RESEARCH

Swiss Finance Institute
Research Paper Series
N°23-92

Climate Value and Values Discovery in Earnings Calls

Zacharias Sautner
University of Zurich and Swiss Finance Institute

Laurence van Lent
Frankfurt School of Finance & Management

Grigory Vilkov
Frankfurt School of Finance & Management

Ruishen Zhang
Shanghai University of Finance and Economics

Climate *Value* and *Values* Discovery in Earnings Calls*

Zacharias Sautner† Grigory Vilkov§

Laurence van Lent‡ Ruishen Zhang¶

October 2023

Abstract

We examine how financial analysts discuss *value*- and *values*-related climate change concerns in earnings calls. Questions on climate change frequently employ specific, and often quantitative, language, and they are tailored to both the industry in question and periods when such concerns are considered relevant. Compared to other questions, climate change questions are less about *value* and more about *values*. Both climate-related question types increased over time, with *value*-related questions becoming relatively more important. Climate change discussions, especially when *value*-related, increase a stock's trading volume, reflecting higher investor disagreement about how to interpret the information provided. Being "green" is not an innate trait among analysts as less than 3 percent of the variance in climate change questions is due to analyst fixed effects. Analyst labor markets care about climate change questions: Both question types positively predict analysts' career trajectories, including promotions and mobility, with *value* queries showing a more pronounced effect.

Keywords: Climate change; earnings calls; financial analysts; *value* and *values* discovery; analyst careers

JEL codes: G18, G32, G38, Q54, Q55

*The data set described in this paper is publicly available at https://osf.io/5amjp/. Participants at Chinese University of Hong Kong (Shenzhen), SUFE, Zhejiang University of Finance and Economics, and Zhejiang Univeristy provided helpful feedback. Van Lent gratefully acknowledges funding from the Deutsche Forschungsgemeinschaft Project ID 403041268 - TRR 266. We thank the Bright Data Initiative for providing tools and programs to retrieve public web data.

†**University of Zurich and Swiss Finance Institute**; Postal Address: Plattenstrasse 14, CH-8032 Zürich, Switzerland; E-mail: zacharias.sautner@bf.uzh.ch.

‡**Frankfurt School of Finance & Management**; Postal Address: Adickesallee 32-34, 60322 Frankfurt am Main, Germany; E-mail: l.vanlent@fs.de.

§**Frankfurt School of Finance & Management**; Postal Address: Adickesallee 32-34, 60322 Frankfurt am Main, Germany; E-mail: vilkov@vilkov.net.

¶**Shanghai University of Finance and Economics**; Postal Address: Guoding Road 777, 200433, Shanghai, China; E-mail: zhangruishen@sufe.edu.cn.

1. Introduction

As research continues to unpack the specific roles of financial analysts in the price discovery process within capital markets, a critical yet less probed question emerges: Do analysts primarily contribute to *value* (i.e., price) discovery, or do they also contribute to *values* discovery (Starks, 2023). *Value* discovery relates to understanding how a firm's business activities affect investors' financial risks and returns, while *values* discovery instead assesses whether the firm's business matches investors' non-monetary preferences or moral concerns.[1]

As the significance of *values*-based sustainable investing strategies has grown substantially, so has potentially the importance of *values* discovery in an analyst's job (in addition to price discovery). Given the rise in the importance of ESG rating agencies in gauging the sustainability profiles of firms, there is also the question of whether financial analysts can maintain their roles as important information intermediaries. Given this backdrop, some analysts might specialize in one type of discovery over the other, and their specialization might stem from inherited (time-invariant) traits or in response to wider market trends. The type of specialization may also affect the career paths of analysts.

These questions are explored within the context of a firm's exposure to climate change. Climate change is a particularly apt arena for this exploration, as both pecuniary *value* and non-pecuniary *values* aspects play crucial roles in shaping climate-related investor decision-making (Krueger et al., 2020). By extension, analysts may address climate change issues motivated by either *value* or *values* reasons in their daily responsibilities. *Value* motives relate to how a firm's financial valuation is impacted by climate change, which may occur, for example, through efforts to decrease emissions or through investments in carbon offsetting technologies. Such corporate efforts ultimately aim at reducing financial risks or boosting financial performance (Bolton and Kacperczyk, 2021; Ilhan et al., 2021). In contrast, *values* motives are associated with understanding a firm's climate change stance, that is, how their

[1] For an overview of studies on the role of analysts for *value* (price) discovery, see Kothari et al. (2016); Ramnath et al. (2008); Schipper (1991); Bradshaw (2011); Beyer et al. (2010). For an economic approach to *values*, see Heckman et al. (2023).

strategies and actions resonate with ecological priorities beyond purely financial considerations. Although differentiating between these two motives is challenging, given their closely intertwined nature, our study offers a first empirical insight into the problem. Achieving a deeper understanding of the role of *value* versus *values* is essential. Besley and Persson (2023) note that the speed of the green transition depends on how the share of those with green *values* in the economy evolves over time (since this affects the profitability of green technologies), and Starks (2023) stresses that the failure to account for *value* and *values* motives leads to major misunderstandings.

Important aspects of an analyst's job come to light during earnings conference calls when they engage in conversations about a firm's past performance and future plans with corporate executives. In these calls, analysts can discover information by challenging management through probing questions. By employing computational linguistics techniques to analyze transcripts of these calls, we study the how, when, and why of analysts' climate change-related questions, and whether an analyst's interest leans more toward the *value* or *values* dimensions of climate change. We can further explore if certain analysts are inherently predisposed to discuss climate change or if their interest is more situational, driven by fundamental factors or market pressures. This analysis relates to the bigger question of whether climate change preferences are a fixed personality trait or instead evolve dynamically and circumstantially. Finally, we can examine how climate change conversations, or the lack thereof, and their emphasis on *value* or *values* discovery influence analysts' performance in the labor market outcomes. Using promotions as a performance measure allows us to indirectly capture analyst success along both the *value* and *values* dimensions.[2]

To be able to address our research questions, we parse the Q&A portion of the earnings calls into unique "conversations"——that is, the complete exchange between a single analyst

[2]Traditional performance measures, such as analyst forecast accuracy, primarily focus on the *value* discovery component and are not well-suited to our aims. Promotions may occur for analysts who successfully discover the financial materiality of climate change for a firm, leading to more accurate forecasts. Alternatively, analysts may be promoted because they successfully identify the *values* dimension of a firm, which aids investors with non-pecuniary preferences in making improved investment decisions through positive or negative screening.

and any company executive.[3] A conversation may encompass multiple questions, each defined as uninterrupted speech by an analyst, and corresponding answers (see Rennekamp et al., 2022). We categorize any exchange involving climate change questions as *climate change conversations*. Further, we introduce an *intensity* measure, which gauges the level of climate change content relative to non-climate change content within a conversation. Collectively, these measures quantify the extent of climate change discourse during the earnings call.

To classify conversations, we fine-tune a large language model (LLM) specifically designed for financial texts.[4] The fine-tuning process entails training the model with researcher-labeled examples to accurately identify climate change-related language within the predominantly financial discussions in earnings calls. The classification involves accurately categorizing relatively short text snippets (i.e., conversations), a task for which LLMs are better suited than alternative methods typically used in the literature.[5]

Based on this approach, we compile a new, publicly accessible database at the analyst-conversation level that uses raw data from 313,380 earnings calls conducted between 2003 and 2021 for a global sample. This database provides i) measures of climate change questions posed to management and ii) measures of an analyst's specialization in climate change (as well as the *value* and *values* dimensions of it). The latter measures are constructed by aggregating the analyst-conversation measure into an overall yearly score for each analyst.

