE	Y	Y

Table 4. Determinants of Underreporting (Facility-Level Analysis)

This table presents an analysis of the factors associated with facility-level emissions underreporting intensity. The dependent variable, *%UNDERREPORTING_FACILITY*, is the facility-year level underreporting intensity, calculated as the difference between facility-level CO_2 emissions from Climate TRACE for year *t* and the corresponding amounts from EPA FLIGHT database, scaled by CO_2 emissions from Climate TRACE. Standard errors are clustered at the facility, firm, or industry level. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

	Dependent Variable: *%UNDERREPORTING_ FACILITY*		
Variable	**(1)**	**(2)**	**(3)**
CARBON METRIC	0.153***	0.153***	0.153
	(3.64)	(2.65)	(1.67)
BIG 3	1.712***	1.712**	1.712**
	(3.49)	(2.39)	(2.67)
NON-BIG 3 PRI	-0.657***	-0.657**	-0.657*
	(-2.82)	(-2.10)	(-1.95)
NON-PRI	-0.316**	-0.316*	-0.316**
	(-2.36)	(-1.85)	(-2.18)
RATED	0.192**	0.192***	0.192**
	(2.00)	(2.52)	(2.30)
ENFORCEMENT_HQ	-0.071***	-0.071*	-0.071
	(-2.91)	(-1.86)	(-1.31)
ENFORCEMENT_FACILITY	-0.088	-0.088	-0.088
	(-0.59)	(-0.54)	(-0.88)
BLUE STATE_HQ	-0.106*	-0.106	-0.106
	(-1.68)	(-1.07)	(-1.51)
BLUE STATE_FACILITY	0.014	0.014	0.014
	(0.25)	(0.19)	(0.29)
NON-ATTAIN_HQ	0.001	0.001	0.001
	(0.01)	(0.01)	(0.01)
NON-ATTAIN_FACILITY	-0.157***	-0.157	-0.157
	(-2.67)	(-1.58)	(-1.24)
SIZE	0.039***	0.039**	0.039*
	(3.26)	(2.18)	(1.75)
MTB	-0.003	-0.003	-0.003
	(-1.20)	(-1.10)	(-0.86)
ROA	-0.280***	-0.280*	-0.280
	(-2.83)	(-1.78)	(-1.56)
LEVERAGE	-0.264**	-0.264	-0.264*
	(-2.08)	(-1.54)	(-2.01)
CASH	0.456**	0.456	0.456
	(2.17)	(1.21)	(1.45)
TANGIBILITY	0.589***	0.589***	0.589***
	(3.86)	(2.65)	(2.97)
R&D INTENSITY	0.394**	0.394	0.394***
	(2.11)	(1.34)	(3.19)
NON-BIG 3 PRI= NON-PRI			
F-stat (p-value)	2.38 (0.124)	1.24 (0.268)	1.20 (0.288)
N	2195	2195	2195
adj. R^2	0.552	0.552	0.552
S.E. Clustering	Facility	Firm	Industry
Industry FE	Y	Y	Y
Reporting Year FE	Y	Y	Y

Table 5. Earnings Surprise Channel (H2: Numerator Effect): Analyst Forecast Revision Following CT Release

This table presents an analysis of analyst forecast revisions following CT data releases. *EPSREV* is the difference between median consensus of one-year ahead EPS forecast within four months following CT data release date and that within four months before the CT data release date, scaled by beginning-of-year stock price, multiplied by 100. *SALEREV* is the difference between median consensus of one-year ahead sales forecast within four months following the data release date and that within four months before the data release date, scaled by beginning-of-year stock price, multiplied by 100. *COVERED* equals to one for firms covered by Climate TRACE at date *t*, and zero otherwise. *UNDERREPORTING* is an indicator variable that equals to one if *%UNDERREPORTING* is above zero, and zero otherwise. Standard errors are clustered at the country-industry level. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

