Climate Talk in Earnings Calls: Effects on Analyst Forecasts and Environmental Strategies

Abstract

Using 48,329 observations across 6,696 unique U.S. firms, we examine the relationship between corporate climate discourse during earnings calls, analyst predictions, and corporate environmental practices. Our findings demonstrate that an increase in executives' climate-related discourse, potentially a form of impression management, correlates with higher analyst forecast bias and dispersion. Executive discourse also prompts analyst attention, leading to more climate-focused inquiries. Further analysis shows that firms enhance their environmental performance in the subsequent year when analysts ask climate-related questions, suggesting that such dialogue could incentivize corporations to improve their environmental efforts to meet stakeholder expectations and maintain legitimacy. We also analyze executive responses to climate inquiries, noting a preference for complex, subjective responses with a positive tone. This illustrates how corporations manage climate disclosures to preserve strategic resources while meeting stakeholder expectations. Our findings highlight the importance of effective communication during earnings calls and the need for transparent disclosure standards for climate strategies and performance, with implications for executives and analysts regarding strategic communication and accountability for environmental performance.

Keywords: Textual Analysis, Climate Talk Tone, Analyst Forecasts, Corporate Environmental Management

JEL Classification: D80, Q50

1 Introduction

As climate change brings forth a range of substantial risks and opportunities, the necessity for robust environmental management within corporate strategy has become increasingly imperative. While the existing literature has delved into the vast implications of corporate environmental actions on their market reputation (Chortareas et al., 2023a,b), operational stability (e.g., Ghadge et al., 2020), regulatory compliance (Aragòn-Correa et al., 2020; Dang et al., 2022), and ultimately, financial performance (e.g., Pankratz et al., 2023), the influence of corporate climate discourse remains relatively unexplored.

With an escalating number of corporations vocalizing their concerns regarding climate change, the distinction between substantive information and mere 'cheap talk' in their discourse is critically important (Chortareas et al., 2023c). Furthermore, the significance extends beyond the mere expression of these concerns; the reception and interpretation of this climate-related discourse by key stakeholders become equally vital. This intricate interplay will ultimately shape a firm's market position, investment attractiveness, and its contribution to a sustainable future.

In this study, we seek to address two pertinent questions. First, we delve into the impact of corporate climate communication on analyst forecast bias. Second, we examine whether, and to what degree, the climate concerns voiced by analysts influence the environmental management embarked upon by corporations. To carry out our analysis, we leverage an extensive dataset incorporating earnings call transcripts, analyst predictions, and a variety of metrics reflecting the environmental performance of 6,696 public U.S. firms, covering a period from 2005 to 2022. We analyze earnings call transcripts to formulate measures of the intensity, complexity, subjectivity, uncertainty, and sentiment of climate dialogue. Additionally, we employ several aspects of analyst forecasts, encompassing individual forecast errors as well as discrepancies among different analysts. For environmental management, we incorporate measures such as emissions, environmental innovation and training, whilst also accounting for factors related to corporate financial performance.

Our empirical examination uncovers a notable correlation between the intensity of executive climate discourse during earnings calls and analyst forecast bias. Specifically, we discern that an amplified intensity of climate dialogue correlates with increased analyst forecast error, dispersion, and optimism, whilst being linked to diminished analyst pessimism. These observations corroborate our theoretical predictions derived from impression management theory and information asymmetry theory.

An intriguing facet of our findings lies in the influence of corporate climate discourse and analyst attention on subsequent corporate environmental performance. We note that companies exhibiting more intensive climate dialogue and those garnering increased analyst attention demonstrate superior environmental performance and management in the ensuing periods. This outcome resonates with social influence theory and agency theory, implying that corporate climate discourse and analyst attention play a pivotal role in motivating firms to enhance their environmental performance.

Furthermore, we discover that analysts are more inclined to pose climate-related inquiries when corporate executives broach the topic of climate change during earnings call presentations. This inclination escalates when the executives' climate dialogue is subjective or exudes a positive or negative sentiment. These findings align with signal detection theory and salience theory, suggesting that analysts interpret corporate climate discourse as a significant signal, prompting them to delve deeper for additional information. Upon examining executives' responses to these climate-related queries, we notice a propensity for nuanced, subjective, and optimistic replies, highlighting how companies navigate climate disclosures to protect strategic assets while meeting stakeholder anticipations.

The remainder of the paper is structured as follows. Section 2 provides a review of the related literature and develops the hypotheses. Section 3 describes the data source, and how we construct climate talk and analyst forecast measures. Section 4 presents the descriptive statistics, and Section 5 discusses the empirical results. Finally, Section 7 concludes the paper.

2 Related Literature

Our research provides a comprehensive analysis that interweaves and augments three distinct yet interconnected realms of literature: corporate communication, financial forecasting, and environmental management. Specifically, we investigate their dynamics within the context of corporate climate discourse during earnings calls. Through this holistic examination, we illuminate the reciprocal influences and intricate interplay among these facets of corporate behaviour and market response.

The first strand of literature our study significantly enhances is the rapidly emerging field of corporate communication. An extensive body of research spotlights the significance of voluntary environmental information disclosure (Milne & Patten, 2002; Dangelico, 2017; Clarkson et al., 2010), emphasising its role in augmenting corporate reputation, and strengthening stakeholder relationships (Williams & Siegel, 2017; Cho et al., 2015; Dupire & M'Zali, 2018). Moreover, the linguistic tone is posited to play a critical role in shaping corporate sustainability narratives (Cho et al., 2015, 2019; Clarkson et al., 2008), influencing stakeholder perceptions and the organisation's legitimacy (Merkl-Davies & Brennan, 2007; Bitektine, 2011). Crucial work contributed by Liedong et al. (2015) by analyzing the substance and repercussions of sustainability dialogue during earnings calls. Besides, Mayew et al. (2013) find that analysts who participate in earnings conference calls by asking questions possess superior private information relative to analysts who do not ask questions. Chen et al. (2018) illustrate how manager-analyst information exchanges evolve on earnings calls and indicate that analysts are the participants on earnings calls whose comments move stock prices during the discussion. Nevertheless, their research and other parallel studies (e.g., Seele & Lock, 2015; Gatti et al., 2019) do not specifically concentrate on climate discourse, a rapidly significant and imperative component of the broader sustainability dialogue. Recognising the urgency and centrality of climate issues, our study propels this line of research by focusing on climate discourse during earnings calls, consequently adding richness to our understanding of this niche aspect of corporate communication.

Secondly, our research supplements the literature on financial forecasting by illuminating the role of analysts in deciphering corporate communications into financial forecasts. Foundational work documents the link between enhanced corporate disclosure and reduced forecast error and dispersion (Lang & Lundholm, 1996; Botosan, 1997; Bartov & Bodnar, 1994; Kimbrough, 2005; Kim et al., 2014). Bowen et al. (2002) argue that analysts with relatively weak prior forecasting performance benefit more from conference calls, suggesting that conference calls help "level the playing field" across analysts. Additionally, a growing body of research acknowledges the importance of non-financial information, including environmental data, in shaping analysts' forecasts (Dhaliwal et al., 2011; Plumlee et al., 2015; Luo et al., 2015; Cheng et al., 2014; Benlemlih et al., 2018). Besides, Du & Yu (2021) suggest that the readability and optimistic tone of a firm's Corporate Social Responsibility (CSR) report are positively associated with better future CSR performance, and the market significantly reacts to these factors upon the report's release, particularly for firms with lower analyst following. Muslu et al. (2019) argue that the content of CSR reports helps to improve analyst forecast accuracy, and this relationship is more pronounced for CSR reports with more substantial content. Existing literature also documents a negative relation between pollution and analysts' earnings forecasts (e.g., Dong et al., 2021). Despite these progressions, the realm of how climate discourse during earnings calls impacts analysts' forecasts remains relatively untapped. Our research addresses this lacuna, providing an in-depth investigation into the ramifications of climate-centric dialogue during these calls on analyst predictions.

Thirdly, our study delivers novel insights into the correlation between corporate communication and environmental performance. Seminal research underscores the role of voluntary environmental disclosures in influencing firms' environmental performance (Clarkson et al., 2008; Cho et al., 2012; Kim et al., 2014; Reimsbach et al., 2018). Notably, Flammer (2013) evidence a positive association between firms' sustainability dialogue during earnings calls and subsequent advancements in corporate social performance. Although these studies lay a strong foundation, the specific impact of climate concerns of financial analysts on corporate environmental management has not been entirely explored. We venture into these untapped areas by scrutinising the effect of analyst climate discourse on corporate environmental performance.

3 Data and Variables

3.1 Sample construction

Our primary research dataset comprises data from 6,696 public firms in the U.S., spanning from 2005 to 2022. This dataset is the product of integrating four distinct databases: Capital IQ, Refinitiv, Institutional Brokers Estimate Systems (I/B/E/S), and Compustat. Earnings conference call transcripts are procured from Capital IQ, while environmental performance data of corporations is sourced from Refinitiv. Analysts' coverage and forecast information is provided by I/B/E/S, and financial data is obtained from Compustat. By merging these sources, we present a comprehensive dataset that encompasses a wide range of financial, environmental, and communicative metrics across U.S. firms.

3.2 Textual Analysis of Climate Discourse

To measure the extent of climate discourse, we employ the natural language processing (NLP) method on earnings conference calls, utilizing the climate change keyword dictionary developed by Sautner et al. (2022).[1] Through the application of NLP, we can systematically and quantitatively probe into the presence, intensity, and tone of climate-related dialogues conducted by corporate executives and financial analysts within their exchanges.

The earnings call is typically partitioned into three segments: an executive presentation, analysts' questions, and executive responses. Our suite of measures captures the depth and nuances of climate change discussions within each segment. We begin by introducing the 'Climate Talk Indicator' variable, denoted as $CC(indicator)$. This binary variable is set to one if the segment contains at least one climate change bigram, signalling the presence of climate change discussion.

Next, we measure the prevalence of climate change discussions with the 'Climate Talk Frequency' metric, denoted as $CC\_Frequency$. This is computed as the proportion of climate change bigrams to the total word count in the segment:

[1] A machine learning algorithm was used to create this dictionary from corporate earnings call transcripts, resulting in 8,924 climate change-related bi-grams.

$$CC\_Frequency = \frac{\text{Number of climate change bigrams}}{\text{Total word count}} \tag{1}$$

To assess the complexity of the climate change discourse, we employ the 'Climate Talk Complexity' measure, denoted as $CC\_Complexity$. This leverages the Gunning Fog Index, averaged over all sentences containing at least one climate change bigram:

$$CC\_Complexity = \frac{1}{N}\sum_{i=1}^{N} \text{Gunning Fog Index}(S_i) \tag{2}$$

where N is the number of sentences containing a climate change bigram and S_i is the i-th sentence.

We evaluate the subjectivity of the climate-related discussion with the 'Climate Talk Subjectivity' measure, denoted as $CC\_Subjectivity$. This lexicon-based measure, provided by the Python Pattern library, calculates the average subjectivity level of words in the climate-related segment, ranging from 0 (objective) to 1 (subjective):

$$CC\_Subjectivity = \frac{1}{W}\sum_{i=1}^{W} \text{Subjectivity}(W_i) \tag{3}$$

where W is the total number of words in the climate-related segment and W_i is the i-th word.

The 'Climate Talk Uncertainty' measure, denoted as $CC\_Uncertainty$, quantifies the uncertainty level expressed in the climate discourse. It tallies the number of Loughran-McDonald uncertainty words and scales them by the total word count in the climate change-related segment:

$$CC\_Uncertainty = \frac{\text{Count of Uncertainty Words in Climate-Related Discourse}}{\text{Total Word Count}} \tag{4}$$

To scrutinize the sentiment of the dialogue, we propose 'Climate Talk Positive Ratio' and 'Climate Talk Negative Ratio,' denoted as CC_RATIO_POS and CC_RATIO_NEG respectively. These ratios quantify the proportions of Loughran-McDonald positive and negative words, respectively, in the climate change-related content:

$$CC\_RATIO\_POS = \frac{\text{Count of Positive Words in Climate-Related Discourse}}{\text{Total Word Count}} \quad (5)$$

$$CC\_RATIO\_NEG = \frac{\text{Count of Negative Words in Climate-Related Discourse}}{\text{Total Word Count}} \quad (6)$$

Finally, we extend the sentiment analysis with the 'Climate Talk Sentiment' measure, denoted as $CC\_Sentiment$. This score calculates the relative frequency of Loughran-McDonald positive and negative words, defined as the difference between the proportions of positive and negative words:

$$CC\_Sentiment = CC\_RATIO\_POS - CC\_RATIO\_NEG \quad (7)$$

These measures collectively provide a comprehensive and nuanced understanding of corporate climate discourse, shedding light on the discourse's frequency, complexity, subjectivity, uncertainty, and sentiment.

3.3 Analyst Forecast Measures

In our investigation, we employ a series of measures related to analyst forecasts, aiming to elucidate the interplay between corporate climate change discourse and the projections of financial analysts.