We begin the analysis by examining the development of climate change conversations over time and across sectors, revealing several new stylized facts. We detect a marked uptick

[3]The Q&A segment follows the management's presentation of the firm's financial health.

[4]Dai et al. (2023) employ a bag-of-words approach incorporating a limited set of environmental keywords to gauge attention to ESG topics in earnings calls. These researchers observe that merely about one percent of earnings calls address broader ESG concerns, including environmental issues. In contrast, we document a substantially higher frequency of discussions related to climate change, evident in approximately 30 percent of earnings calls with at least one question related to climate change. About three percent of all questions are about climate change. These findings tally with the extent of firm-level climate change discussions in earnings calls used to measure exposure as documented in Sautner et al. (2023). Our purpose-developed methodology specifically differentiates between climate change conversations and other queries in earnings calls, increasing the likelihood of pinpointing calls that engage in such discussions.

[5]These alternatives often aim to categorize entire earnings call transcripts or other financial disclosures such as 10-Ks (see, e.g., Hassan, Hollander, van Lent, and Tahoun, 2019, 2023; Hassan, Hollander, van Lent, Schwedeler, and Tahoun, 2023).

in climate change conversations within the first five years of our sample (from 2003 to 2008). While the overall number of exchanges during calls diminishes and fewer questions are raised, *climate change* conversations tend to lengthen, with the topic assuming increasing importance within these discussions. Notably, *value*-centered questions gain relative prominence after 2012 compared to *values*-centered questions, particularly since 2018.

The variation in conversations about climate change during earnings calls is approximately equally attributed to firm- and analyst-level characteristics. At the firm level, sector characteristics (industry fixed effects) and time-varying firm characteristics (firm $\times$ year-quarter fixed effects) account for 16.7 and 14.2 percent of the variation in the measure, respectively. The variation driven by analysts arises from time-varying analyst characteristics (analyst $\times$ year-quarter fixed effects) and changes over time in the analyst's assignment to specific sectors (analyst $\times$ industry $\times$ year-quarter fixed effects), accounting for 15.7 and 10.5 percent of the variation, respectively. Importantly, the role of persistent differences between analysts (analyst fixed effects) is minimal, explaining only 2.6 percent of the variation. This implies that initiating "green" topics in earnings calls is *not* a fixed analyst trait or style, but rather a feature that evolves dynamically and circumstantially.[6]

Questions related to *value* in the context of climate change are markedly more frequent than those on *values*. Climate change conversations tend to be less *value*-centered overall compared to other conversations, even when analysts incorporate non-climate questions into the discussion. Conversely, discussions that feature climate change often employ more *values*-centric language. Upon further examination of climate conversations, we note that *value*-centered discussions involve relatively more inquiries about money and time, aligning with a deeper exploration into the valuation aspects of climate change. In *values*-centered dialogues, analysts more frequently address specific regulations, organizations, and nationalities. These observations align with Starks (2023)'s observation that *values* investors often want their portfolio firms to adhere to ESG-related principles set out by international organizations

[6]Our approach to identifying analyst styles using fixed effects follows a large literature, initiated by Bertrand and Schoar (2003), that uses the same idea to identify managerial styles.

(e.g., the UN SDGs or the UN Biodiversity Conference).

Despite that climate change is one of the most pressing issues of our time, not everyone agrees on the causes, consequences, and solutions of this global challenge. Investors may have divergent views on how climate change impacts firms and how firms should respond. Consequently, conversations during earnings calls on climate change might be a source of uncertainty and disagreement among investors. We hypothesize that earnings calls that mention climate change might trigger different reactions from investors with heterogeneous prior beliefs or divergent interpretations of the climate-related information (Harris and Raviv, 1993; Kandel and Pearson, 1995). For example, some investors might view climate change as a material risk for firms, while others might see it as an opportunity or a negligible factor. Similarly, some investors might applaud firms for taking proactive measures to reduce their carbon footprint, while others might criticize them for wasting resources or greenwashing. These conflicting views might lead investors to trade with each other because they essentially "agree to disagree" in equilibrium. This prediction is based on investors having heterogeneous priors and the assumption that investors do not fully update their beliefs based on each other's trading decisions (Hong and Stein, 2007). Such trading behavior could affect volume in ways that reflect the level and evolution of investor disagreement. Consistent with this prediction, abnormal trading volume is positively associated with the degree of climate change discussions in earnings calls. Notably, investors disagree more about the financial consequences of climate change (*value*) than about the normative issues related to it (*values*). This result also suggests that investors are more motivated by economic incentives (rather than moral preferences) when trading on climate change information.

Given that analyst characteristics account for a significant portion of the variation in climate change dialogues, we shift our analysis to the analyst level. We identify "climate change analysts" as those who, in a given year, pose more questions on this subject than their peers covering the same firms. Climate change analysts use specialized language, incorporating more references to numbers, locations, organizations, and nationalities than their peers.

Refining the categorization of climate change analysts into those stressing *value* and those emphasizing *values*, we observe that the former frequently discuss money, numbers, time, and organizations, while the latter focuses more on location, organizations, and nationalities.

Exploring whether these distinctions have implications for analysts' career trajectories, we leverage data from LinkedIn profiles. We find that as analysts accumulate a more specialized climate change profile, they exhibit increased job mobility, both internally and externally. A more granular analysis reveals that *value*-centric climate analysts experience particular advantages, displaying higher probabilities of promotion and transitions to new firms compared to their non-climate and *values*-centric climate counterparts.

Finally, climate change analysts are less likely to stop covering a firm; in particular, if they are more *value*-centric. Such "behavioral" differences might partly explain the reasons for diverging career performance. Moreover, Broccardo et al. (2022) raise the possibility that "voice" and "exit" decisions of green investors might have different effectiveness in changing the policies of "brown" firms, with voice being more effective. These insights may extend to analysts, who eventually cater their work to investors at their own or other institutions. Our results suggest that climate change analysts do not end their coverage of firms as frequently as non-climate change analysts, which is consistent with them shying away from exit.

Related Literature and Contribution. A nascent literature in finance and accounting studies the association between a firm's climate change-related profile (or other sustainability attributes captured under the ESG or CSR umbrellas) and analysts' assessments of the firm, focusing on analysts' research *outputs*, such as recommendations, earnings and growth forecasts (see, e.g., Park et al., 2022; Derrien et al., 2023), and their coverage decisions (see, for a summary, Hinze and Sump, 2019). Our interests diverge significantly: We emphasize the production and processing of climate change-related information by analysts, particularly along *values* and *value* dimensions. We aim to understand what questions analysts ask, what prompts their curiosity, and the potential implications of these inquiries for their professional advancement. This allows us to identify and dissect the key inputs and open up the black box of analysts' research output (to the extent that it is related to climate change).