Sample	**International Sample**		**US Sample**			
			Dependent Variable:			
	EPSREV	*SALEREV*	*EPSREV*		*SALEREV*	
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVERED	-0.041***	-1.891	-0.119**	-0.102**	-5.531	-5.209
	(-2.87)	(-1.47)	(-2.58)	(-2.32)	(-1.51)	(-1.45)
COVERED UNDERREPORTING*				-0.055*		-1.226
				(-1.76)		(-0.32)
SIZE	0.009***	1.458***	0.012***	0.012***	1.728***	1.732***
	(3.31)	(6.59)	(2.70)	(2.63)	(4.68)	(4.68)
MTB	0.002***	0.076	0.000*	0.000*	0.000***	0.000***
	(2.80)	(1.27)	(1.98)	(1.96)	(33.59)	(33.53)
ROA	-0.010	-0.710***	0.001	-0.001	-0.590***	-0.594***
	(-1.41)	(-3.11)	(0.11)	(-0.09)	(-2.79)	(-2.82)
LEVERAGE	0.009	0.440	-0.004	-0.007	-0.311	-0.315
	(0.69)	(0.40)	(-0.42)	(-0.76)	(-0.35)	(-0.35)
CASH	0.037**	0.829	0.049**	0.047*	1.806	1.806
	(2.05)	(0.60)	(2.15)	(1.87)	(1.37)	(1.36)
TANGIBILITY	-0.074***	-1.868	-0.016	-0.011	-1.186	-1.195
	(-3.45)	(-1.30)	(-0.46)	(-0.35)	(-0.68)	(-0.68)
R&D INTENSITY	0.001	0.062	0.002***	0.002***	0.035***	0.035***
	(1.47)	(1.60)	(4.88)	(5.02)	(6.37)	(6.38)
N	13194	13194	3387	3387	3387	3387
Adj. R^2	0.036	0.096	0.053	0.052	0.110	0.110
Industry FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y

Table 6. Expected Return Channel (H3: Denominator Effect)

This table presents the analysis of changes in implied volatility, market liquidity (Panel A), and ownership by Big 3 investors (Panel B) following the CT data release date. *ABNIMPVOL* is the mean value of implied volatility of standardized options over date t and t+1 minus mean value of implied volatility over date t-2 and t-1 among standardized options with a time to maturity of 30 calendar days. *ABNVOLUME1W* (*ABNVOLUME1M*) is the mean value of log trading volume over next week (month) minus mean value of log trading volume over the prior week (month). *ABNSPREAD1W* (*ABNSPREAD1M*) is the mean value of bid-ask spread as a percentage of mid-price over next week (month) minus mean value of bid-ask spread as a percentage of mid-price over the prior week (month). *ΔBIG3 OWNERSHIP* is a change in Big 3 ownership from three months prior to CT release to three months post release. *ΔNON-BIG3 OWNERSHIP* is a change in the ownership by non-Big 3 institutions from three months prior to CT release to three months post release. *COVERED* equals to one for firms covered by Climate TRACE at date *t*, and zero otherwise. *UNDERREPORTING* is an indicator variable that equals to one if *%UNDERREPORTING* is above zero, and zero otherwise. Standard errors are clustered at the country-industry level. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