The first measure, 'Analyst Coverage,' quantifies the number of analysts monitoring a firm in a given year. This metric provides an indication of the scrutiny level the firm attracts from the financial community, which can affect the firm's strategic decisions, including those related to climate change.

To gauge the precision of analysts' predictions, we compute 'Forecast Error' (ferror). This measure captures the absolute difference between the mean of analysts' estimates and the actual earnings per share (EPS) for a firm in a given year. To control for extreme values, ferror is winsorized at the 1% and 99% levels. The Forecast Error is expressed as:

$$\text{Forecast Error}_{i,t} = |\text{Mean of analysts' estimates}_{i,t} - \text{Actual EPS}_{i,t}| \quad (8)$$

Analysts' agreement on a firm's future earnings is assessed via 'Forecast Dispersion' (fdispersion), which is the standard deviation of individual analysts' forecast estimates. We also winsorize this measure at the 1% and 99% levels to mitigate the influence of outliers.

$$\text{Forecast Dispersion}_{i,t} = \text{Standard Deviation of analysts' individual forecast estimates}_{i,t} \quad (9)$$

We introduce two measures to capture analysts' bias in their forecasts: 'Forecast Optimism' (foptimism_analyst) and 'Forecast Pessimism' (fpessimism_analyst). The foptimism_analyst variable equals 1 if an analyst's forecast of EPS is higher than a firm's actual EPS, while the fpessimism_analyst is set to 1 if the forecast is lower than the actual EPS. We take the average of these measures if multiple analysts make the EPS forecasts for a firm in the same fiscal year. Both these measures are winsorized at the 1% and 99% levels.

$$\text{Forecast Optimism}_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} (1[\text{Analyst's forecast EPS}_{i,t,n} > \text{Actual EPS}_{i,t}]) \quad (10)$$

$$\text{Forecast Pessimism}_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} (1[\text{Analyst's forecast EPS}_{i,t,n} < \text{Actual EPS}_{i,t}]) \quad (11)$$

The 'Earnings Surprise' (surprise) measure denotes the unexpected portion of earnings announcement, calculated as the difference between actual EPS and the median of analysts' annual EPS forecasts, scaled by the median of the analysts' annual EPS forecasts. This provides insights into the accuracy of consensus analyst forecasts.

$$\text{Earnings Surprise}_{i,t} = \frac{\text{Actual EPS}_{i,t} - \text{Median of analysts' forecasts}_{i,t}}{\text{Median of analysts' forecasts}_{i,t}} \quad (12)$$

Finally, we consider the 'Forecast Horizon' (fhorizon), which is the median number of days between analyst forecasts and earnings announcements. This measure provides a sense of the timing of analyst forecasts relative to earnings announcements.

These measures together paint a comprehensive picture of analyst forecasts in the context of corporate climate change discussions.

3.4 Additional Control Variables

Beyond the primary measures pertaining to climate change discourse and analyst forecasts, our analysis incorporates a set of control variables that account for various firm characteristics.

Firstly, the stock *Price* of a firm is included as it reflects the market's aggregate assessment of the firm's current and prospective performance. The stock price at the end of the fiscal year is considered as it provides a comprehensive outlook of the firm's performance and investor sentiment throughout the year. Secondly, we introduce binary indicators for a firm's R&D and intangible assets. The *R&D Indicator* is set to 1 if a firm's research and development expense is positive for a fiscal year, and 0 otherwise. R&D expenses can signal a firm's commitment to innovation and its potential for future growth, both of which are crucial aspects of a firm's valuation. Similarly, the *Intangible Assets Indicator* is 1 if a firm possesses intangible assets in a fiscal year, and 0 otherwise. Intangible assets, such as patents or trademarks, can also provide unique value to a firm and influence investor perception. The *Book-to-Market Ratio* is included as it represents the ratio of the firm's book value of equity to its market value of equity at the end of a fiscal year. This ratio provides insights into the firm's valuation relative to its accounting fundamentals, helping to highlight any potential discrepancies between the two. Next, the *Firm Age* measure is computed as the natural logarithm of the number of years since a firm's first appearance in the CRSP database. This measure captures the firm's maturity. Mature firms often have more stable operations and are generally better understood by the market, influencing both investor sentiment and analyst forecasts. The *Capital Expenditure Ratio*, *Leverage*, *Return on Assets*, and *Firm Size* measures capture various aspects of a firm's financial performance and market position. These measures provide insights into the firm's investment behaviour, capital structure, profitability, and scale. All these factors can have a significant influence on analyst forecasts, sentiment, as well as corporate environmental performance.

In aggregate, these control variables offer a comprehensive view of a firm's characteristics and financial performance, aiding in the interpretation and robustness of our main results. By controlling for these factors, we aim to isolate the impact of climate change discourse on analyst forecasts and corporate environmental practices.

4 Descriptive Statistics

4.1 Climate change discussion in conference calls over time

Figure 1 offers a detailed portrayal of the temporal progression of climate change discussions during conference calls. It specifically targets three key areas: the frequency of climate change discussions initiated by corporate executives during their presentation session (referred to as Pre_CC_Frequency), the frequency of such discussions initiated by analysts during the question session (referred to as Q_CC_Frequency), and the frequency of climate change discussions conducted by corporate executives during the answer session (referred to as A_CC_Frequency). These frequencies are represented as yearly averages in the plot.

Insightful patterns emerge from the data, particularly concerning the distribution of climate change discussions between corporate managers and analysts during conference calls. Moreover, the data encapsulated in the figure reveals a steady upward trajectory in the frequency of climate change discussions over time, spanning across all three sections of the conference calls. This trend signifies an escalating focus on climate change themes and underscores the rising consciousness among stakeholders such as analysts and investors towards the corporate sector's responsibility to tackle climate-related issues.

The surge in climate change discussions in recent years mirrors the evolving societal and corporate landscape, as well as the growing recognition of the role of sustainability and environmental considerations in corporate decision-making. This increased emphasis on climate change falls in line with a broader societal transition towards prioritizing environmental responsibility and sustainable practices. As a result, businesses are recognizing the necessity to integrate climate change discussions into their communications with stakeholders, as demonstrated by the intensified discourse during both the presentation and question-and-answer sessions of conference calls.

Therefore, Figure 1 offers an exhaustive examination of the progression of climate change discussions during conference calls. It underscores the heightened involvement of corporate managers compared to analysts, as well as the overall upward trend in climate change discussions over time. These insights emphasize the growing relevance of climate change as a corporate conversation topic and the increasing awareness of environmental responsibilities among key stakeholders.

4.2 Industry Distribution

Table 1 presents a thorough breakdown of the firms by industry based on two-digit Standard Industrial Classification (SIC) codes. The industry with the most significant representation in the sample is the Business Services sector (SIC code 73), accounting for a considerable 12.43% of the total observations. The preponderance of this sector may be attributable to the diversity of services it covers, such as technology, consulting, and administration. Companies in this sector frequently hold earnings calls to update investors on a wide range of business operations, thereby contributing to the sector's substantial representation in the sample. Second in line is the Chemicals and Allied Products industry (SIC code 28), making up 10.76% of the sample. The high representation of this industry may be due to the complex and capital-intensive nature of the chemical sector. Given the large capital investments and the volatility of input costs, firms in this industry likely hold regular earnings calls to provide updates to investors and mitigate information asymmetry. The third and fourth most represented industries are Electronic and Other Electrical Equipment and Components (SIC code 36) and Holding and Other Investment Offices (SIC code 67), accounting for 6.72% and 6.52% of the observations, respectively. The prominence of these sectors is perhaps explained by their inherent characteristics. For instance, the rapid technological advancement and competitive environment in the electronics sector might prompt firms to regularly hold earnings calls to communicate their strategic positioning. On the other hand, investment offices, given their role in managing assets and creating wealth, might frequently engage in earnings calls to build investor trust and assure them of their investment strategies.

Other notable industries include Depository Institutions (SIC code 60), Measuring, Photographic, Medical, and Optical Goods, and Clocks (SIC code 38), Electric, Gas, and Sanitary Services (SIC code 49), Industrial and Commercial Machinery and Computer Equipment (SIC code 35), Transportation Equipment (SIC code 37), and Communications (SIC code 48). These industries collectively account for around 19.37% of the observations in the sample. The prevalence of earnings calls in these sectors may be driven by various factors such as their market influence, the complexity of their operations, and the need to maintain transparency with investors.

In summary, the distribution of earnings calls across industries in our sample seems to reflect the nature of the industries themselves. Industries that are more complex, capital-intensive, or rapidly changing appear more inclined to hold earnings calls, presumably to communicate effectively with investors and reduce information asymmetry.

[Table 1 about here.]

4.3 Comparative T-Test Results: Climate Change Discussions in Executive Presentations

Table 2 presents the results of a comparative analysis conducted using a series of t-tests to examine the differences in firm and analyst characteristics based on the presence or absence of climate change discussions in executive presentations. The t-test results provide valuable insights into the contrasting attributes between firms that address climate change (Group 2, Pre_CC_D=1) and those that do not (Group 1, Pre_CC_D=0) during executive presentations.

[Table 2 about here.]

The findings reveal notable distinctions between the two groups across various variables. Firstly, there is a significant disparity in analyst coverage, with Group 2 firms attracting higher analyst attention. This could be attributed to the perception that firms discussing climate change are more transparent and proactive in addressing environmental risks and opportunities. It suggests that climate change discussions during executive presentations serve as a signal for increased analyst interest.

Furthermore, the Forecast Error (FError) and Forecast Dispersion (FDispersion) exhibit substantial differences between the two groups. Group 1 firms, which do not incorporate climate change discussions, have significantly higher forecast error and dispersion. This could be indicative of the greater uncertainty and risk associated with climate change, leading to more divergent and less accurate forecasts among analysts for these firms. In contrast, Group

2 firms, addressing climate change, have more precise and consistent forecasts, potentially reflecting their proactive approach to managing climate-related risks. Regarding sentiment variables, analysts tend to exhibit slightly higher optimism towards firms without climate change discussions (Group 1), while displaying a slightly more pessimistic sentiment towards firms addressing climate change (Group 2). This finding suggests that analysts perceive increased risks for firms discussing climate change, possibly due to concerns about the financial implications of environmental challenges. The slight difference in sentiment reflects analysts' expectations of potential impacts on the financial performance and prospects of these firms. The Forecast Horizon (FHorizon) demonstrates minimal variation between the two groups, implying that climate change discussions during executive presentations do not significantly influence the time horizon of analysts' forecasts. This suggests that analysts consider a similar time frame when evaluating the future performance of both groups, regardless of climate change discussions.

Moving on to the question and answer sections of earnings calls, Group 2 firms, which incorporate climate talk in executive presentations, exhibit higher complexity, subjectivity, and frequency of climate change-related questions. This indicates that analysts tend to engage in more in-depth discussions on climate change with executives from these firms. It suggests that proactive climate change discussions of executives elicit a higher level of interest and inquiry from analysts, resulting in a more thorough exploration of the topic during Q&A sessions. Moreover, the answer section reveals that executives from Group 2 firms provide more complex, subjective, and frequent responses related to climate change. This suggests that firms addressing climate change in executive presentations tend to provide more detailed and nuanced answers.

Upon scrutinizing firm-specific variables, we observe that firms in Group 2 typically exhibit greater size and age, higher stock prices, lower leverage, and marginally superior returns on assets. These characteristics suggest that firms proactively talking about climate change issues are more likely to be mature, well-established, and financially stable. Conversely, firms in Group 1, those not mentioning climate change in executive presentation, exhibit a moderately higher loss rate. This may hint at potential financial repercussions tied to inadequate engagement with climate change concerns.

Overall, the comparative analysis of firms with and without climate change discussions in executive presentations reveals significant differences across various firm and analyst characteristics. Firms addressing climate change attract greater analyst coverage, exhibit lower forecast error and dispersion, and elicit more complex and subjective discussions during Q&A sessions. These findings highlight the importance of climate change discussions in executive presentations and their implications for analyst behaviour and firm attributes.

4.4 Summary Statistics

Table 3 provides the summary statistics for the variables employed in our primary analysis. These are derived from a total of 48,329 firm-year observations. Regarding the discourse related to climate change (CC), we observe varying characteristics across the different sections of the earnings calls. During the executive presentation (Pre) phase, the mean frequency of CC-related discourse is 0.001. This frequency significantly reduces during the question (Q) and answer (A) sections. We also see a difference in the complexity of the discussions across these sections. The mean complexity scores for the Pre, Q, and A sections are 13.533, 4.050, and 9.389, respectively, which suggests a higher complexity level in the discourse during the executive presentation phase. The subjectivity scores, on average, stand at 0.317, 0.122, and 0.267 for the Pre, Q, and A sections respectively. This implies a higher subjectivity level in the discussions related to CC during the executive presentation and answer sessions. The level of uncertainty in these discussions also varies across the three sections. The mean uncertainty scores are highest for the executive presentation phase at 0.006. In terms of sentiment, we observe that the positive sentiment tends to exceed the negative across all sections. The mean positive and negative sentiment ratios for the Pre, Q, and A sections indicate that companies and analysts generally express more positive sentiments during their discussions on climate change.