Our work converges with the sentiment expressed in Starks (2023)'s Presidential Address concerning the improved measurement and understanding of the distinctive effects of ESG *values* and *value*. Previous studies have examined the linguistic style employed in earnings calls conversations (Rennekamp et al., 2022), demonstrating that the level of *engagement*, as measured by the inadvertent use of similar types of words by analysts and management, is informative to capital market participants, especially when managers interact with more senior analysts or when analysts question executives from larger firms. Mayew et al. (2020) reveal that analysts with beatable versus unattainable forecasts behave differently during conversations, with the latter engaging in more informative dialogues. Additionally, they find that stock prices respond to analysts' linguistic cues, particularly their tone. Our focus diverges from linguistic style to the substance of the dialogue, specifically concerning the analysts' expertise in climate change. We demonstrate that the linguistic style varies across topics and is conditional on the analysts' expertise in a given field.

Our work also builds upon previous research on the careers of financial analysts (Hong and Kubik, 2003). For example, Cen et al. (2021) show that analysts who ask questions earlier in an earnings call are more successful in the labor market. Extending these insights, we propose that the text of the questions analysts pose can be used to define their specialties, offering a more nuanced approach compared to earlier efforts that mainly considered traits such as an analyst's industry experience, gender, and education (Wu and Zang, 2009; Li et al., 2023). Using CV data from analysts' LinkedIn profiles, combined with their participation in earnings calls, allows us to track how their climate change specialization and emphasis on *value* or *values* is associated with career outcomes. This methodology can easily be generalized to other areas of specialization beyond climate change. We complement earlier insights that have emphasized analyst accuracy above any other aspect of their performance as a determinant of their career path (Groysberg et al., 2011; Wu and Zang, 2009).

2. Data

2.1. Earnings Call Transcripts Data

we build our analysis on the conversations between analysts and executives as recorded on transcripts of quarterly earnings calls held by publicly listed firms. We obtain these transcripts from Refinitiv Eikon. Our initial sample contains 363,423 transcripts that are in English and available for 13,171 firms headquartered in 87 countries from January 1, 2003 to December 31, 2021.[7] Earnings calls are important corporate events for firms' investor relations. They let analysts and other participants hear senior management talk about the firm's situation, ask them questions about the firm's performance in the past quarter, and discuss important current developments (Hassan et al., 2019, 2023; Bae et al., 2023).[8] This paper focuses on the Q&A part of the earnings call, not the management presentation.

To create a sample for our analysis, which is either at the analyst-conversation level or at the analyst level, we stipulate that each analyst must attend at least ten earnings calls. We also require that every brokerage house (or other institution) sampled be present in at least 50 calls. These criteria ensure we sample only professional sell- or buy-side analysts (and financial institutions) that discover information that stock traders likely pay attention to. When applying these criteria, our final sample, drawn from 313,380 quarterly earnings call transcripts, comprises 11,855 unique firms and a pool of 21,431 analysts from 1,907 brokers and other institutions. We identify 1,738,571 conversations in the final sample of 313,380 earnings calls. Table 1, Panel A, provides summary statistics of key conversation characteristics, and Panel B reports summary statistics for climate change conversations only. We detail below how we identify conversations and construct the reported measures.

[7] In some cases, these transcripts are translated from the original language. Hassan et al. (2023) report that there is no meaningful difference between the original language and translated transcripts.

[8] Earnings calls have been used in various settings to study corporate exposures and responses to shocks, including Brexit, the COVID-19 pandemic, technological breakthroughs, and climate change.

2.2. Analyst Characteristics Data

We construct metrics for each analyst's employer institution type, stock coverage, experience, and specialization from the headers of the earnings call transcripts. Internet Appendix (IA) Section I provides details on how we extract analyst information from the transcripts and how we identify and match individual analysts across calls.

We use this information to create the following analyst variable: $Buyside_{a,t}$ equals one if the affiliation of analyst a is classified as buy-side as of quarter t, and zero otherwise. Three variables gauge the extent of analyst coverage at the earnings-call, firm, and industry levels every year: ii) $\#FirmCoverage_{a,t}$ counts the number of distinct firms that an analyst covers as of year t; ii) $\#IndustryCoverage_{a,t}$ counts the number of unique industries that analyst a covers as of year t; and iii) $\#CallsAttended_{a,t}$ quantifies the number of earnings calls that analyst a participates in during a specific year. To measure analyst experience, we consider i) their history in attending earnings calls per se and ii) their history of attending the calls of a specific firm. Hence, $Experience_{a,t}$ signifies the duration since an analyst's inaugural attendance at an earnings call included in our database (in years), while $FirmExperience_{a,i,t}$ indicates the time span since the analyst first participated in a call from a particular firm i, measured in quarter t (also in years). We measure analyst specialization using $SpecializedIndustry_{a,i,t}$, which equals one if the analyst specialized in the industry of firm i conducting the earnings call (the majority of firms covered by the analyst are in the same SIC2 industry) in year t, and zero otherwise. Table 1, Panel C, provides summary statistics of these measures at the analyst-conversation level.

2.3. Trading Volume Data

We use data from CRSP to create measures of abnormal trading volume around earnings announcements of firm i in quarter t ($LogAbnVol_{i,t}$). We merge these data with data from IBES to create control variables for analyst- and earnings-related determinants of trading volume around earnings announcements (e.g., $Dispersion_{i,t}$ or $UE_{i,t}$). Summary statistics are reported in Table 1, Panel D.

2.4. LinkedIn Profile Data

Some of our tests make use of public profile data from LinkedIn. The LinkedIn dataset was obtained from the Bright Data Initiative, a public web data service platform. This dataset includes names, titles, positions, current companies, work experience, and education backgrounds. Each LinkedIn profile in the dataset has a unique ID that links back to the original LinkedIn profile webpage. Matching the analysts included in the earnings calls data with LinkedIn profiles presents a challenge due to the sheer size of the LinkedIn data (it contains hundreds of millions of records). Searching through the entire LinkedIn dataset to locate matching profiles for analysts is highly resource-intensive and impractical. We address this issue through a two-step process.

First, we procure the names of all LinkedIn profiles and analysts in the transcripts data and formulate a Term Frequency - Inverse Document Frequency (TF-IDF) vector for each name based on sequences of two contiguous characters. We then compute the cosine similarity among all these names. From this process, we select the top matches of analysts' names from the transcripts data within the LinkedIn profile names and use the unique ID of these matched profiles to retrieve the full profile data. This step yields around 2.7 million profiles. Second, we cross-verify the LinkedIn profiles and analysts' information from the transcripts to ensure correct matches. We require the analysts' affiliation, as shown in the transcripts, to correspond with the firm name presented in the LinkedIn work experience. Additionally, the earnings call hosting time should fall within the same work experience timeline (as indicated in the LinkedIn profile). After this matching process, we have 1,848 unique analysts who appear in 91,872 transcripts corresponding to 7,743 firms.

Three indicator variables at the analyst-year level capture career progressions based on the LinkedIn data. First, $Promotion_{a,t+1}$ indicates when analyst a achieves a more senior corporate title within the same brokerage in the subsequent year. We classify the seniority of analysts based on the job titles reported in their LinkedIn profiles into three sets: mid (e.g., manager, vice president), mid-senior (director, desk head), and senior (managing director). For robustness, we refine the senior classification based on the prefix of job titles within the mid, mid-senior, and senior brackets. For example, changing the title from "associate director" to "director" is now considered a promotion as well. Second, $NewCompany_{a,t+1}$ captures analyst a's transition to a new firm in year $t+1$. Third, $ESGJob_{a,t+1}$ represents the case when an analyst shifts to a role with ESG specified in its title in the next year.