Panel A: Implied Volatility and Market Liquidity Following CT Release

Dependent Variable	*ABNIMPVOL*		*ABNVOLUME1W*		*ABNVOLUME1M*		*ABNSPREAD1W*		*ABNSPREAD1W*	
Sample	**International**	**US**	**International**	**US**	**International**	**US**	**International**	**US**	**International**	**US**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
COVERED	0.021***	0.014**	0.025	0.085***	0.051**	0.073*	-0.048	-0.157*	-0.065	-0.076**
	(3.57)	(2.45)	(1.07)	(2.72)	(2.56)	(1.81)	(-0.66)	(-1.76)	(-0.76)	(-1.99)
*COVERED*UNDERREPORTING*		0.028**		-0.082*		-0.077*		0.220*		0.044
		(2.17)		(-1.97)		(-1.91)		(1.92)		(0.69)
SIZE	-0.019***	-0.020***	-0.020***	-0.038***	-0.023***	-0.041***	0.005	-0.004	0.032***	0.020***
	(-6.48)	(-6.92)	(-5.80)	(-8.98)	(-7.26)	(-8.40)	(0.54)	(-0.55)	(3.93)	(2.83)
MTB	-0.001*	-0.001	-0.000	-0.001	0.000	0.000	0.000	0.002	-0.001	0.002**
	(-1.89)	(-1.68)	(-0.16)	(-0.55)	(0.06)	(0.19)	(0.11)	(1.14)	(-0.38)	(2.06)
ROA	-0.018**	-0.018**	-0.003	-0.006	0.010**	0.007	0.075	0.019	-0.005	-0.023*
	(-2.42)	(-2.40)	(-0.37)	(-0.59)	(1.98)	(0.50)	(1.41)	(1.18)	(-0.10)	(-1.88)
LEVERAGE	-0.003	-0.002	-0.040	0.012	-0.002	-0.052	0.218	0.086	-0.013	0.041
	(-0.17)	(-0.10)	(-1.55)	(0.25)	(-0.13)	(-1.23)	(1.40)	(1.60)	(-0.09)	(1.39)
CASH	-0.058**	-0.060**	-0.011	0.013	-0.013	-0.043	0.066	0.219***	0.109	0.056
	(-2.61)	(-2.53)	(-0.26)	(0.17)	(-0.41)	(-0.75)	(0.80)	(2.62)	(1.03)	(0.93)
TANGIBILITY	-0.026	-0.024	-0.036	0.068	-0.025	-0.006	0.073	-0.180*	0.168**	-0.033
	(-1.62)	(-1.30)	(-1.04)	(0.90)	(-0.84)	(-0.10)	(0.61)	(-1.93)	(1.98)	(-0.39)
R&D INTENSITY	0.001	0.001	0.001	0.000	0.001	-0.000	-0.000	-0.006***	0.001	-0.004
	(1.02)	(0.93)	(0.63)	(0.17)	(0.72)	(-0.11)	(-0.04)	(-2.76)	(0.26)	(-1.47)
N	1854	1625	34074	3917	34074	3917	34074	3917	34074	3917
Adj. R^2	0.068	0.072	0.016	0.032	0.028	0.045	0.012	0.033	0.018	0.112
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	N	Y	N	Y	N	Y	N	Y	N
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Big 3 Ownership

Sample	International Sample		US Sample	
	Dependent Variable:			
	ΔBIG3 OWNERSHIP	*ΔNON-BIG3 OWNERSHIP*	*ΔBIG3 OWNERSHIP*	*ΔNON-BIG3 OWNERSHIP*
Variable	**(1)**	**(2)**	**(3)**	**(4)**
COVERED	-0.070***	-0.063	-0.049*	0.198
	(-3.48)	(-0.80)	(-2.26)	(0.55)
*COVERED*UNDERREPORTING*			-0.043*	0.045
			(-2.04)	(0.20)
SIZE	0.035***	0.070***	0.033***	0.173***
	(5.94)	(4.13)	(18.10)	(4.07)
MTB	-0.000*	0.000	-0.000	-0.000
	(-1.68)	(1.20)	(-1.76)	(-0.70)
ROA	0.002	0.070	0.010***	0.043
	(0.34)	(1.21)	(7.15)	(0.37)
LEVERAGE	0.000	0.006	0.000	0.009
	(0.06)	(1.37)	(1.19)	(1.35)
CASH	0.018	0.364***	0.020	1.606**
	(0.95)	(3.18)	(1.52)	(3.11)
TANGIBILITY	-0.043*	0.234	-0.070**	0.942
	(-1.79)	(1.47)	(-2.64)	(0.86)
R&D INTENSITY	-0.006**	-0.006	-0.001**	-0.022***
	(-1.99)	(-1.27)	(-2.63)	(-4.77)
N	24656	24656	3922	3922
Adjusted R^2	0.029	0.032	0.137	0.026
Country FE	Y	Y	N	N
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 7: Cross-sectional Analysis Using International Sample

This table presents the results of a cross-sectional analysis of market reactions, forecast revisions, and implied volatility around CT data releases. *E-REPORTING MANDATE* equals one if a firm is located in a country that mandates E-reporting, and zero otherwise. *RULE OF LAW* is the value of a country-level Rule of Law in the previous year. *ENV. STRINGENCY INDEX* captures the degree to which environmental policies put an explicit or implicit price on polluting or other environmentally harmful behavior. *ENV. PERF. INDEX* is the value of a country-level Environmental Performance Index in the previous year. *BIG 3 OWNERSHIP_COUNTRY* is the country-level value weighed Big 3 institutional ownership in the previous year. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