Moving on to the variables related to financial analysts, the data reveals that firms, on average, are covered by approximately 48 analysts. The mean forecast error (FError) stands at 2516.957, with a substantial standard deviation, signifying a considerable range in the accuracy of analysts' forecasts. The mean forecast dispersion (FDispersion) is 2431.095, indicating a significant variation across individual analysts' forecasts. Interestingly, the average analyst appears to be slightly more pessimistic than optimistic, with mean FPessimism and FOptimism scores of 0.504 and 0.467 respectively.

For firm-specific control variables, the data shows a mean firm age (in natural logarithm terms) of 2.520. This suggests that our sample includes both relatively young and more mature firms. The mean firm size, as measured by the natural logarithm of total assets, is 7.275. The average leverage ratio (LEV ratio) is 0.236, suggesting that the firms in our sample typically have moderate debt levels. The mean return on assets (ROA) is -0.033, which, despite its negative skew due to extreme values, is indicative of generally positive returns at the 25th percentile and above.

In sum, these summary statistics provide a broad overview of the firms, analyst behavior, and climate change discourse characteristics represented in our sample. The data highlights significant heterogeneity both across firms and over time, underlining the necessity of accounting for these differences in our main regression analyses.

[Table 3 about here.]

Tables 4a - 4d display the Spearman correlation matrix and Appendix A presents detailed definitions of all the variables used in the study.

[Table 4a–4d about here.]

5 Research Design and Empirical Results

5.1 Corporate Climate Talk: Impact on Analyst Forecasting

As stakeholders become more attentive to corporations' environmental footprints, climate talk during earnings calls – a critical platform for corporate communication – gains increasing relevance. However, how this climate talk influences financial analysts' forecasts, and whether it is perceived as valuable information or mere "window dressing", remains an open question. The motivation for our inquiry stems from the rising importance of climate issues in corporate strategies and the evolving role of financial analysts in incorporating non-financial information into their forecasts.

Our investigation is embedded in two theoretical frameworks: *Impression Management Theory* and *Information Asymmetry Theory*. *Impression Management Theory* suggests that corporations might use climate talk strategically to manage analysts' perceptions and influence their forecasts. This could result in forecast biases, particularly optimistic ones, as analysts may interpret increased climate talk as an indication of a firm's commitment to sustainability. Meanwhile, the *Information Asymmetry Theory* underscores the potential discrepancies in information between executives and analysts, which could lead to forecast errors and biases if analysts struggle to incorporate climate-related elements accurately into their forecasts. Hence, we hypothesise that the climate talk of executives in the presentation session during the earnings calls can have an impact on analyst forecasts (Hypothesis 1). To empirically test the influence of executive climate talk on analyst forecast bias, we estimate the following regression model:

$$Analyst\ Forecast_{i,t} = \alpha_0 + \alpha_1 Pre\_CC\_Frequency_{i,t-1} + \alpha_2 Controls_{i,t-1} + \gamma_t + \lambda_s + \varepsilon_{i,t}, \quad (13)$$

where $Analyst\ Forecast_{i,t}$ includes analysts' forecast error (Ferror), forecast dispersion among analysts (Fdispersion), analysts' propensity for optimism (FOptimism), and analysts' propensity for pessimism (FPessimism) for firm i in year t; $Pre\_CC\_Frequency_{i,t-1}$ represents the frequency of climate change discussions in the presentation session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the presentation session) for a specific firm i in year $t-1$; and $Controls_{i,t-1}$ is a vector of firm-specific characteristics that may influence the analyst forecast performance, such as *Analyst Coverage* (Number of analysts following the firm in a given year), *ln (firm size)* (Natural logarithm of firm size, computed as common shares outstanding multiplied by fiscal year-end price), *Loss* (Dummy variable equals 1 if actual EPS is a negative value, 0 otherwise), *FHorizon* (The median number of days between analyst forecasts and earnings announcements), *LEV ratio* (Long-term debt scaled by total assets), *ROA* (Net income scaled by lagged total assets), *CAPX ratio* (The level of capital expenditures scaled by total assets), and *ln (firm age)* (Natural logarithm of the number of years since a firm's first appearance in CRSP). In addition, we include both industry-fixed effect and year-fixed effect in all specifications to account for general time trends or time-varying industry characteristics. In all specifications, the t-statistics are heteroskedastic, and the sample is clustered at both firm and year levels.

[Table 5 about here.]

Our empirical results shown in Table 5 elucidate that the intensity of climate discourse during the presentation segment of the earnings call has a substantial impact on analyst forecast bias. Specifically, an increase in the intensity of climate discourse corresponds to a rise in the analysts' forecast error, suggesting that analysts might grapple with integrating more comprehensive climate-related information into their forecasts, which, in turn, escalates forecast errors. Moreover, an amplified intensity of climate discourse coincides with a larger forecast dispersion among analysts, suggesting that more elaborate climate-related information from executives leads to wider divergence in analysts' interpretations and forecasts. Interestingly, our findings also indicate that a surge in climate discourse intensity is related to a more optimistic bias of analysts, intimating that climate discourse can direct analysts' expectations towards rosier outlooks. Conversely, an increase in climate discourse intensity correlates with a reduction in analysts' propensity for pessimism, reinforcing the idea that climate discourse can function as a strategic signal showcasing the firm's commitment to environmental initiatives.

In light of our findings, it is clear that the theoretical frameworks examined – *Impression Management Theory* and *Information Asymmetry Theory* – both have significant relevance in this context. For example, as posited by *Impression Management Theory*, corporations seemingly utilize climate talk as a strategic device to shape analysts' perceptions, thereby affecting their forecasts. The corresponding increase in analysts' forecast error and dispersion with the intensification of climate discourse demonstrates this influence, underlining the role of climate talk in framing analysts' perspectives. Our results, showing a surge in optimistic bias alongside increased climate discourse intensity, further consolidate the notion that corporations can sway the sentiment of analysts' forecasts through their climate discussions. Simultaneously, the implications of *Information Asymmetry Theory* become evident in the disparities in analysts' interpretations of climate talk. An uptick in forecast dispersion with heightened climate discourse suggests differing comprehension of non-financial, climate-related information amongst analysts, indicating potential information asymmetry between corporate executives and financial analysts.

5.2 Analyst Climate Talk: Impact on Corporate Environmental Action

The role of financial analysts in influencing corporate environmental performance has emerged as a critical facet of contemporary studies (e.g., Jing et al., 2023). Positioned as information intermediaries, analysts are tasked with deciphering complex corporate information and relaying comprehensible insights to the investor community. In earnings calls, financial analysts play a direct monitoring role by raising climate-related questions. In this context, understanding the connection between analyst climate dialogue and corporate environmental management becomes crucial. It can guide both corporations and financial analysts in navigating the complex terrain of climate-related challenges and opportunities. Moreover, this understanding contributes to the expanding body of research investigating the role of financial markets in fostering sustainable business operations.

Our analysis of the influence exerted by analyst climate dialogue on corporate environmental performance draws upon two key theoretical frameworks: *Stakeholder Theory* and *Legitimacy Theory*. *Stakeholder Theory* suggests that analysts can play a crucial role in mediating potential conflicts of interest between corporate management and stakeholders. By fostering a dialogue on climate-related issues, analysts can help align corporate actions with stakeholder expectations. *Legitimacy Theory*, on the other hand, posits that corporations strive to conform to societal norms and expectations in a bid to maintain their legitimacy. Seen through this lens, analyst climate dialogue can be viewed as a reflection of these evolving societal expectations. As such, it can spur corporations into enhancing their environmental performance to uphold their societal standing and legitimacy. Thus, we posit that analyst climate-related questions potentially act as catalysts for corporations to augment their environmental management efforts (Hypothesis 2).

Our study explores six empirical relationships, each examining how a unique dimension of analysts' climate discussions influences subsequent corporate environmental actions. Specifically, we identify the frequency, complexity, subjectivity, uncertainty, and sentiment (both optimism and pessimism) of analysts' climate dialogue as distinct variables. We then scrutinize their respective impacts on corporate environmental management. Our objective is to gauge how these various facets of climate-centric dialogues can shape a corporation's environmental trajectory. For each dimension of analysts' discourse, we probe its association with a variety of environmental performance indicators, ranging from CO2e emission reductions to proactive environmental investments. The regression model is:

$$
\begin{aligned}
\textit{Environmental Performance}_{i,t} = \alpha_0 + \alpha_1 \textit{Climate Questions Tone}_{i,t-1} \\
+ \alpha_2 \textit{Controls}_{i,t-1} + \gamma_t + \lambda_s + \varepsilon_{i,t},
\end{aligned} \tag{14}
$$

where $Environmental\ Performance_{i,t}$ includes *pcg_Emission* (percentage change of CO2e emission), *Env Innovation Score* (environmental innovation score, the higher the better), *Env Inv Initiatives* (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), *Env Mgt Training* (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), *Env Expenditure Inv* (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and *Env Mgt Team Score* (environmental management team score, the higher the better), respectively, for firm i in year t; $Q\_CC_{i,t-1}$ is an indicator variable that equals one if the question session includes at least one climate change bigram for a specific firm i in year $t-1$; *Climate Talk Presentation Tone*$_{i,t}$ includes *q_cc_subjectivity* (The average of the subjectivity scores of words in the climate change-related question component. The subjectivity score ranges from 0 (objective) to 1 (subjective)), *q_cc_ratio_pos* (The number of Loughran-McDonald positive words divided by the total number of words in the climate change-related question component), and *q_cc_ratio_neg*(The number of Loughran-McDonald negative words divided by the total number of words in the climate change-related question component); and $Controls_{i,t-1}$ is a vector of firm-specific characteristics that may influence corporate environmental performance, such as *Analyst Coverage* (Number of analysts following the firm in a given year), *ln (firm size)*

(Natural logarithm of firm size, computed as common shares outstanding multiplied by fiscal year-end price), *LEV ratio* (Long-term debt scaled by total assets), *ROA* (Net income scaled by lagged total assets), *MB* (Market to book ratio), and *Intan* (Intangible assets scaled by total assets). In addition, we include both industry-fixed effect and year-fixed effect in all specifications to account for general time trends or time-varying industry characteristics. In all specifications, the t-statistics are heteroskedastic, and the sample is clustered at both firm and year levels.

[Table 7 – 12 about here.]

Our empirical findings, presented in 7 – 12, elucidate that the climate-related queries posed by analysts in the previous year have a significant bearing on a company's subsequent environmental performance. We find that companies tend to achieve higher environmental and environmental innovation scores when analysts pose climate-related queries in the prior year. This suggests that these queries can serve as a catalyst for companies to bolster their environmental performance, reflecting the capacity of analysts to influence corporate environmental actions in response to stakeholder expectations and concerns. An increase in the frequency of climate change discussions of analysts in earnings calls is associated with a significant decrease in the percentage change of CO2e emission, as indicated by the negative coefficient at a 5% significance level. This implies that the more often climate change is discussed by analysts, the more likely the company is to reduce its CO2e emissions. A higher frequency of climate change discussions is also significantly associated with higher scores on environmental innovation, investment initiatives, management training, expenditure investment, and management team effectiveness, with all being significant at least at the 10% level. The observed correlations suggest that companies subjected to a higher frequency of climate-related queries appear more inclined to ramp up their investments in environmental innovations and initiatives. Additionally, these companies tend to prioritize the training of their employees on environmental matters and cultivate more competent environmental management teams. Our findings underscore that the regularity of climate change discussions by analysts can exert significant influence on a company's environmental performance. It's as if the analyst discourse serves as a stimulus, propelling companies to make strategic choices towards environmental stewardship across various measures. This relationship might stem from the increasing societal and market awareness of environmental sustainability. Companies faced with persistent climate-related inquiries are likely to respond proactively, implementing environmental initiatives and fostering informed teams. Thus, the intensity of climate change conversations instigated by analysts may serve as a potent lever to enhance a company's environmental performance.

Furthermore, our findings reveal a compelling link between the nature and tone of analysts' climate-related inquiries and corporate environmental performance. When analysts' questions reflect uncertainty or convey positive or negative sentiment, companies respond by amplifying their environmental performance. This suggests that analysts' queries' sentiment and uncertainty can serve as a barometer of societal expectations and pressures regarding corporate environmental responsibility. Responding to these cues, companies strive to enhance their environmental performance to maintain societal legitimacy and conform to evolving norms. Additionally, we observe that the complexity and subjectivity inherent in analysts' climate-related inquiries can act as catalysts for improvements in corporate environmental performance. Subjective inquiries – reflections of analysts' personal interpretations and perceptions – can spotlight potential avenues for environmental enhancements in corporate practices. Simultaneously, complex queries can provoke companies to scrutinize their environmental strategies more thoroughly, thereby spurring efforts to boost environmental performance.