LinkedIn data also allows us to create career-related control variables ($AttendingCalls_{a,t}$, $PostAttendingCalls_{a,t}$, $Mid_{a,t}$, $Mid\text{-}Senior_{a,t}$, $Senior_{a,t}$, $BusinessDegree_{a,t}$, $PhD_{a,t}$, and $WorkExperience_{a,t}$). The Appendix defines all variables in detail. Table 1, Panel E, provides summary statistics of the LinkedIn variables at the analyst-year level.

2.5. Other Data Sources

Financial statement data, which includes information on $MarketCap_{i,t}$, $ROA_{i,t}$ or $Cash_{i,t}$ at the quarterly level, are taken from Standard & Poor's Compustat North America and Global files. We use data from Sautner et al. (2023) on firms' quarterly exposures to climate change, measured for the presentation part of the call ($CCExposure_{i,t}^{Pres}$). Table 1, Panel E, provides summary statistics for the full set of variables at the firm-quarter level.

3. Identifying Climate Change Questions

3.1. Classifying Climate Change Questions: Measurement Overview

Conversations. We develop a method that reliably identifies questions on climate change topics in a conversation between an analyst and the firm's management. Previous work has used various methods to identify climate change discussions in earnings calls. For instance, Sautner et al. (2023) use a keyword discovery algorithm to identify climate change bigrams that are then used to determine whether a call has climate change content. Other efforts rely on specialized BERT language models pre-trained to separate climate from non-climate text (Webersinke et al., 2021). In many of these applications, the ultimate goal is to derive a measure at the *firm* or *earnings call* level. For that purpose, inaccurately identified bigrams or misclassified single discussions wash out because firm- or call-level measures sum across many bigrams. This advantage disappears when the objective is to correctly classify smaller text snippets, such as a specific conversation between an analyst and a CEO. These discussions can consist of a single question and answer, covering perhaps only a few sentences in total, and shorter fragments are more challenging to classify correctly.[9] For this reason, we propose a more refined approach tailored to the task of identifying climate change questions in the conversation between an analyst and management.

Our methodology starts by dividing the Q&A session of each earnings call transcript into "conversations" between a unique analyst and management. We define a conversation as the collection of questions a single analyst poses during a specific earnings call and management's answers to these questions. Any analyst speech is considered a *question*, and management responses are referred to as *answers*. Thus, a conversation can have multiple questions and answers, possibly containing more than one sentence. Our approach identifies a total of 1,738,571 conversations in the sample.

Climate Conversation. We submit each question within a conversation to an LLM, which classifies the text as either climate change-related or not. We describe the LLM in the next subsection. This step enables us to construct an indicator variable at the *analyst-conversation* level. The indicator aggregates the classification of all questions in the conversation with analyst a in the transcript of firm i in quarter t as follows:

$$ClimateConv_{a,i,t} = \mathbb{1}[\exists q \in \mathcal{C}], \text{for } q \in Q_{a,i,t},$$

where $\mathbb{1}$ is the indicator function for the presence of a question classified as a member of the climate change questions set $\mathcal{C}$, and $q \in Q_{a,i,t}$ represents the questions q posed in

[9] See, e.g., the comments in Crowley et al. (2019) on identifying ESG discussions in firms' Twitter accounts using topic modeling.

conversation with analyst a in the transcript of firm i in quarter t. $Q_{a,i,t}$ denotes the set of questions in the conversation. If the LLM classifies at least one question in a conversation as containing climate change content (i.e., it belongs to $\mathcal{C}$), then the conversation-level indicator $ClimateConv_{a,i,t}$ is set to one; otherwise, it is zero.

In the figure below, we illustrate how we decompose analyst conversations into building blocks to create these measures. In the example, we consider three different conversations each consisting of seven questions. The figure illustrates how we classify the conversations to construct $ClimateConv_{a,i,t}$, based on whether questions are on climate change topics.

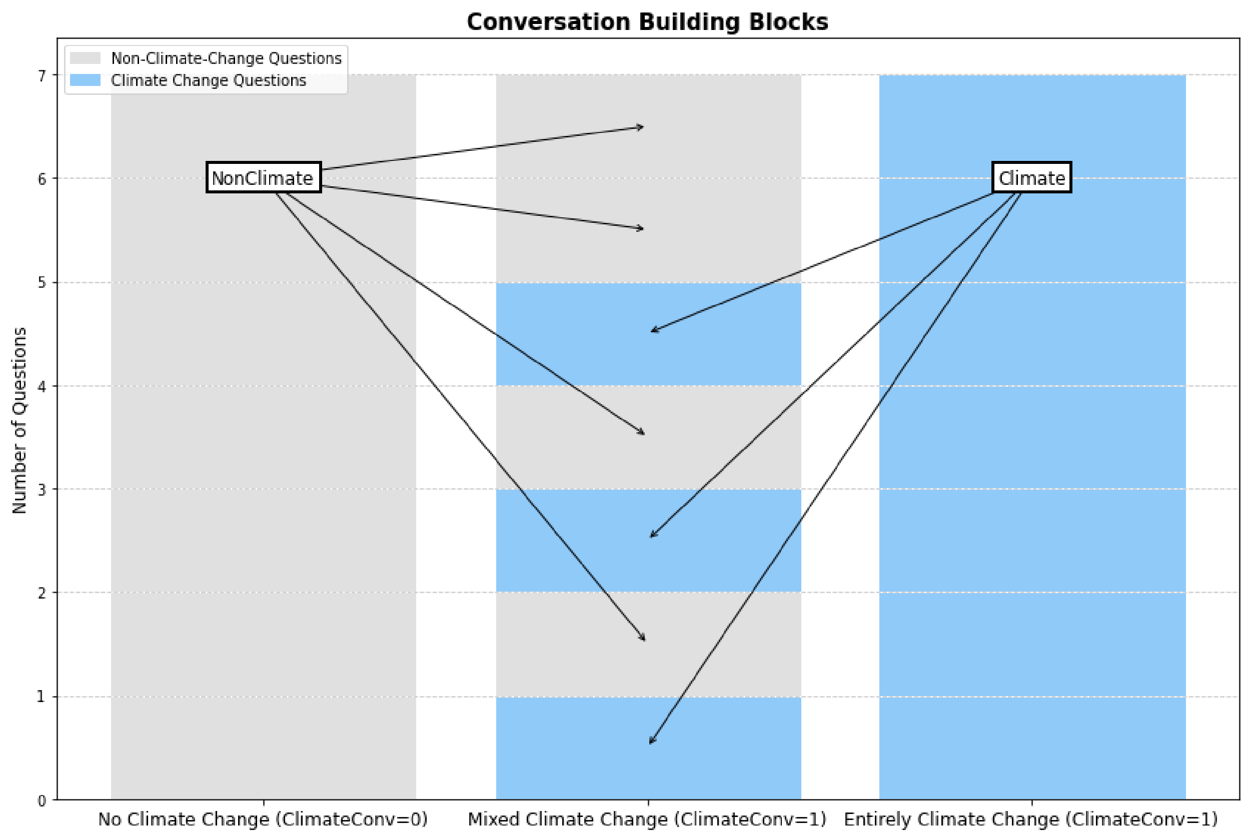


Figure: Conversation Building Blocks

Climate Conversation Intensity. We introduce a second variable at the analyst-conversation level. $ClimateConvIntensity_{a,i,t}$ captures the intensity of climate change questions in the conversation with analyst a at firm i in quarter t. It is constructed by calculating the ratio of the number of climate change questions to the total number of questions in the conversation:

$$ClimateConvIntensity_{a,i,t} = \frac{\sum_{\exists q \in Q_{a,i,t}} \mathbb{1}[q \in \mathcal{C}]}{|Q_{a,i,t}|},$$

where $\mathbb{1}[q \in \mathcal{C}]$ is the indicator function taking the value one if question q belongs to climate change questions set $\mathcal{C}$. $Q_{a,i,t}$ denotes again the set of questions in the conversation with analyst a in a transcript of firm i and quarter t, and $|Q_{a,i,t}|$ the size of the set of questions.[10]