Panel A: Reporting Mandate

	Dependent Variable:		
	CAR	*EPSREV*	*ABNIMPVOL*
Variable	**(1)**	**(2)**	**(3)**
COVERED	-0.009***	-0.076***	0.021***
	(-2.46)	(-3.42)	(2.86)
*COVERED * E-REPORTING MANDATE*	0.007*	0.048*	0.010
	(1.81)	(1.84)	(1.26)
N	36876	13196	1854
Adj. R^2	0.045	0.036	0.066
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: Rule of Law

	Dependent Variable:		
	CAR	*EPSREV*	*ABNIMPVOL*
Variable	**(1)**	**(2)**	**(3)**
COVERED	-0.000	-0.003	0.040***
	(-0.26)	(-0.17)	(2.58)
*COVERED * RULE OF LAW*	-0.005***	-0.032*	-0.012
	(-3.29)	(-1.89)	(-1.16)
N	36876	13194	1854
Adj. R^2	0.053	0.038	0.066
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Panel C: Environmental Stringency

	Dependent Variable:		
	CAR	*EPSREV*	*ABNIMPVOL*
Variable	**(1)**	**(2)**	**(3)**
COVERED	-0.002	0.062	0.020***
	(-0.95)	(1.13)	(2.76)
*COVERED * ENV. STRINGENCY INDEX*	-0.001*	-0.050**	0.001
	(-1.67)	(-2.11)	(0.46)
N	36876	13194	1854
Adj. R^2	0.045	0.036	0.067
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Panel D: Environmental Performance Index

	Dependent Variable:		
	CAR	*EPSREV*	*ABNIMPVOL*
Variable	**(1)**	**(2)**	**(3)**
COVERED	0.004*	0.010	0.060*
	(1.70)	(0.42)	(1.77)
*COVERED * ENV. PERF. INDEX*	-0.0002***	-0.001**	-0.0005
	(-3.40)	(-2.27)	(-1.11)
N	36876	13194	1854
Adj. R^2	0.046	0.037	0.066
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Panel E: Big 3 Ownership at the Country Level

	Dependent Variable:		
	CAR	*EPSREV*	*ABNIMPVOL*
Variable	**(1)**	**(2)**	**(3)**
COVERED	0.002	-0.009	0.030***
	(1.11)	(-0.49)	(3.91)
BIG 3 OWNERSHIP_COUNTRY	0.501	1.247	0.089
	(1.42)	(0.47)	(0.73)
*COVERED * BIG 3 OWNERSHIP_COUNTRY*	-0.137***	-0.663***	-0.076
	(-3.98)	(-2.80)	(-0.99)
N	36876	13194	1854
Adj. R^2	0.046	0.036	0.067
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Country FE	Y	Y	Y
Year FE	Y	Y	Y

Table 8: Ex Post Responses from Regulators and Firms: EPA Penalty and Abatement Initiatives

This table presents an analysis of responses to Climate TRACE coverage by environmental regulators and firms. *LOG(PENALTY)* is the natural logarithm of one plus the EPA penalty amount. *LOG(TOXIC RELEASES)* is the natural logarithm of one plus the toxic releases amount. *COVERED* equals one for firms covered by Climate TRACE at date *t*, and zero otherwise. *POST* equals one for firm-year observations in 2023 fiscal year, and zero for 2020 and 2021. Standard errors are clustered at the country-industry level. All variables are defined in Appendix A. ***, **, and * denote 1%, 5%, and 10% significance level, respectively. Intercepts are omitted.

	Dependent Variable:	
	LOG(PENALTY)	*LOG(TOXIC RELEASES)*
Variable	**(1)**	**(2)**
COVERED	-1.646	0.480***
	(-1.40)	(2.56)
*COVERED*POST*	2.051*	-0.133**
	(1.63)	(-2.11)
SIZE	0.386**	0.321***
	(2.15)	(9.67)
MTB	-0.006	-0.010*
	(-0.30)	(-1.77)
ROA	0.363**	1.020***
	(2.22)	(6.18)
LEVERAGE	0.276	0.074
	(0.67)	(0.52)
CASH	-3.286**	-2.764***
	(-2.00)	(-7.18)
TANGIBILITY	1.682	0.175
	(1.03)	(0.29)
R&D INTENSITY	-0.066	-0.066***
	(-1.10)	(-5.97)
LOG(SALES)	0.447***	0.331***
	(5.09)	(7.23)
N	6912	6912
Pseudo R^2	0.202	0.531
Country FE	N	N
Industry FE	Y	Y
Year FE	Y	Y