Collectively, these findings underscore the significant role analyst climate discourse plays in shaping corporate environmental management. The attention, inquiries, and perceptions of analysts become instrumental in triggering improvements in environmental management and aligning corporate actions with broader stakeholder expectations. In essence, our results lend empirical support to *Stakeholder Theory* and *Legitimacy Theory*, emphasizing the crucial function of analysts as conduits and the profound influence societal expectations have in dictating corporate environmental responsibility.

Our insights illuminate the capacity of analyst discourse on climate change to steer corporate actions towards heightened environmental responsibility. Regular engagement with climate-related discussions prompts companies to invest more profoundly in environmental innovations, employee training, and efficient environmental management, thereby boosting their overall environmental performance. Our findings provide valuable strategic directions for amplifying corporate environmental practices and leveraging the influence of financial analysts to foster sustainable business practices.

6 Additional Evidence

6.1 Corporate Climate Talk and Its Influence on Analyst Attention

In the preceding section, we unveil the significant influence of analyst climate-related questions on corporate environmental management. Following these revelations, a logical query emerges: What specific circumstances prompt analysts to elevate their attention to climate-related matters during earnings calls?

Deciphering the association between executive climate discourse and the tendency of analysts to pose climate-related questions can yield critical insights. These insights can streamline how corporations articulate their environmental strategies, fostering better engagement with financial analysts on topics related to sustainability. Further, by identifying the conditions that accentuate analysts' attention towards climate-related issues, we can unravel the intricacies of their decision-making processes and the factors that guide their environmental focus.

Our empirical exploration of the impact of corporate climate discourse during earnings calls on analyst attention is grounded in two theoretical frameworks: *Signal Detection Theory* and *Salience Theory*. *Signal Detection Theory* posits that analysts perceive certain aspects of corporate climate talk as signals of the importance of climate-related issues, which in turn prompt them to seek additional insights. *Salience Theory*, on the other hand, suggests that information perceived as subjective or salient, such as the tone or sentiment of executives' climate discourse, captures more attention and increases the likelihood of analysts posing climate-related questions.

We posit that the content and tone of executives' climate-related discussions during the presentation segment may provoke analysts to pose additional questions on the same topic in the follow-up session. To empirically test the influence of corporate climate talk on analyst attention, we estimate the following regression model:

$$
\begin{aligned}
Q\_CC_{i,t} = \alpha_0 + \alpha_1 Pre\_CC_{i,t} \\
+ \alpha_2 Pre\_CC\_Tone_{i,t} \\
+ \alpha_3 Pre\_CC_{i,t} \times Pre\_CC\_Tone_{i,t} \\
+ \alpha_4 Controls_{i,t} + \gamma_t + \lambda_s + \varepsilon_{i,t},
\end{aligned}
\tag{15}
$$

where $Q\_CC_{i,t}$ is an indicator variable that equals one if the question session includes at least one climate change bigram for firm i in year t; $Pre\_CC_{i,t}$ is an indicator variable that equals one if the presentation session includes at least one climate change bigram for a specific firm i in year t; $Pre\_CC\_Tone_{i,t}$ includes *pre_cc_subjectivity* (The average of the subjectivity scores of words in the climate change-related presentation component. The subjectivity score ranges from 0 (objective) to 1 (subjective)), *pre_cc_ratio_pos* (The number of Loughran-McDonald positive words divided by the total number of words in the climate change-related presentation component), and *pre_cc_ratio_neg* (The number of Loughran-McDonald negative words divided by the total number of words in the climate change-related presentation component); and $Controls_{i,t-1}$ is a vector of firm-specific characteristics such as *Analyst Coverage* (Number of analysts following the firm in a given year), *ln (firm size)* (Natural logarithm of firm size, computed as common shares outstanding multiplied by fiscal year-end price), *LEV ratio* (Long-term debt scaled by total assets), *ROA* (Net income scaled by lagged total assets), and *CAPX ratio* (The level of capital expenditures scaled by total assets). In addition, we include both industry-fixed effect and year-fixed effect in all specifications to account for general time trends or time-varying industry characteristics. In all specifications, the t-statistics are heteroskedastic, and the sample is clustered at both firm and year levels.

[Table 6 about here.]

Our empirical findings, presented in Table 6, reveal several conditions under which analysts are more inclined to raise climate-related queries during earnings calls. First, we find that an explicit mention of climate change by executives during their presentations elicits a heightened propensity among analysts to pose climate-related queries. This suggests that explicit climate talk signals the importance of climate-related issues and captures analysts' attention, thereby prompting further inquiries. Second, our study underscores the significant role the subjective content in executives' climate discourse plays in provoking analyst inquiries. When executives share personal views or interpretations on climate-related matters, analysts are inclined to delve deeper for clarity. This aligns with *Signal Detection Theory*, which suggests that subjective information acts as a 'signal' amidst the noise, signifying the relevance of climate issues and thus motivating further investigation. Lastly, our findings indicate that the sentiment conveyed in executives' climate discourse significantly impacts the likelihood of analysts posing climate-related questions. Notably, negative sentiment within climate dialogue instigates more climate-related inquiries from analysts compared to positive sentiment. This observation corroborates the *Salience Theory*, which suggests that negative aspects or concerns regarding climate issues stand out more vividly, thereby stimulating a heightened level of attention and subsequent inquiry from analysts.

Taken together, our empirical findings underscore the instrumental role of executives' climate discourse during earnings calls in shaping analyst attention towards climate-related issues. Our results emphasise the significance of effective communication, explicit climate talk, and the subjective aspects of climate discourse in capturing analysts' attention and inciting climate-related queries. By identifying the factors that influence analysts' propensity to ask climate-related questions, our study provides valuable insights into the mechanisms by which corporate climate talk influences analyst attention and contributes to our understanding of how climate-related concerns are integrated into financial markets.

6.2 Corporate Executives' Reactions to Climate-Related Inquiries

In this section, we turn our attention to the nature and characteristics of executive responses to climate-related inquiries posed by financial analysts during earnings calls. While our preceding analysis illuminates the factors prompting analysts to ask climate-centric questions, the essence of corporate responses carries equal significance. Executive reactions serve as reflections of a firm's commitment to environmental sustainability, shedding light on their level of awareness, attitudes towards climate change, and strategic considerations informing their environmental disclosures. We meticulously dissect these responses, evaluating elements such as complexity, subjectivity, uncertainty, sentiment, and frequency to assess the efficacy of their environmental strategy communication.

To decipher these dynamics, we engage the *Proprietary Cost Theory* in our analysis. This theory advocates that companies might withhold the dissemination of specific information, including climate-related insights if they assess that disclosure costs — such as the potential compromise of a competitive advantage — outweigh the benefits. This theoretical lens equips us to better interpret the strategies that executives employ in discussions revolving around climate change. Thus, we propose that executives strategically adjust their disclosures in response to climate-related inquiries during earnings calls. To empirically assess this hypothesis, we implement the following regression model:

$$Answers\ Tone_{i,t} = \alpha_0 + \alpha_1 Q\_CC_{i,t} + \alpha_2 Controls_{i,t} + \gamma_t + \lambda_s + \varepsilon_{i,t}, \tag{16}$$

where $Answers\ Tone_{i,t}$ includes *answer_cc_d* (an indicator variable that equals one if the executives' answer session includes at least one climate change bigram), *A_CC_Complexity* (The average of the Gunning Fog Index of the climate change-related answer component (i.e., all sentences containing at least one climate change bigram)), *A_CC_Subjectivity* (The average of the subjectivity scores of words in the climate change-related answer component. The subjectivity score ranges from 0 (objective) to 1 (subjective)), *A_CC_Uncertainty* (The number of Loughran-McDonald uncertainty words scaled by the total number of words in the climate change-related answer component), and *A_CC_Sentiment* (The relative frequency of Loughran-McDonald positive and negative words in the climate change-related answer component which is defined as the difference in the proportions of positive and negative words (i.e., POS minus NEG)) for firm i in year t; $Q\_CC_{i,t}$ is an indicator variable that equals one if the question session includes at least one climate change bigram; and $Controls_{i,t}$ includes *Analyst Coverage* (Number of analysts following the firm in a given year), *ln (firm size)* (Natural logarithm of firm size, computed as common shares outstanding multiplied by fiscal year-end price), *LEV ratio* (Long-term debt scaled by total assets), *ROA* (Net income scaled by lagged total assets), and *CAPX ratio* (The level of capital expenditures scaled by total assets). In addition, we include both industry-fixed effect and year-fixed effect in all specifications to account for general time trends or time-varying industry characteristics. In all specifications, the t-statistics are heteroskedastic, and the sample is clustered at both firm and year levels.

[Table 13 about here.]

Our empirical investigation reveals specific patterns in executive responses to climate-related inquiries. Initially, we find that executives are notably more likely to provide responses focused on climate issues when queried about these matters. This highlights the increasing importance of climate change within corporate discussions, suggesting executives are acknowledging its global significance. We also note a higher complexity in climate-related responses compared to other topics, which could indicate that executives are engaging in more comprehensive dialogues about climate change due to its intricate and multifaceted nature. Concurrently, these responses carry greater subjectivity and uncertainty, which might reflect the evolving landscape of climate science and its continuous advancements. Besides, the application of the *Proprietary Cost Theory* sheds light on these findings, suggesting the observed complexity and uncertainty in executive responses might be strategic moves to address climate concerns while protecting proprietary information or strategic plans.

Despite the complexity and uncertainty, we find a predominant optimistic tone in executive responses. This might indicate confidence in their respective organizations' ability to confront and adapt to climate-related challenges, promoting a proactive, solution-driven culture. Moreover, this optimistic stance could also signal that executives view climate change not only as a risk, but also as an opportunity for innovation and the development of sustainable solutions. This observed optimism, however, warrants judicious examination. It harbors the potential to breed complacency and understate the profound challenges inherent to climate change. Hence, it is essential for stakeholders to measure a company's commitment to environmental sustainability not solely by the optimism of its rhetoric, but importantly, through its tangible actions and verifiable progress. Moreover, it is crucial to acknowledge the possibility that an overly optimistic tone may function as a strategic obfuscation tool, designed to mask the authentic risks and complexities associated with climate change. Therefore, stakeholders should exercise rigorous discernment, recognizing that an excessively positive narrative might potentially distort the true breadth and depth of an organization's climate-related risks.

In conclusion, our findings shed light on the delicate equilibrium executives maintain between transparency on their companies' climate initiatives and safeguarding strategic information. This highlights the intricate, strategic considerations executives grapple with when responding to climate-related inquiries.

7 Conclusion

In this study, we delve into the effects of executive discourse on climate change during earnings calls and its impact on financial forecasting and environmental management. Our results reveal a significant link between the intensity of climate dialogue and an uptick in analyst forecast errors. This implies that the assimilation of intricate climate-related data presents challenges to analysts, leading to more pronounced forecast discrepancies. Additionally, we observe that a more intensive climate discourse correlates with wider forecast dispersion, suggesting that complex climate data engenders a broader array of interpretations by analysts. Intriguingly, our study indicates that heightened climate discourse inclines analysts towards an optimistic bias, inferring that these conversations may shape analysts' expectations towards more favourable forecasts. Concurrently, our research exposes the pivotal role that analysts' climate-related inquiries play in promoting improved corporate environmental performance and management. This is likely a reflection of the escalating societal and market recognition of environmental sustainability. Firms facing regular climate-related inquiries tend to respond proactively by launching environmental strategies and cultivating informed teams. Therefore, the frequency of climate-related discussions instigated by analysts can act as a powerful driver for improving a firm's environmental performance.

Furthermore, we find that straightforward climate-related executive discourse during presentations and the subjective nature of their discourse significantly prompts analysts to probe deeper into climate-related issues. Additionally, the negative sentiment expressed in these dialogues incites more inquiries from analysts. Our findings also show that executives' responses to climate-related inquiries exhibit more complexity and uncertainty compared to non-climate discussions, mirroring the multi-dimensional nature of climate change and the dynamic landscape of climate science. Despite this complexity, the responses from executives predominantly emit an optimistic tone, possibly indicating confidence in their organizations' ability to address climate challenges and strategic attempts to safeguard sensitive information.

Our research offers valuable insights to a broad spectrum of stakeholders. Corporations stand to gain from maintaining transparent and thorough climate dialogue during earnings calls, a strategy that can result in both financial and environmental benefits, thereby highlighting the importance of climate discourse to their financial stability and societal impact. For financial analysts and investors, our insights can augment their valuation techniques and forecasting models, facilitating a more accurate and pertinent integration of non-financial, specifically climate-related, data into their evaluations. From a regulatory perspective, our findings bolster the case for policies advocating transparent climate-related disclosures during corporate communications. Understanding the influence of climate discourse on analyst forecasts and environmental performance provides policymakers with the necessary evidence to promote a regulatory framework that endorses such communication.

In conclusion, our research unveils the critical role that corporate climate dialogue can play in mitigating climate change and advancing global sustainability. Transparent conversations about climate initiatives and commitments can define strategic priorities for firms, shape interactions with analysts and investors, and crucially, contribute to societal benefits through improved environmental stewardship. This shift in perspective emphasizes that a corporation's approach to climate dialogue can serve as a powerful tool in building a sustainable future.