Summary Statistics. Table 1, Panel A, provides summary statistics of these measures at the analyst-conversation level. Of the 1,738,571 sample conversations, 10.2 percent contain at least one climate change question (i.e., $ClimateConv_{a,i,t}$=1). The ratio of the total number of climate change questions to all questions in a conversation ($ClimateConvIntensity_{a,i,t}$) equals about three percent. Conditional on a conversation about climate change (i.e., $ClimateConv_{a,i,t}$=1), 33.7 percent of the questions within such conversations are climate change-related.[11]

3.2. Classifying Value *versus* Values *Questions*

Value-related Questions. A key objective of our paper is to distinguish between climate change questions that are *value*- or *values*-centric. To identify *value*-related questions, we follow Hassan et al. (2023) and employ a word-pattern-based algorithm for identifying if analysts include valuation-related terms in their questions. To this end, we reference a curated list of keywords, such as "earnings," "investment," "revenues," and "costs," among others.[12] Any question containing at least one of these specified keywords is categorized as *value*-related.

[10]To complete the characterization of the conversation, we also define corresponding measures using the answers part of the Q&A. We do not examine these measures in this paper.

[11]Table IA. I looks at the interplay between questions and answers within a conversation. Around six percent of the discussions involve measured climate change questions that receive corresponding responses. In about four percent of the exchanges, a question on climate change receives a *non-climate change* answer. More than half of the climate change answers by management are in response to questions not directly related to climate issues.

[12]A comprehensive list of value-related keywords is available in Table IA.II.

We create three variables at the conversation level using this classification. The most general case is captured using $ValueConv_{a,i,t}$, which equals one if a conversation with analyst a contains at least one *value* question, and zero otherwise:

$$ValueConv_{a,i,t} = \mathbb{1}[\exists q \in Value], \text{for } q \in Q_{a,i,t},$$

where $\mathbb{1}$ is the indicator function for the presence of a question classified as a member of the *value* questions set $Value$, and $Q_{a,i,t}$ denote the set of questions in the conversation with analyst a in a transcript of firm i and quarter t.

The next variables condition the variable construction based on whether a *value* term is present in a climate change or non-climate change question. $ValueConv^{Climate}_{a,i,t}$ equals one if the analyst conversation a contains at least one climate change question that is also a *value* question, and zero otherwise. Similarly, $ValueConv^{NonClimate}_{a,i,t}$ equals one if a conversation includes at least one non-climate change question that is also a *value* question, and zero otherwise.

$$ValueConv^{Climate}_{a,i,t} = \mathbb{1}[\exists q \in Value], \text{for } q \in Q_{a,i,t} \cap \mathcal{C},$$
$$ValueConv^{NonClimate}_{a,i,t} = \mathbb{1}[\exists q \in Value], \text{for } q \in Q_{a,i,t} \setminus \mathcal{C},$$

where $Q_{a,i,t} \cap \mathcal{C}$ now denote the set of climate change questions and $Q_{a,i,t} \setminus \mathcal{C}$ the set of non-climate change questions.

Values-related Questions. Detecting *values*-centric climate change questions is more complex. Building upon prior research in computational extraction of latent moral content, we use the extended Moral Foundation Dictionary (eMFD) introduced by Hopp et al. (2021). This dictionary relies on human assessments from a broad group of raters to label the moral content in short text fragments. From these labeled texts, keywords are extracted for the dictionary. The eMFD ultimately consists of over 3,000 keywords, each allocated a probability across five moral dimensions. Employing the scoring algorithm from Hopp et al. (2021), we calculate the composite *values* content—across all dimensions—of questions in our sample.

We create three variables at the conversation level using this classification. The most general case for all conversations is again captured using $ValuesConv_{a,i,t}$, which equals one if the conversation with analyst a contains a *values* question, and zero otherwise:

$$ValuesConv_{a,i,t} = \mathbb{1}[\exists q \in Values], \text{for } q \in Q_{a,i,t},$$

where $Values$ is a set of *values* questions defined as questions with an eMFD score ranking in the top decile of our sample. All variables are defined as above, except that $Values$ now reflects the set of *values* questions.

For the two remaining variables, we construct $ValuesConv^{Climate}$ such that it equals one if the analyst asks at least one climate change question that is a *values* question, $ValuesConv^{NonClimate}$ is defined accordingly for non-climate change questions:

$$ValuesConv_{a,i,t}^{Climate} = \mathbb{1}[\exists q \in Values], \text{for } q \in Q_{a,i,t} \cap \mathcal{C},$$
$$ValuesConv_{a,i,t}^{NonClimate} = \mathbb{1}[\exists q \in Values], \text{for } q \in Q_{a,i,t} \setminus \mathcal{C},$$

In summary, questions—and, as a result, conversations—may relate to climate change or not, contain *value*-related content or not, and feature *values*-related discussions or not. Importantly, the categories of *value* and *values* are not mutually exclusive; a analyst asking a *values*-related question may also touch upon financial aspects like earnings or investments.

Summary Statistics. Table 1, Panel A, reports summary statistics of *value*- and *values*-centric questions, reported at the conversation level. We find that 72.5 percent of all conversations contain at least one *value*-related question, and 29.4 percent at least one *values*-related question. The table also show that questions related to *value* in the context of climate change ($ValueConv_{a,i,t}^{Climate}$ are markedly more frequent than those on *values* ($ValueConv_{a,i,t}^{Climate}$). This is the case when we compute the statistics across all conversations (reported in Panel A), and only within climate change conversations (in Panel C).[13]

3.3. *Using LLM to Classify Climate Change Questions*

We now sketch the LLM used to classify climate change questions (we provide details in IA Section IV). Our model has to balance several requirements. Primarily, the model must be powerful enough to detect climate change speech in relatively short text fragments. Pilot tests reveal that a BERT model performs better in earnings call *snippets* than other alternatives, such as the bigram-based approach by Sautner et al. (2023). We opt for FinBERT, a version of BERT trained on SEC filings, analyst reports, and earnings call transcripts, because non-climate change discussion in earnings calls often revolves around the firm's financial health. This pre-trained Natural Language Processing (NLP) model is chiefly used to obtain the sentiment of financial text (Huang et al., 2023). A pre-trained model is beneficial because it allows us to fine-tune it for identifying climate change discussions *within* financial text. Fine-tuning is typically fast and requires relatively limited *labeled* training sets. We employ the set of labeled snippets used in Sautner et al. (2023)'s validation test, which has labeled (using multiple coders) approximately 2,400 snippets taken from a random sample of earnings call transcripts. In our fine-tuning, about 80 percent of this labeled data is used for training FinBERT for climate change identification, with the remainder used for validation (approximately 10 percent) and testing (also 10 percent). This process produces good performance metrics for the final LLM used for classification. F1 statistics are 96 percent in the validation and 94 percent in the test samples.[14]

[13] In an unreported analysis, we hone in on the analysis in Panel C and the intensity of *value* and *values* questions within climate change conversations. We observe that 34.2 percent of climate change questions (and 30.5 percent of non-climate change questions) are flagged as *value*-related. Meanwhile, 11.4 percent (and 10 percent for non-climate change questions) are designated as *values*-centric. Furthermore, 3.5 percent (and 3.2 percent for non-climate change questions) contain both *value* and *values* content.

[14] The F1 statistic trades off precision and recall, where precision is defined as the number of true positives among all positives, and recall is the number of true positives among the sum of true and false positives. The F1 statistic is the harmonic mean of precision and recall, and the score ranges between 0 and 100 percent.

4. Describing Climate Change Conversations

4.1. Climate Change Conversations over Time

We start the analysis by exploring the occurrence of climate change discussions in earnings calls. In Figure 1, we exhibit the quarterly time average of the number of conversations, whether climate-related or not, per earnings call (left axis). We also plot the number of words per conversation (right axis). The number of conversations increased steadily between 2003 and 2007 and again between 2009 and 2013, peaking at around 6.2 end of 2013. We observe a decline in the number of conversations during the Great Recession in 2008 and another one in 2017 and 2021, with the two latter declines corresponding with periods of heightened political instability due to Brexit, the Trump election, and the Covid pandemic. Simultaneously, conversations have lengthened over the sample period, with the number of words per exchange rising from 560 in 2003 to around 700 in 2021. Collectively, the sample period experienced fewer conversations over time, but each was more extended in duration.

In Figure 2, we focus on conversations with climate change questions. Recall that we define climate change conversation as those that contain at least one climate change-related question. We present the quarterly time average of the number of such conversations (left axis), as well the number of climate change conversations *per call* (right axis). Climate change conversations became more frequent between 2003 and 2011, after which their occurrence more or less steadied at around 3,200 conversations per quarter. Climate change conversations in each call exhibit an inverse-U shape pattern over time, with the average escalating from 0.47 early in the sample to approximately 0.8 in 2011 (i.e, an average call contains 0.8 conversations devoted to climate change). This statistic declines post-2015, returning to a level closer to the beginning of the sample period, around an average of 0.5.

In Figure 3, we open up the conversation and examine individual questions. Relying on $ClimateConvIntensity_{a,i,t}$, we graph the quarterly time-average of this intensity of climate change questions *within* a climate change conversation. We observe a marked surge between

2003 and 2010, followed by a plateau until 2016. Subsequently, the prominence of climate change questions, compared with non-climate content, shows a rising trend again. Hence, while the number of climate change conversations did not increase over the recent years, the intensity of such discussions did surge.

An alternative approach to evaluating the prominence of climate change queries in conversations is examining whether the first conversation in an earnings call centers on climate change issues (Mayew et al., 2020). This would suggest management's priority to engage with an analyst interested in climate issues (Mayew, 2008). Figure 4 illustrates the quarterly time-average frequency of calls that initiate a climate change conversation (red line, left axis). Approximately 9.5 percent of earnings calls, on average, commence with a climate change-focused conversation, with the quarterly average fluctuating around this value (except for the first five years of the sample). Next, *within* each climate change conversation, we assess if the first question raised by an analyst is related to climate change. The quarterly time average of this variable is also shown in the figure (blue line, right axis). The data reveals three periods of relative stability, each subsequent period at a higher level. Between 2003 and 2010, an analyst asked about climate change first in about four percent of climate change conversations. This statistic increased to about seven percent after 2017.

In sum, earnings call conversations evolved over the years and appear subject to various contextual factors, including economic uncertainties (e.g., the COVID-19 pandemic). Despite a decrease in the frequency of climate conversations over the past decade, conversations on the topics have become more intense. Moreover, those analysts who do broach the topic give it greater prominence and depth as evidenced by their order in the conversation and the increased word count in their questions.

4.2. Climate Change Conversations across Countries and Sectors

We employ $ClimateConvIntensity_{a,i,t}$ to investigate the differences in climate change conversations across countries and sectors. Figure 5, Panel A, illustrates the variable's distribution by quarter-country. We concentrate on the ten countries with the largest number of earnings calls and rank countries based on the mean value of $ClimateConvIntensity_{a,i,t}$. We discern notably *intense* climate change debates on average in Brazil, Canada, and Germany, as well as in Australia and the UK. Australia exhibits a particularly broad dispersion of climate change discussions (the intensity measure ranges from 0 to 0.08).

We provide a corresponding figure at the quarter-industry level in Figure 5, Panel B, utilizing the 17-sector Fama-French industry breakdown. Relatively tightly grouped distributions of climate change intensity can be observed in the Consumption, Financial, and Retail sectors. In contrast, the Utilities, Oil, Chemicals, and Mining sectors—predictably—record high intensities, with the apex of the distribution in Utilities.

4.3. Variance Decomposition of Climate Change Conversations

A question that arises from the descriptive evidence is why climate change questions emerge in earnings calls. An initial answer to this question can be found by determining the relative contributions of aggregate, industry, firm-level, *and* analyst-level factors in explaining the variation in $ClimateConv_{a,i,t}$ and $ClimateConvIntensity_{a,i,t}$. For this purpose, in Table 2, we use an analysis of variance at the analyst-conversation level to examine the extent of the variation in both metrics accounted for by various sets of fixed effects.

Panel A captures variation related to time, country, industry, or firm factors. Column 1 explains variation in $ClimateConv_{a,i,t}$ and reveals two notable observations: First, approximately 40 percent of the variation in the measured climate change conversations is attributed to analyst-level factors. Second, a nearly equivalent proportion is explained by the combined industry (accounting for 16.3 percent), firm (10.6 percent), and firm-year-quarter (14.1 percent) fixed effects. The roles of country-fixed effects and time-fixed effects are minor.

Panel B focuses on the role of analysts and whether some analysts have a "green style" and persistently ask climate change questions. We evaluate this question by following the approach in Bertrand and Schoar (2003) and including analyst fixed effects to the variance decomposition. Despite the significant role of analysts in generating climate change conversations, unconditional analyst *fixed effects* contribute only marginally, accounting for a mere 2.6 percent of the variation. Importantly, the bulk of the variation accounted for by analysts stems from their inquiries about climate change issues *at specific times* (15.6 percent), within *specific industries* (3.2 percent), at *certain firms* (7.3 percent), or in *specific industries* at isolated times (11 percent). These observations are reflected by the respective interaction fixed effects with the analyst fixed effects. These inferences are reinforced when we examine the variance decomposition of $ClimateConvIntensity_{a,i,t}$ in Column 2.

Collectively, these findings do *not* corroborate the notion of a distinct set of analysts who invariably ask about climate change in earnings calls, regardless of a firm's situation or whether climate change is a salient issue in a sector. There appears to be no such thing as a green style among analysts. Instead, the findings suggest that analysts purposefully choose their questions, addressing climate change concerns when they deem them relevant to a firm's future, or when they believe investors—their clients—require such information.