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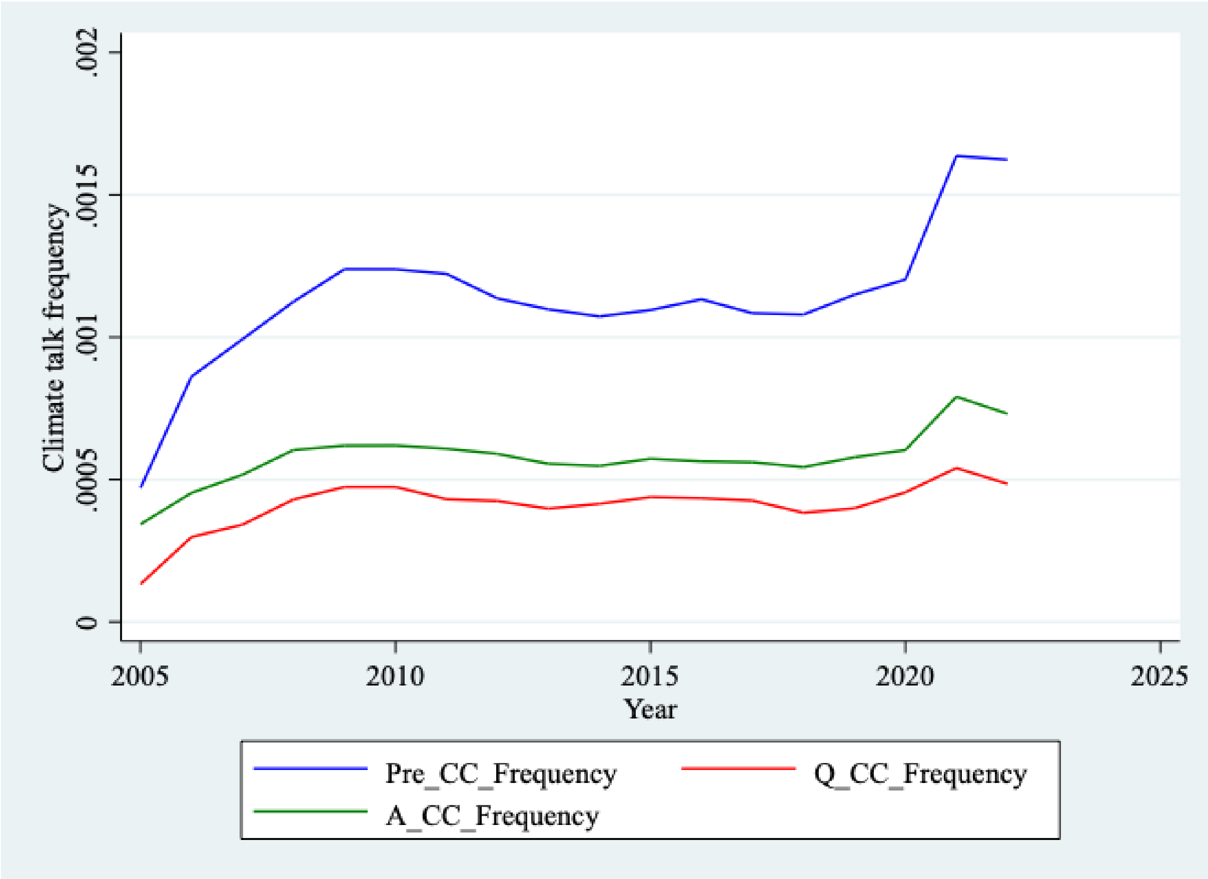
Figures

Figure 1: Climate change discussion in conference calls over time



This figure shows the trend in climate change discussion in conference calls over time. Pre_CC_Frequency is climate talk frequency of corporate executives in the presentation session. Pre_CC_Frequency is climate talk frequency of analysts in the question session. Pre_CC_Frequency is climate talk frequency of corporate executives in the answer session. The figure plots yearly averages.

Table 1: Industry Distribution

This table presents the distribution of sample firms by industry, based on the first two digits of their Standard Industrial Classification (SIC) codes. The sample consists of 48,329 firm-year observations between 2005 and 2022 for 6,696 individual firms.

2-digit SIC	Description	Number of obs	% of obs
1	Agricultural production—Crops	58	0.12
7	Agricultural Services	16	0.03
10	Metal mining	363	0.75
12	Coal mining	133	0.28
13	Oil and gas extraction	1,734	3.59
14	Mining and quarrying of nonmetallic minerals, except fuels	131	0.27
15	Construction—General contractors and operative builders	248	0.51
16	Heavy construction, except building construction, contractor	238	0.49
17	Construction—Special trade contractors	114	0.24
20	Construction—Special trade contractors	898	1.86
21	Tobacco products	63	0.13
22	Textile mill products	92	0.19
23	Apparel, finished products from fabrics and similar materials	325	0.67
24	Lumber and wood products, except furniture	182	0.38
25	Furniture and fixtures	217	0.45
26	Paper and allied products	319	0.66
27	Printing, publishing, and allied industries	280	0.58
28	Chemicals and allied products	5,199	10.76
29	Petroleum refining and related industries	361	0.75
30	Rubber and miscellaneous plastic products	220	0.46
31	Barter transactions involving advertising services	127	0.26
32	Stone, clay, glass, and concrete products	180	0.37
33	Primary metal industries	435	0.90
34	Fabricated metal products	552	1.14
35	Industrial and commercial machinery and computer equipment	2,200	4.55
36	Electronic and other electrical equipment and components	3,248	6.72
37	Transportation equipment	1,148	2.38
38	Measuring, photographic, medical, and optical goods, and clocks	2,670	5.52
39	Miscellaneous manufacturing industries	265	0.55
40	Railroad transportation	75	0.16
41	Local & Suburban Transit & Interurban Highway Transportation	28	0.06
42	Motor freight transportation	244	0.50
44	Water transportation	497	1.03
45	Transportation by air	314	0.65
46	Pipelines, except natural gas	135	0.28
47	Transportation services	168	0.35
48	Communications	1,306	2.70
49	Electric, gas, and sanitary services	1,672	3.46
50	Wholesale trade—Durable goods	741	1.53
51	Wholesale trade—Nondurable goods	482	1.00
52	Building Materials, Hardware, Garden Supplies & Mobile Homes	77	0.16
53	General merchandise stores	216	0.45
54	Building materials, hardware, garden supplies, and mobile homes	144	0.30
55	General merchandise stores	330	0.68
56	Food stores	510	1.06
57	Home Furniture, Furnishings and Equipment Stores	143	0.30
58	Eating and drinking places	634	1.31
59	Miscellaneous retail	751	1.55
60	Depository Institutions	2,533	5.24
61	Nondepository Credit Institutions	516	1.07
62	Security and commodity brokers, dealers, exchanges, and services	981	2.03
63	Insurance Carriers	1,337	2.77
64	Insurance agents, brokers, and service	201	0.42
65	Real estate	284	0.59
67	Holding and other investment offices	3,152	6.52
70	Hotels, Rooming Houses, Camps, and Other Lodging Places	169	0.35
72	Personal Services	129	0.27
73	Business services	6,005	12.43
75	Automotive Repair, Services and Parking	98	0.20
78	Motion Pictures	145	0.30
79	Amusement and Recreation Services	419	0.87
80	Health services	718	1.49
81	Legal Services	17	0.04
82	Educational services	346	0.72
83	Social Services	28	0.06
87	Engineering, accounting, research, and management services	640	1.32
89	Services, Not Elsewhere Classified	1	0.00
99	Nonclassifiable establishments	127	0.26
Total		48,329	100.00

Table 2: Characteristics Comparison between Firms with and without Climate Change Discussions in Executive Presentations

This table presents the mean comparison between firms with and without climate change discussions in executive presentations. We use the t-test by Pre_CC_D (Pre_CC_D=0 if there is no climate change discussion in the presentation) for the difference in means. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Appendix A provides descriptions of the variables.

	Mean (Pre_CC_D=0)	Mean(Pre_CC_D=1)	Diference in mean
Analyst_Coverage	38.11	48.06	-9.95***
FError	21134.56	1565.99	19568.57***
FDispersion	26289.8	1194.43	25095.37***
FOptimism_Analyst	0.49	0.47	0.02***
FPessimism_Analyst	0.48	0.5	-0.02***
Surprise	0.01	0.02	-0.01
FHorizon	213.41	213.57	-0.16
Question_CC_D	0.41	0.64	-0.23***
Q_CC_Frequency	0	0	-0.00***
Q_CC_Complexity	2.65	4.12	-1.47***
Q_CC_Subjectivity	0.08	0.12	-0.04***
Q_CC_Uncertainty	0	0	-0.00***
Q_CC_RATIO_POS	0	0	-0.00***
Q_CC_RATIO_NEG	0	0	-0.00***
Q_CC_Sentiment	0	0	0.00*
Answer_CC_D	0.71	0.91	-0.20***
A_CC_Frequency	0	0	-0.00***
A_CC_Complexity	7.1	9.51	-2.41***
A_CC_Subjectivity	0.2	0.27	-0.07***
A_CC_Uncertainty	0	0	-0.00***
A_CC_RATIO_POS	0.01	0.01	-0.00***
A_CC_RATIO_NEG	0	0	-0.00***
A_CC_Sentiment	0	0	-0.00***
Loss	0.23	0.22	0.01
Price	37.67	39.24	-1.57
ln (firm age)	2.3	2.53	-0.23***
CAPX ratio	0.04	0.04	-0.00**
LEV ratio	0.21	0.24	-0.03***
R&D	0.38	0.46	-0.08***
ROA	-0.08	-0.03	-0.05***
ln (firm size)	6.74	7.3	-0.56***

Table 3: Summary statistics

This table presents the summary statistics for the variables used in the main analysis. Appendix A provides descriptions of the variables.

	N	Mean	SD	Median	p25	p75	Min	Max
Pre_CC_Frequency	48329	0.001	0.002	0.001	0.000	0.001	0.000	0.045
Pre_CC_Complexity	48329	13.533	6.106	14.350	10.103	17.218	0.000	112.040
Pre_CC_Subjectivity	48329	0.317	0.152	0.338	0.219	0.424	0.000	1.000
Pre_CC_Uncertainty	48329	0.006	0.008	0.003	0.000	0.008	0.000	0.129
Pre_CC_RATIO_POS	48329	0.016	0.013	0.014	0.006	0.023	0.000	0.211
Pre_CC_RATIO_NEG	48329	0.006	0.008	0.003	0.000	0.009	0.000	0.126
Pre_CC_Sentiment	48329	0.010	0.015	0.008	0.000	0.018	-0.118	0.211
Q_CC_Frequency	48329	0.000	0.001	0.000	0.000	0.001	0.000	0.042
Q_CC_Complexity	48329	4.050	4.360	3.158	0.000	6.590	0.000	43.150
Q_CC_Subjectivity	48329	0.122	0.141	0.092	0.000	0.202	0.000	1.000
Q_CC_Uncertainty	48329	0.004	0.007	0.000	0.000	0.006	0.000	0.125
Q_CC_RATIO_POS	48329	0.003	0.006	0.000	0.000	0.003	0.000	0.100
Q_CC_RATIO_NEG	48329	0.003	0.006	0.000	0.000	0.004	0.000	0.143
Q_CC_Sentiment	48329	0.000	0.007	0.000	0.000	0.000	-0.143	0.100
A_CC_Frequency	48329	0.001	0.001	0.000	0.000	0.001	0.000	0.025
A_CC_Complexity	48329	9.389	5.628	9.573	5.213	13.463	0.000	65.910
A_CC_Subjectivity	48329	0.267	0.167	0.268	0.135	0.394	0.000	1.000
A_CC_Uncertainty	48329	0.004	0.006	0.002	0.000	0.006	0.000	0.133
A_CC_RATIO_POS	48329	0.008	0.009	0.005	0.000	0.012	0.000	0.137
A_CC_RATIO_NEG	48329	0.003	0.005	0.000	0.000	0.005	0.000	0.121
A_CC_Sentiment	48329	0.004	0.010	0.002	0.000	0.009	-0.121	0.137
Analyst_Coverage	48329	47.571	48.532	31.000	15.000	63.000	1.000	634.000
FError	47061	2516.957	270428.500	0.154	0.057	0.425	0.000	43200000.000
FDispersion	47891	2431.095	239730.400	0.181	0.084	0.446	0.000	45500000.000
FOptimism_Analyst	48329	0.467	0.361	0.448	0.104	0.807	0.000	1.000
FPessimism_Analyst	48329	0.504	0.360	0.500	0.158	0.857	0.000	1.000
Surprise	46961	0.018	7.554	0.012	-0.087	0.107	-442.000	980.818
FHorizon	47968	213.558	46.463	206.000	190.000	232.000	-322.000	1622.000
Loss	48329	0.225	0.417	0.000	0.000	0.000	0.000	1.000
Price	48329	39.162	75.073	21.770	8.880	45.450	0.011	3334.340
ln (firm age)	48327	2.520	0.973	2.708	1.792	3.258	0.000	4.111
CAPX ratio	48138	0.039	0.056	0.022	0.007	0.050	-0.186	1.406
LEV ratio	48119	0.236	0.245	0.188	0.030	0.368	0.000	7.558
R&D	48329	0.455	0.498	0.000	0.000	1.000	0.000	1.000
ROA	48321	-0.033	0.331	0.024	-0.022	0.066	-33.807	5.003
ln (firm size)	48308	7.275	1.961	7.248	5.938	8.538	0.572	14.659

Table 4a: Correlation Matrix

	Pre_CC_Frequency	Pre_CC_Complexity	Pre_CC_Subjectivity	Pre_CC_Uncertainty	Pre_CC_RATIO_POS	Pre_CC_RATIO_NEG	Pre_CC_Sentiment
Pre_CC_Frequency	1						
Pre_CC_Complexity	0.195***	1					
Pre_CC_Subjectivity	0.277***	0.653***	1				
Pre_CC_Uncertainty	0.027***	0.337***	0.215***	1			
Pre_CC_RATIO_POS	0.092***	0.351***	0.446***	0.019***	1		
Pre_CC_RATIO_NEG	0.052***	0.259***	0.203***	0.153***	0.033***	1	
Pre_CC_Sentiment	0.054***	0.175***	0.286***	-0.062***	0.859***	-0.483***	1
Q_CC_Frequency	0.556***	0.081***	0.149***	0.00200	0.041***	0.037***	0.017***
Q_CC_Complexity	0.313***	0.084***	0.143***	0.008*	0.061***	0.060***	0.022***
Q_CC_Subjectivity	0.321***	0.071***	0.139***	-0.00200	0.058***	0.048***	0.026***
Q_CC_Uncertainty	0.174***	0.049***	0.078***	0.00300	0.039***	0.037***	0.015***
Q_CC_RATIO_POS	0.151***	0.034***	0.069***	-0.008*	0.059***	0.021***	0.041***
Q_CC_RATIO_NEG	0.148***	0.042***	0.077***	0.008*	0.037***	0.059***	0.00200
Q_CC_Sentiment	-0.00600	-0.008*	-0.010**	-0.013***	0.014***	-0.032***	0.029***
A_CC_Frequency	0.714***	0.113***	0.190***	-0.00200	0.061***	0.034***	0.036***
A_CC_Complexity	0.211***	0.139***	0.175***	0.020***	0.100***	0.049***	0.063***
A_CC_Subjectivity	0.230***	0.116***	0.176***	0.009**	0.098***	0.043***	0.064***
A_CC_Uncertainty	0.069***	0.028***	0.040***	0.029***	0.00400	0.047***	-0.020***
A_CC_RATIO_POS	0.093***	0.062***	0.091***	-0.00700	0.119***	-0.00200	0.105***
A_CC_RATIO_NEG	0.059***	0.028***	0.047***	0.012***	0.019***	0.083***	-0.026***
A_CC_Sentiment	0.051***	0.040***	0.057***	-0.013***	0.096***	-0.047***	0.108***
Analyst_Coverage	-0.045***	0.013***	0.055***	0.00200	0.056***	0.020***	0.039***
FError	-0.00300	-0.00600	-0.00400	-0.00400	-0.00400	-0.00200	-0.00300
FDispersion	-0.00400	-0.010**	-0.009*	-0.00500	-0.00700	-0.00400	-0.00400
FOptimism_Analyst	0.013***	0.00500	-0.011**	0.00300	-0.048***	0.036***	-0.060***
FPessimism_Analyst	-0.014***	-0.00400	0.011**	-0.00500	0.048***	-0.033***	0.058***
Surprise	-0.00300	-0.00300	0.00100	-0.00400	0.00200	-0.00200	0.00300
FHorizon	-0.013***	0.00400	-0.020***	-0.00600	-0.017***	-0.00200	-0.014***
Loss	0.00100	0.045***	0.00100	0.00500	-0.038***	-0.00100	-0.033***
Price	0.00100	-0.00500	0.025***	-0.00400	0.034***	-0.00500	0.032***
ln (firm age)	0.092***	0.008*	0.027***	-0.015***	0.038***	0.073***	-0.00400
CAPX ratio	0.084***	-0.00200	0.043***	-0.017***	-0.018***	-0.028***	-0.00200
LEV ratio	0.00200	-0.013***	0.016***	-0.017***	0.010**	-0.008*	0.012***
R&D	0.020***	0.105***	0.077***	-0.024***	0.068***	-0.034***	0.077***
ROA	0.00600	-0.024***	0.010**	-0.00300	0.041***	0.00700	0.032***
ln (firm size)	0.041***	0.008*	0.081***	-0.030***	0.101***	0.00200	0.088***

Table 4b: Correlation Matrix

	Q_CC_Frequency	Q_CC_Complexity	Q_CC_Subjectivity	Q_CC_Uncertainty	Q_CC_RATIO_POS	Q_CC_RATIO_NEG	Q_CC_Sentiment
Q_CC_Frequency	1						
Q_CC_Complexity	0.589***	1					
Q_CC_Subjectivity	0.579***	0.833***	1				
Q_CC_Uncertainty	0.349***	0.533***	0.492***	1			
Q_CC_RATIO_POS	0.301***	0.442***	0.442***	0.235***	1		
Q_CC_RATIO_NEG	0.299***	0.431***	0.399***	0.268***	0.171***	1	
Q_CC_Sentiment	-0.016***	-0.016***	0.010**	-0.040***	0.610***	-0.676***	1
A_CC_Frequency	0.608***	0.346***	0.345***	0.201***	0.169***	0.168***	-0.008*
A_CC_Complexity	0.193***	0.288***	0.258***	0.166***	0.139***	0.143***	-0.012**
A_CC_Subjectivity	0.222***	0.302***	0.294***	0.181***	0.156***	0.155***	-0.008*
A_CC_Uncertainty	0.069***	0.104***	0.097***	0.064***	0.041***	0.061***	-0.019***
A_CC_RATIO_POS	0.088***	0.142***	0.139***	0.093***	0.093***	0.067***	0.015***
A_CC_RATIO_NEG	0.068***	0.120***	0.105***	0.072***	0.047***	0.088***	-0.036***
A_CC_Sentiment	0.042***	0.062***	0.068***	0.045***	0.058***	0.013***	0.033***
Analyst_Coverage	-0.026***	0.150***	0.142***	0.102***	0.083***	0.088***	-0.009**
FError	-0.00200	-0.00200	-0.00200	-0.00500	-0.00400	-0.00400	0
FDispersion	0	-0.00400	-0.00300	-0.00500	0.00300	-0.00500	0.00600
FOptimism_Analyst	-0.008*	-0.039***	-0.039***	-0.030***	-0.034***	-0.008*	-0.019***
FPessimism_Analyst	0.008*	0.040***	0.040***	0.031***	0.035***	0.010**	0.017***
Surprise	-0.00300	-0.00700	-0.00700	-0.00100	-0.00500	0.00400	-0.00700
FHorizon	-0.012***	-0.059***	-0.049***	-0.030***	-0.019***	-0.033***	0.012***
Loss	-0.035***	-0.106***	-0.097***	-0.064***	-0.059***	-0.070***	0.012***
Price	0.014***	0.069***	0.070***	0.057***	0.051***	0.032***	0.012***
ln (firm age)	0.067***	0.103***	0.101***	0.073***	0.061***	0.066***	-0.00700
CAPX ratio	0.043***	0.050***	0.047***	0.016***	0.013***	0.021***	-0.00700
LEV ratio	0.00400	0.024***	0.029***	0.022***	0.013***	0.00600	0.00500
R&D	0.011**	0.014***	0.00500	0.009**	0.015***	0.00500	0.008*
ROA	0.033***	0.087***	0.081***	0.054***	0.048***	0.049***	-0.00400
ln (firm size)	0.057***	0.216***	0.202***	0.143***	0.116***	0.136***	-0.023***

Table 4c: Correlation Matrix

	A_CC_Frequency	A_CC_Complexity	A_CC_Subjectivity	A_CC_Uncertainty	A_CC_RATIO_POS	A_CC_RATIO_NEG	A_CC_Sentiment
A_CC_Frequency	1						
A_CC_Complexity	0.388***	1					
A_CC_Subjectivity	0.409***	0.784***	1				
A_CC_Uncertainty	0.140***	0.314***	0.292***	1			
A_CC_RATIO_POS	0.189***	0.429***	0.466***	0.117***	1		
A_CC_RATIO_NEG	0.134***	0.297***	0.284***	0.156***	0.094***	1	
A_CC_Sentiment	0.097***	0.224***	0.264***	0.020***	0.844***	-0.454***	1
Analyst_Coverage	-0.039***	0.175***	0.200***	0.067***	0.128***	0.065***	0.079***
FError	-0.00600	-0.013***	-0.014***	-0.00500	-0.00700	-0.00500	-0.00400
FDispersion	-0.00600	-0.015***	-0.014***	-0.00600	-0.008*	-0.00400	-0.00500
FOptimism_Analyst	0.00300	-0.043***	-0.052***	-0.00700	-0.045***	0	-0.041***
FPessimism_Analyst	-0.00500	0.042***	0.052***	0.00700	0.045***	0.00100	0.040***
Surprise	-0.00400	-0.00100	-0.00400	-0.00300	0.00400	-0.00400	0.00600
FHorizon	-0.016***	-0.067***	-0.065***	-0.034***	-0.033***	-0.032***	-0.012***
Loss	-0.018***	-0.084***	-0.100***	-0.039***	-0.062***	-0.045***	-0.032***
Price	0.00700	0.081***	0.102***	0.030***	0.072***	0.025***	0.051***
ln (firm age)	0.066***	0.067***	0.089***	0.036***	0.048***	0.056***	0.012***
CAPX ratio	0.073***	0.033***	0.044***	0.010**	0.00400	-0.00100	0.00500
LEV ratio	0	0.011**	0.027***	-0.00400	0.019***	0.00600	0.013***
R&D	0.033***	0.069***	0.052***	-0.013***	0.048***	-0.023***	0.055***
ROA	0.018***	0.068***	0.083***	0.028***	0.057***	0.038***	0.030***
ln (firm size)	0.046***	0.230***	0.261***	0.079***	0.166***	0.094***	0.098***

Table 4d: Correlation Matrix

	Analyst_Coverage	FError	FDispersion	FOptimism_Analyst	FPessimism_Analyst	Surprise	FHorizon	Loss	Price	ln (firm age)	CAPX ratio	LEV ratio	R&D	ROA
Analyst_Coverage	1													
FError	0.002	1												
FDispersion	0.004	0.897***	1											
FOptimism_Analyst	-0.073***	0.010**	0.010**	1										
FPessimism_Analyst	0.083***	-0.010**	-0.010**	-0.986***	1									
Surprise	0	0	0	-0.022***	0.022***	1								
FHorizon	-0.129***	0.003	0.002	0.054***	-0.050***	-0.029***	1							
Loss	-0.159***	0.007	0.002	0.240***	-0.232***	-0.009**	0.102***	1						
Price	0.270***	-0.004	-0.005	-0.142***	0.154***	0.002	-0.060***	-0.176***	1					
ln (firm age)	0.185***	-0.007	-0.008*	-0.059***	0.058***	-0.002	0.022***	-0.245***	0.158***	1				
CAPX ratio	0.222***	0.011**	0.025***	0.065***	-0.062***	0.004	-0.051***	-0.023***	-0.006	-0.039***	1			
LEV ratio	0.043***	-0.002	-0.003	0.048***	-0.041***	-0.005	0.024***	0.027***	0.025***	-0.017***	0.089***	1		
R&D	-0.059***	0	-0.002	-0.064***	0.058***	-0.003	0.054***	0.180***	0.011**	-0.049***	-0.111***	-0.181***	1	
ROA	0.121***	-0.017***	-0.026***	-0.138***	0.136***	-0.006	-0.106***	-0.397***	0.130***	0.167***	-0.042***	-0.039***	-0.158***	1
ln (firm size)	0.566***	-0.010**	-0.011**	-0.226***	0.232***	0.010**	-0.230***	-0.385***	0.428***	0.283***	0.018***	0.074***	-0.041***	0.313***