4.4. Determinants of Climate Change Conversations

Motivated by the comparatively large amount of variation accounted for by the interaction of time fixed effects with fixed effects at the firm and analyst levels, we probe in Table 3 which time-varying characteristics explain $ClimateConv_{a,i,t}$. We are interested not only in firm and analyst characteristics but also in earnings call features that could potentially vary across calls. Accordingly, we examine how $ClimateConv_{a,i,t}$ correlates with various possible determinants using two specifications that both include industry-by-quarter fixed effects. The first model highlights the time-varying characteristics of analysts. Because the analyst coverage of firms is subject to endogenous matching, we compare the traits of *all* analysts attending the same earnings call of firm i in quarter t by including firm-by-quarter fixed effects. The second model removes these fixed effects and keeps only the industry-by-quarter fixed effects. This specification has two benefits: it allows us to study the time-varying firm characteristics of climate change conversations, and it shows which analyst traits are important in explaining how these conversations differ among firms in the same industry at a certain time. Since analysts do not randomly match with firms within an industry, these results are due to selection effects as well as analyst differences. We estimate for the conversation with analyst a in the earnings call of firm i at quarter t the following model:

$$ClimateConv_{a,i,t} = \delta_{s\times t} + \delta_{i\times t} + \gamma X_{i,t} + \lambda Y_{a,i,t} + \mu Z_{a,i,t} + \epsilon_{a,i,t}, \tag{1}$$

where $ClimateConv_{a,i,t}$ equals 1 if analyst a asks at least one question classified as climate change-related in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. $\delta_{s\times t}$ represents industry-by-quarter fixed effects, and $\delta_{i\times t}$ are firm-by-quarter fixed effects. The vector $X_{i,t}$ includes firm characteristics, such as its market capitalization and leverage, $Y_{a,i,t}$ denotes the number of questions raised ($Questions_{a,i,t}$), and $Z_{a,i,t}$ is a vector of analyst-specific variables, which include whether the analyst is a buy-side analyst and their industry coverage. Standard errors are three-way clustered by firm, analyst, and quarter.

We present the two estimations of Equation 1 in Table 3. In Column 1, which estimates effects within a given earnings call and across analysts, we observe that longer earnings calls, marked by more $\#Questions_{a,i,t}$, have a higher propensity to include climate change discussions. The presence of buy-side analysts in a call is inversely related to discussions on climate change. When considering the role of other analyst characteristics, it is important to remember we are contrasting individuals participating in the *same* call. Interestingly, we find that their observable characteristics do not significantly determine the occurrence of climate change conversations. Beyond $Buyside_{a,i,t}$, the only exception is the presence of an analyst with specialized industry experience $SpecializedIndustry_{a,i,t}$, which is positively associated with the occurrence of climate change discussions.

In Column 2, we find a negative correlation between $Experience_{a,t}$ and $FirmExperience_{a,i,t}$ and the occurrence of climate change conversations. We also observe that analysts who cover more firms in a specific industry engage more in climate change discussions. This is in contrast to the findings in Column 1, which are based on a comparison of all analysts attending a firm's quarterly earnings call; here, we infer that less experienced analysts, compared to others in the same *industry*, pose fewer climate change questions. In conjunction with earlier results, we interpret this as an indication that such less experienced individuals are more likely to represent different firms within the industry and ask fewer climate change questions.

Turning to the firm characteristics, we note that conversations about climate change are more common in firms with higher profitability ($ROA_{i,t}$) and higher book-to-market ratios, suggesting these are more mature, financially stable entities. These firms also report higher levels of investments ($Investment_{i,t}$) and experience more cash constraints ($Cash_{i,t}$), which hints at the relevance of queries about investing in (green) technologies. Additionally, we notice a greater likelihood of discussions on climate change when management broaches the subject during the presentation portion of the call ($CCExposure^{Pres}_{i,t}$).

5. Climate Change Conversations in Earnings Calls: Value versus Values

5.1. *Are Climate Change Conversations* Value- *and* Values-*Related?*

Recalling our discussion from Table 1, Panel A, questions related to *value* in the context of climate change are markedly more frequent than those on *values*. Based on our classification of questions into *value*- and *values*-centric ones, we next examine the correlation between climate change conversations and the presence of either *value*- or *values*-related content in the questions within these conversations. Our goal is to understand whether climate change conversations are more (or less) *value*- and *values*-related *compared to other conversations in the same call*. We estimate the following two specifications for the conversation with analyst

a in the earnings call of firm i at time t:

$$(2) \qquad ValueConv_{a,i,t} = \beta\ ClimateConv_{a,i,t} + \delta_{s\times t} + \delta_{i\times t} + \lambda Y_{a,i,t} + \mu Z_{a,t} + \epsilon_{a,i,t},$$

$$(3) \qquad ValuesConv_{a,i,t} = \beta\ ClimateConv_{a,i,t} + \delta_{s\times t} + \delta_{i\times t} + \lambda Y_{a,i,t} + \mu Z_{a,t} + \epsilon_{a,i,t},$$

where $ValueConv_{a,i,t}$ ($ValuesConv_{a,i,t}$) equals 1 if analyst a asks at least one *value* (*values* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. $ClimateConv_{a,i,t}$ is defined as before. $\delta_{s\times t}$ and $\delta_{i\times t}$ represents again industry-by-quarter and firm-by-quarter fixed effects. As before, the firm-by-quarter fixed effects enable comparison within the earnings call, that is, across all conversations of the group of analysts participating. $Y_{a,i,t}$ and $Z_{a,i,t}$ include the number of questions asked and analyst characteristics, respectively. Standard errors are three-way clustered by firm, analyst, and quarter.

Our findings are documented in Table 4. In Columns 1 and 3, we present results for questions covering the entirety of the conversations using $ValueConv_{a,i,t}$ and $ValuesConv_{a,i,t}$. We also estimate in Columns 2 and 4 variants of these regressions in which we replace the dependent with $ValueConv_{a,i,t}^{NonClimate}$ and $ValuesConv_{a,i,t}^{NonClimate}$, that is, we consider conversations from which we excluded any climate change questions in Columns 2 and 4. These regressions allow us to examine whether the non-climate change content of climate change conversations differs from that of non-climate change conversations.[15]

In Column 1, we observe a *negative* and significant association between climate change conversations and the occurrence of *value*-related content in the conversation. This implies that *across* conversations of the same earnings call, climate change conversations are generally less about *value* issues than other conversations. In Column 2, this negative relationship is much more pronounced for non-climate change questions as evidenced by an estimated coefficient more than five times larger in magnitude. This comparison across coefficients indi-

[15]Because cases where $ValueConv^{Climate} = 1$ are a subset of cases where $ClimateConv = 1$, we do not include $ValueConv^{Climate}$ as a dependent variable (it would create a mechanical correlation that is embedded in variable construction). The same holds for $ValuesConv^{Climate}$.

cates that *within* a given conversation, climate change questions are characterized by having less *value*-centric content in the non-climate change questions of a given conversation, and relatively more *value*-related content in the questions about climate change.

In contrast, in Column 3, climate change conversations are positively and significantly correlated with *values*-centric content. In other words, climate change conversations are more about *values*-related issues than other conversations in the same call. This association is driven by climate change questions, given that the estimated coefficient for $ClimateConv_{a,i,t}$ becomes *negative* and statistically significant when we exclude climate change-related content in Column 4. When an analyst probes *values* in climate change questions, they eschew similar queries when discussing non-climate change topics, perhaps consistent with analysts avoiding a moralizing tone throughout their exchange with management.

To conclude, conversations that encompass climate change questions have a decreased propensity to have *value*-related content compared to other conversations. This effect is more pronounced when focusing strictly on non-climate change questions within climate change conversations. In contrast, *values*-related content is more common within climate change conversations. When isolating non-climate change questions within such dialogues, the likelihood of them containing *values* content diminishes. This suggests that the presence of climate change discussions tilts the balance of the entire conversation towards *values* considerations, but this tilt is only observable in the direct climate change questions.