Table 5: Impact of Corporate Climate Talk on Analyst Forecast Bias

This table reports regression results on the effect of corporate climate talk in the earnings call on analyst forecast bias. The dependent variables are Ferror, Fdispersion, FOptimism_Analyst, and FPessimism_Analyst, respectively. The Pre_CC_Frequency is defined as the Frequency of climate change discussions in the presentation session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the presentation session). The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Ferror	Fdispersion	FOptimism_Analyst	FPessimism_Analyst
	(1)	(2)	(3)	(4)
Pre_CC_Frequency	34.864*	30.873*	3.068*	-3.401**
	(1.872)	(1.662)	(2.070)	(-2.317)
Analyst_Coverage	0.002**	0.003***	-0.000*	0.000**
	(2.591)	(3.181)	(-1.950)	(2.368)
ln (firm size)	-0.081***	-0.073***	-0.028***	0.028***
	(-3.044)	(-3.464)	(-8.791)	(9.346)
Loss	0.305**	0.252***	0.062***	-0.054***
	(2.584)	(3.184)	(6.529)	(-5.673)
FHorizon	-0.000	-0.000	-0.000***	0.000***
	(-0.210)	(-0.169)	(-3.790)	(3.106)
LEV ratio	0.014	-0.068	0.031**	-0.024**
	(0.090)	(-0.503)	(2.881)	(-2.220)
ROA	-1.672***	-2.128***	0.007	0.004
	(-4.640)	(-6.548)	(0.401)	(0.195)
CAPX ratio	0.316	0.813	0.299***	-0.267***
	(0.416)	(1.094)	(5.485)	(-5.145)
ln (firm age)	-0.022	-0.022	0.000	-0.000
	(-0.768)	(-0.795)	(0.006)	(-0.032)
Constant	1.145***	1.060***	0.670***	0.301***
	(6.022)	(6.612)	(29.588)	(13.164)
Observations	39,508	40,241	40,479	40,479
R-squared	0.055	0.075	0.072	0.071
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 6: Impact of Corporate Climate Talk on Analyst Attention

This table reports regression results on the effect of corporate climate talk on the analyst's attention. The dependent variable is the indicator variable that equals one if the question session includes at least one climate change bigram. The Pre_CC is an indicator variable that equals one if the presentation session includes at least one climate change bigram. pre_cc_subjectivity refers to the average of the subjectivity scores of words in the climate change- related presentation component. The subjectivity score ranges from 0 (objective) to 1 (subjective). pre_cc_ratio_pos is the number of Loughran-McDonald positive words divided by the total number of words in the climate change-related presentation component. pre_cc_ratio_neg is the number of Loughran-McDonald negative words divided by the total number of words in the climate change-related presentation component. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: climate change in analysts' questions				
	(1)	(2)	(3)	(4)
Pre_CC	0.140***	0.094***	0.133***	0.132***
	(13.195)	(7.381)	(12.771)	(11.849)
Pre_CC * pre_cc_subjectivity		0.142***		
		(7.190)		
Pre_CC * pre_cc_ratio_pos			0.446**	
			(2.286)	
Pre_CC * pre_cc_ratio_neg				1.323***
				(3.042)
Analyst_Coverage	0.001***	0.001***	0.001***	0.001***
	(11.141)	(11.140)	(11.100)	(11.099)
ln (firm size)	0.037***	0.037***	0.037***	0.037***
	(17.245)	(16.720)	(17.133)	(17.381)
LEV ratio	0.087***	0.087***	0.087***	0.086***
	(7.083)	(7.051)	(7.069)	(7.035)
ROA	0.109***	0.112***	0.109***	0.109***
	(6.174)	(6.368)	(6.128)	(6.150)
CAPX ratio	0.063	0.060	0.065	0.068
	(0.875)	(0.842)	(0.905)	(0.941)
Constant	0.158***	0.161***	0.159***	0.157***
	(9.553)	(9.716)	(9.664)	(9.623)
Observations	47,918	47,918	47,918	47,918
R-squared	0.114	0.116	0.114	0.115
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 7: Impact of Analyst Climate Talk Intensity on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate talk frequency on Corporate Environmental Performance. The q_cc_frequency is the frequency of climate change discussions in the question session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the question session). The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_frequency	-0.629**	2,995.590***	1,498.432*	61.622***	72.592***	90.564***
	(-2.122)	(4.480)	(1.683)	(5.548)	(5.115)	(7.372)
Analyst_Coverage	-0.000*	0.002	0.053**	0.000	0.001***	0.000
	(-1.756)	(0.169)	(2.331)	(0.476)	(2.829)	(0.065)
ln (firm size)	0.001*	6.834***	9.735***	0.056***	0.104***	0.094***
	(1.834)	(14.288)	(13.773)	(8.365)	(13.135)	(9.859)
LEV ratio	0.000	-0.104	4.781	0.094***	0.143***	0.111**
	(0.094)	(-0.042)	(1.164)	(3.171)	(2.763)	(2.439)
ROA	-0.020***	-12.833***	-14.699***	-0.068*	-0.220***	-0.173**
	(-4.576)	(-4.113)	(-2.580)	(-1.814)	(-3.014)	(-2.538)
MB	-0.000	0.003	-0.001	-0.000	0.000	0.000
	(-1.559)	(0.711)	(-0.094)	(-0.218)	(0.406)	(0.324)
R&D	0.000	7.357***	-2.047	0.012	0.088***	0.050**
	(0.226)	(3.355)	(-0.624)	(0.763)	(3.704)	(2.099)
Intan	-0.002*	-6.748**	-6.749	-0.138***	-0.066	-0.247***
	(-1.846)	(-2.361)	(-1.433)	(-4.886)	(-1.257)	(-5.155)
Constant	0.001	-41.369***	-55.011***	-0.384***	-0.622***	-0.596***
	(0.490)	(-11.048)	(-9.598)	(-8.100)	(-11.168)	(-8.899)
Observations	10,303	10,301	7,949	8,101	8,117	6,471
R-squared	0.045	0.423	0.345	0.112	0.179	0.173
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 8: Impact of Analyst Climate Talk Complexity on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate talk complexity on Corporate Environmental Performance. The q_cc_complexity is the average of the Gunning Fog Index of the climate change-related question component (i.e., all sentences containing at least one climate change bigram). The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_complexity	-0.000**	0.900***	0.008***	0.011***	0.012***	0.461***
	(-2.030)	(8.568)	(5.593)	(5.517)	(5.910)	(4.377)
Analyst_Coverage	-0.000**	-0.048***	-0.000	0.001**	-0.000	0.057**
	(-2.385)	(-3.434)	(-0.233)	(2.170)	(-0.684)	(2.805)
ln (firm size)	0.001***	6.808***	0.055***	0.102***	0.094***	9.026***
	(2.640)	(13.445)	(8.054)	(12.777)	(9.799)	(12.192)
LEV ratio	-0.001	2.548	0.092***	0.139***	0.104**	4.793
	(-0.999)	(1.011)	(3.131)	(2.701)	(2.250)	(1.078)
ROA	-0.021***	9.972***	-0.072*	-0.225***	-0.195***	-10.732
	(-5.515)	(2.890)	(-1.913)	(-3.115)	(-2.812)	(-1.633)
MB	-0.000	0.004	-0.000	0.000	0.000	-0.003
	(-1.607)	(1.025)	(-0.259)	(0.354)	(0.299)	(-0.315)
R&D	0.001	12.175***	0.012	0.087***	0.045*	0.626
	(1.246)	(8.808)	(0.747)	(3.707)	(1.890)	(0.203)
Intan	-0.001	-11.886***	-0.148***	-0.077	-0.266***	-3.227
	(-1.351)	(-4.312)	(-5.114)	(-1.451)	(-5.484)	(-0.680)
Constant	0.001	-39.288***	-0.319***	-0.536***	-0.592***	-50.821***
	(0.543)	(-9.945)	(-5.716)	(-7.854)	(-8.819)	(-8.087)
Observations	10,306	10,304	8,092	8,108	6,471	7,953
R-squared	0.031	0.193	0.106	0.177	0.162	0.263
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 9: Impact of Analyst Climate Talk Subjectivity on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate talk subjectivity on Corporate Environmental Performance. The q_cc_subjectivity is the average of the subjectivity scores of words in the climate change- related question component. The subjectivity score ranges from 0 (objective) to 1 (subjective). The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_subjectivity	-0.001	15.735***	0.121***	0.129**	0.140***	9.805**
	(-0.484)	(5.793)	(3.387)	(3.149)	(3.566)	(2.935)
Analyst_Coverage	-0.000	-0.015	0.000	0.000	0.000	0.057**
	(-1.290)	(-0.958)	(1.575)	(1.516)	(0.149)	(2.759)
ln (firm size)	0.000	6.575***	0.046***	0.109***	0.084***	9.145***
	(1.107)	(10.481)	(6.437)	(10.051)	(7.487)	(12.418)
LEV ratio	-0.001	0.706	0.050	0.125**	0.040	4.915
	(-0.325)	(0.268)	(1.573)	(2.312)	(0.864)	(1.102)
ROA	-0.020**	0.937	-0.014	-0.163*	-0.131*	-10.922
	(-2.710)	(0.252)	(-0.392)	(-1.834)	(-2.150)	(-1.652)
MB	-0.000	0.003	-0.000	0.000	0.000	-0.003
	(-1.260)	(0.659)	(-0.265)	(0.295)	(0.803)	(-0.304)
R&D	0.001	7.557***	0.024	-0.011	-0.021	0.636
	(0.950)	(3.464)	(1.097)	(-0.361)	(-0.671)	(0.207)
Intan	-0.002*	-6.690	-0.117***	-0.035	-0.210***	-3.253
	(-1.890)	(-1.798)	(-3.484)	(-0.577)	(-4.009)	(-0.686)
Constant	0.000	-36.615***	-0.309***	-0.586***	-0.451***	-52.543***
	(0.098)	(-8.618)	(-5.835)	(-8.330)	(-5.974)	(-10.084)
Observations	10,320	10,318	8,100	8,116	6,471	7,962
R-squared	0.037	0.298	0.195	0.261	0.323	0.263
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 10: Impact of Analyst Climate Talk Uncertainty on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate talk uncertainty on Corporate Environmental Performance. The q_cc_uncertainty is the number of Loughran-McDonald uncertainty words scaled by the total number of words in the climate change-related question component. The subjectivity score ranges from 0 (objective) to 1 (subjective). The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_uncertainty	-0.002	213.115***	1.677**	1.835**	2.399**	134.610*
	(-0.031)	(4.670)	(2.618)	(2.561)	(3.014)	(2.208)
Analyst_Coverage	-0.000	-0.016	0.000	0.000	0.000	0.057**
	(-1.320)	(-0.991)	(1.566)	(1.507)	(0.140)	(2.759)
ln (firm size)	0.000	6.689***	0.047***	0.109***	0.084***	9.208***
	(1.071)	(10.750)	(6.607)	(10.141)	(7.681)	(12.560)
LEV ratio	-0.001	0.774	0.051	0.127**	0.040	5.001
	(-0.327)	(0.295)	(1.616)	(2.345)	(0.889)	(1.129)
ROA	-0.020**	0.991	-0.013	-0.162*	-0.134*	-11.098
	(-2.709)	(0.264)	(-0.380)	(-1.818)	(-2.178)	(-1.666)
MB	-0.000	0.002	-0.000	0.000	0.000	-0.003
	(-1.248)	(0.644)	(-0.282)	(0.286)	(0.808)	(-0.314)
R&D	0.001	7.548***	0.024	-0.011	-0.022	0.625
	(0.945)	(3.478)	(1.091)	(-0.368)	(-0.686)	(0.204)
Intan	-0.002*	-6.715	-0.117***	-0.035	-0.212***	-3.307
	(-1.883)	(-1.797)	(-3.471)	(-0.585)	(-4.046)	(-0.696)
Constant	0.000	-36.229***	-0.306***	-0.582***	-0.446***	-52.235***
	(0.090)	(-8.612)	(-5.789)	(-8.316)	(-5.949)	(-10.099)
Observations	10,320	10,318	8,100	8,116	6,471	7,962
R-squared	0.037	0.296	0.194	0.260	0.323	0.262
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 11: Impact of Analyst Climate Optimism on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate optimism on Corporate Environmental Performance. The q_cc_ratio_pos is the number of Loughran-McDonald positive words divided by the total number of words in the climate change-related presentation component. The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_ratio_pos	-0.025	321.130***	1.955***	1.699	1.939*	86.392*
	(-0.829)	(5.834)	(3.185)	(1.712)	(2.123)	(2.070)
Analyst_Coverage	-0.000	-0.015	0.000	0.000	0.000	0.057**
	(-1.296)	(-0.934)	(1.586)	(1.531)	(0.166)	(2.777)
ln (firm size)	0.000	6.673***	0.047***	0.110***	0.085***	9.239***
	(1.121)	(10.621)	(6.539)	(10.254)	(7.625)	(12.584)
LEV ratio	-0.001	0.709	0.050	0.126**	0.040	4.963
	(-0.324)	(0.268)	(1.589)	(2.332)	(0.870)	(1.117)
ROA	-0.020**	0.874	-0.013	-0.162	-0.134*	-11.026
	(-2.708)	(0.235)	(-0.387)	(-1.810)	(-2.177)	(-1.658)
MB	-0.000	0.003	-0.000	0.000	0.000	-0.003
	(-1.266)	(0.720)	(-0.260)	(0.300)	(0.863)	(-0.303)
R&D	0.001	7.519***	0.024	-0.011	-0.022	0.623
	(0.942)	(3.457)	(1.087)	(-0.368)	(-0.683)	(0.203)
Intan	-0.002*	-6.733	-0.117***	-0.035	-0.211***	-3.291
	(-1.884)	(-1.801)	(-3.466)	(-0.578)	(-4.028)	(-0.693)
Constant	0.000	-36.170***	-0.306***	-0.582***	-0.446***	-52.190***
	(0.090)	(-8.571)	(-5.795)	(-8.290)	(-5.931)	(-10.083)
Observations	10,320	10,318	8,100	8,116	6,471	7,962
R-squared	0.037	0.297	0.194	0.260	0.322	0.262
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 12: Impact of Analyst Climate Pessimism on Corporate Environmental Performance

This table reports regression results on the impact of analyst climate pessimism on Corporate Environmental Performance. The q_cc_ratio_neg is the number of Loughran-McDonald negative words divided by the total number of words in the climate change-related presentation component. The dependent variables are pcg_Emission (percentage change of CO2e emission), Env Innovation Score (environmental innovation score, the higher the better), Env Inv initiatives (A dummy that equals 1 if the company reports on making proactive environmental investments or expenditures to reduce future risks or increase future opportunities), env mgt training (A dummy that equals 1 if the company trains its employees on environmental issues and 0 otherwise), env expenditure inv (A dummy that equals 1 if the company reports on its environmental expenditures and/or reports to make proactive environmental investments to reduce future risks or increase future opportunities, and 0 otherwise), and env mgt team score (environmental management team score, the higher the better), respectively. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	pcg_Emission	Env Innovation Score	Env Inv Initiatives	Env Mgt Training	Env Expenditure Inv	Env Mgt Team Score
	(1)	(2)	(4)	(5)	(6)	(7)
q_cc_ratio_neg	-0.051*	198.082***	2.123***	3.871***	2.293***	239.421***
	(-1.749)	(4.125)	(3.621)	(4.615)	(2.867)	(3.801)
Analyst_Coverage	-0.000**	-0.049***	-0.000	0.001**	-0.000	0.046**
	(-2.323)	(-3.508)	(-0.242)	(2.164)	(-0.747)	(2.383)
ln (firm size)	0.001**	7.263***	0.060***	0.109***	0.100***	9.413***
	(2.573)	(14.370)	(8.512)	(13.674)	(10.209)	(15.112)
LEV ratio	-0.001	3.373	0.100***	0.150***	0.115**	5.013
	(-1.096)	(1.318)	(3.359)	(2.918)	(2.466)	(1.276)
ROA	-0.021***	10.436***	-0.069*	-0.219***	-0.199***	-9.099
	(-5.535)	(2.967)	(-1.821)	(-3.027)	(-2.839)	(-1.492)
MB	-0.000	0.004	-0.000	0.000	0.000	-0.003
	(-1.589)	(0.947)	(-0.270)	(0.333)	(0.285)	(-0.340)
R&D	0.000	12.304***	0.011	0.086***	0.045*	7.784***
	(1.149)	(8.793)	(0.663)	(3.641)	(1.862)	(4.245)
Intan	-0.001	-12.729***	-0.157***	-0.089*	-0.280***	-3.685
	(-1.253)	(-4.573)	(-5.309)	(-1.696)	(-5.702)	(-0.878)
Constant	0.000	-40.606***	-0.390***	-0.637***	-0.597***	-57.078***
	(0.223)	(-11.590)	(-8.087)	(-11.508)	(-8.753)	(-13.366)
Observations	10,320	10,318	8,101	8,117	6,471	7,963
R-squared	0.031	0.181	0.097	0.172	0.151	0.200
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 13: Executive Responses to Climate-Related Questions

This table reports regression results on the executive responses to climate-related questions. The dependent variables are answer_cc_d, A_CC_Complexity, A_CC_Subjectivity, A_CC_Uncertainty, and A_CC_Sentiment, respectively. The Q_CC is an indicator variable that equals one if the question session includes at least one climate change bigram. The sample period is 2005–2022. Refer to Appendix A for definitions of variables. All regressions include year and industry fixed effects. Robust standard errors double-clustered by firm and year are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	answer_cc_d	A_CC_Complexity	A_CC_Subjectivity	A_CC_Uncertainty	A_CC_Sentiment
	(1)	(2)	(3)	(4)	(5)
Q_CC	0.109***	1.901***	0.061***	0.001***	0.001***
	(21.516)	(29.816)	(28.080)	(10.620)	(5.568)
Analyst_Coverage	0.000***	0.009***	0.000***	0.000***	0.000***
	(7.124)	(6.655)	(9.085)	(3.710)	(5.178)
ln (firm size)	0.018***	0.506***	0.015***	0.000***	0.000***
	(9.861)	(13.015)	(13.575)	(7.182)	(5.910)
LEV ratio	0.047***	0.401*	0.018***	-0.000	0.000
	(3.806)	(2.091)	(3.327)	(-0.118)	(1.472)
ROA	0.037***	-0.578**	-0.012	-0.000	-0.000
	(3.131)	(-2.443)	(-1.709)	(-0.389)	(-0.203)
CAPX ratio	0.068*	0.723	0.059**	0.000	-0.003**
	(1.871)	(0.925)	(2.463)	(0.207)	(-2.165)
Constant	0.664***	3.967***	0.096***	0.002***	0.001*
	(50.990)	(15.626)	(12.783)	(12.819)	(1.866)
Observations	47,918	47,918	47,918	47,918	47,918
R-squared	0.100	0.141	0.154	0.024	0.030
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y

A Variable Definitions

Variable	Definition
Earnings Call	
audiolengthsec	Audio Length in Seconds
Presentation Session	
Pre_NumWords	The number of words in the presentation session.
Pre_NumSentences	The number of sentences in the presentation session.
Pre_CC (indicator)	An indicator variable that equals one if the presentation session includes at least one climate change bigram.
Pre_CC_Frequency	Frequency of climate change discussions in the presentation session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the presentation session).
Pre_CC_Complexity	The average of the Gunning Fog Index of the climate change-related presentation component (i.e., all sentences containing at least one climate change bigram). The index is calculated as: $0.4 \cdot [(\frac{\#Words}{\#Sentences}) + 100 \cdot (\frac{\#ComplexWords}{\#Words})]$.
Pre_CC_Subjectivity	The average of the subjectivity scores of words in the climate change-related presentation component. The subjectivity score ranges from 0 (objective) to 1 (subjective). It is a lexicon-based measure provided by Python library Pattern.
Pre_CC_Uncertainty	The number of Loughran-McDonald uncertainty words scaled by the total number of words in the climate change-related presentation component.
Pre_CC_RATIO_POS	The number of Loughran-McDonald positive words divided by the total number of words in the climate change-related presentation component.
Pre_CC_RATIO_NEG	The number of Loughran-McDonald negative words divided by the total number of words in the climate change-related presentation component.
Pre_CC_Sentiment	The relative frequency of Loughran-McDonald positive and negative words in the climate change-related presentation component which is defined as the difference in the proportions of positive and negative words (i.e., POS minus NEG).
Pre_CC_Sentiment_POS (indicator)	Equals 1 if the sentiment score of the climate change-related presentation component is positive and 0 otherwise.

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Variable	Definition
Pre_CC_Sentiment_NEG (indicator)	Equals 1 if the sentiment score of the climate change-related presentation component is negative and 0 otherwise.
Question Session	
Q_NumWords	The number of words in the question session.
Q_NumSentences	The number of sentences in the question session.
Q_CC (indicator)	An indicator variable that equals one if the question session includes at least one climate change bigram.
Q_CC_Frequency	Frequency of climate change discussions in the question session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the question session).
Q_CC_Complexity	The average of the Gunning Fog Index of the climate change-related question component (i.e., all sentences containing at least one climate change bigram). The index is calculated as: $0.4 \cdot [(\frac{\#Words}{\#Sentences}) + 100 \cdot (\frac{\#ComplexWords}{\#Words})]$.
Q_CC_Subjectivity	The average of the subjectivity scores of words in the climate change-related question component. The subjectivity score ranges from 0 (objective) to 1 (subjective). It is a lexicon-based measure provided by Python library Pattern.
Q_CC_Uncertainty	The number of Loughran-McDonald uncertainty words scaled by the total number of words in the climate change-related question component.
Q_CC_RATIO_POS	The number of Loughran-McDonald positive words divided by the total number of words in the climate change-related question component.
Q_CC_RATIO_NEG	The number of Loughran-McDonald negative words divided by the total number of words in the climate change-related question component.
Q_CC_Sentiment	The relative frequency of Loughran-McDonald positive and negative words in the climate change-related question component which is defined as the difference in the proportions of positive and negative words (i.e., POS minus NEG).
Q_CC_Sentiment_POS (indicator)	Equals 1 if the sentiment score of the climate change-related question component is positive and 0 otherwise.

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Variable	Definition
Q_CC_Sentiment_NEG (indicator)	Equals 1 if the sentiment score of the climate change-related question component is negative and 0 otherwise.
Answer Session	
A_NumWords	The number of words in the answer session.
A_NumSentences	The number of sentences in the answer session.
A_CC (indicator)	An indicator variable that equals one if the answer session includes at least one climate change bigram.
A_CC_Frequency	Frequency of climate change discussions in the answer session (i.e., the number of all occurrences of climate change bigrams divided by the total number of words in the presentation session).
A_CC_Complexity	The average of the Gunning Fog Index of the climate change-related answer component (i.e., all sentences containing at least one climate change bigram). The index is calculated as: $0.4\cdot[(\frac{\#Words}{\#Sentences}) + 100\cdot(\frac{\#ComplexWords}{\#Words})]$.
A_CC_Subjectivity	The average of the subjectivity scores of words in the climate change-related answer component. The subjectivity score ranges from 0 (objective) to 1 (subjective). It is a lexicon-based measure provided by Python library Pattern.
A_CC_Uncertainty	The number of Loughran-McDonald uncertainty words scaled by the total number of words in the climate change-related answer component.
A_CC_RATIO_POS	The number of Loughran-McDonald positive words divided by the total number of words in the climate change-related answer component.
A_CC_RATIO_NEG	The number of Loughran-McDonald negative words divided by the total number of words in the climate change-related answer component.
A_CC_Sentiment	The relative frequency of Loughran-McDonald positive and negative words in the climate change-related answer component which is defined as the difference in the proportions of positive and negative words (i.e., POS minus NEG).
A_CC_Sentiment_POS (indicator)	Equals 1 if the sentiment score of the climate change-related answer component is positive and 0 otherwise.
A_CC_Sentiment_NEG (indicator)	Equals 1 if the sentiment score of the climate change-related answer component is negative and 0 otherwise.
Analyst Forecast	
analyst_coverage	Number of analysts following the firm in a given year

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Variable	Definition
ferror	The absolute value of the difference between the mean of analysts' estimates and actual earnings per share for a given year. The ferror is winsorized at the 1% and 99% levels, respectively.
fdispersion	The standard deviation of analysts' individual forecast estimates. dispersion is winsorized at the 1% and 99% levels, respectively.
foptimism_analyst	The *foptimism_analyst* equals 1 if an analyst's forecast of EPS is higher than a firm's actual EPS. Average is taken of *foptimism_analyst* if multiple analysts make the forecasts of EPS for a firm for the fiscal year. *foptimism_analyst* is winsorized at the 1% and 99% levels, respectively.
fpessimism_analyst	The *fpessimism_analyst* equals 1 if an analyst's forecast of EPS is lower than a firm's actual EPS. Average is taken of *fpessimism_analyst* if multiple analysts make the forecasts of EPS for a firm for the fiscal year. *fpessimism_analyst* is winsorized at the 1% and 99% levels, respectively.
surprise	The actual EPS minus the median of analysts' annual EPS forecasts for a firm for a fiscal year, divided by the median of the analysts' annual EPS forecasts.
fhorizon	The median number of days between analyst forecasts and earnings announcements.
Control Variables	
Price	The stock price of a firm at the fiscal year-end date.
r&d_d (indicator)	1 if the research and development expense of a firm is positive for a fiscal year, and 0 otherwise.
intangible_d (indicator)	1 if a firm has intangible assets for a fiscal year, and 0 otherwise.
btm	The book value of firm equity divided by the market value of firm equity at the end of a fiscal year.
stdearnings	The standard deviation of net income before extraordinary items in the current and previous four years.
salesgrowth	Sales revenues for fiscal year t minus sales revenues for fiscal year t-1, scaled by sales revenues for fiscal year t-1.
bidaskspread	Bid-ask spreads, which are estimated by using daily relative effective spreads averaged over a fiscal year for a firm.

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Variable	Definition
ln_AGE	Natural logarithm of the number of years since a firm's first appearance in CRSP
CAPX	The level of capital expenditures scaled by total assets
LEV	Long-term debt scaled by total assets
MKTSHARE	The firm's fraction of sales in its Fama and French (1997) 48 industry
R&D	Research and development expenditures scaled by total sales
ROA	Net income scaled by lagged total assets
ln_SIZE	Natural logarithm of firm size, computed as common shares outstanding multiplied by fiscal year-end price