5.2. *Time Trends in* Value- *and* Values-*Related Climate Change Conversations*

Given the heightened attention to ESG investing in recent times, it is interesting to investigate whether there has been a corresponding increase in *value*- or *values*-related discovery in earnings calls. This allows for an assessment of whether one form of discovery has gained relative prominence over the other, as perhaps the demand for such information has grown among investors who base their investments on either *value* or *values* (Starks, 2023).

To address these questions, in Figure 6, we plot the quarterly time series variation of *value*- and *values*-related climate change questions ($\#ValueCCQ$ and $\#ValuesCCQ$) across the sample period. The bar plot shows the quarterly counts of *value*- and *values*-related climate change questions, respectively ($\#ValueCCQ$ in blue, $\#ValuesCCQ$ in red, left axis). The solid line in black depicts the ratio between the number of *value*-related climate change questions and the number of *values*-related climate change questions (right axis).

We observe two patterns. First, there has been an increase in the count of *value*- and *values*-related climate change questions over time. This overall surge aligns with Figure 3, where we documented an increase in the intensity of climate change questions. Second, *value*-related conversations have become significantly more prevalent, especially in the last three years of the sample. If analysts' questions are in response to information demand by investors, this suggests that analysts cater mostly to sustainable investing strategies that incorporate climate issues to generate financial value, that is, by addressing through investment decisions the firm's risk and return characteristics related to climate change.

5.3. *Content of* Value- *and* Values-*Related Climate Change Conversations*

We next characterize the content of *value*- and *values*-related climate change conversations by imposing the sample restriction that $ClimateConv$=1. We then separate questions in these conversations into different content categories. The goal is to gauge the specific content of the interaction between analysts and management (Hope et al., 2016) when conversations are about climate change and how this varies between *value*- and *values*-related climate change conversations. Discerning the content of the conversations regarding the covered topics can illuminate the circumstances under which the different types of climate questions emerge.

Measuring the content of climate change questions at a large scale is challenging. We tackle this challenge by employing the Named Entity Recognition (NER) technique, which separates climate change questions into different content categories. NER allows us to identify and extract from a conversation specific names belonging to eight entity categories: (1) monetary values ($\#Money_{a,i,t}$); (2) named documents related to laws ($\#Law_{a,i,t}$);

(3) measurements of weight, distance, percentage, other numerals including ordinal words ($\#Number$); (4) date and times ($\#Time_{a,i,t}$); (5) names of locations ($\#Location_{a,i,t}$); (6) events ($\#Event_{a,i,t}$); (7) organizations ($\#Org_{a,i,t}$), and (8) nationalities ($\#Nat_{a,i,t}$).[16] Apart from considering the number of named entities by category, we also report the number of named entities ($\#NER$), calculated across all categories of named entities available.[17]

To investigate the conversation content and how it relates to *value*- versus *values*-based conversations, we estimate the following regression for a conversation with analyst a during the earnings call of firm i in quarter t:

(4)

$$NER_{a,i,t} = \delta_{s\times t} + \delta_{i\times t} + \gamma_1 ValueConv^{Climate}_{a,i,t} + \gamma_2 ValuesConv^{Climate}_{a,i,t} + \lambda Y'_{i,t} + \mu Z_{a,t} + \epsilon_{a,i,t}$$

where $NER_{a,i,t}$ represents the overall NER metric and one of the eight NER categories. Our variables of interest, $ValueConv^{Climate}_{a,i,t}$ and $ValuesConv^{Climate}_{a,i,t}$, are indicators contrasting conversations that include *value*- or *values*-centric climate change queries from those that do not. The vector $Y'_{a,t}$ denotes conversation control variables (number of questions raised and number of words used in the questions), and $Z_{a,t}$ contains analyst-specific control variables.[18] We estimate Equation 4 using Poisson regressions to account for the distributional features of the count-based NER outcomes and to permit the inclusion of fixed effects without biasing the estimation (Cohn et al., 2022) (we use the same set of fixed effects as before). Standard errors are three-way clustered at the analyst, firm, and year-quarter level.

The results are compiled in Table 5. We observe significant disparities between the two conversation groups. *Value*-related climate conversations feature more named entities in

[16] The original version of NER (Finkel et al., 2005) considered a more limited set of named entities. We discuss our implementation in detail in IA Section V.

[17] Turning to some examples for each of these NER categories, the algorithm recognizes important environmental events in the "events" category, such as hurricanes, the El Niño phenomenon, and the Deepwater Horizon disaster. In the "organization" category, we identify conversations centered on the Environmental Protection Agency; in the "law" category, we find mentions of the Clean Air Act and the Alternative Energy Directive. We provide examples of how NER categorizes climate change-related questions in Table IA. III.

[18] We control for the word count in the questions as the use of named entities is generally expected to rise with lengthier questions.

the categories of money ($\#Money_{a,i,t}$) and dates and time ($\#Time_{a,i,t}$). These correlations are reassuring and consistent with the definition of *value* conversations, as they employ keywords related to earnings, revenues, costs, and investments. In contrast, conversations mentioning *values*-related climate change topics contain more instances of named regulations ($\#Law_{a,i,t}$), specific cities or plants ($\#Location_{a,i,t}$), organizations ($\#Org_{a,i,t}$), and nationalities ($\#Nat_{a,i,t}$). Overall, we observe that conversations classified as *value*-related employ more specific language (as measured by $\#NER_{a,i,t}$) compared to those categorized as *values*-related; however, the latter also use concrete language.

6. Climate Change Conversations and Trading Volume

One of the main hypotheses in the literature on investor disagreement and stock volume reactions is that disagreement among investors leads to higher trading volume, as investors with different beliefs trade with each other (Harris and Raviv, 1993; Kandel and Pearson, 1995). How climate change affects firms, but also how firm activities affect climate change, is complex and uncertain. This in turn can generate heterogeneous beliefs among investors about the impact of climate change on firm performance and valuation. Investors might also disagree fundamentally about the moral implications of climate change. Climate change conversations in earnings calls reflect the level of attention and concern that managers and analysts have about these issues and the amount and quality of information they provide to the market. Accordingly, climate change conversation might deepen disagreements among investors due to divergent interpretations of the information provided about climate change. If so, this should imply an increase in the trading volume reaction around earnings calls (Holthausen and Verrecchia, 1990; Kim and Verrecchia, 1991, 1997).

To investigate this hypothesis, we move from the conversation level to the firm-quarter level and estimate the following two regression models for firm i and quarter t:

$$(5) \qquad LogAbnVol_{i,t} = \beta \ Call^{Climate}_{i,t} + \mu K_{i,t} + \epsilon_{i,t},$$

$$(6) \qquad LogAbnVol_{i,t} = \beta_1 \ ValueCall^{Climate}_{i,t} + \beta_2 \ ValuesCall^{Climate}_{i,t} + \mu K_{i,t} + \epsilon_{i,t},$$

where $LogAbnVol_{i,t}$ is the natural logarithm of the average daily share turnover (trading volume divided by the number of shares outstanding) over the [-1,+1]-day window around the earnings announcement day of firm i in quarter t (calculated net of the average daily share turnover in the [-40,-11]-days window). The variables of interest in Equation 5 is $Call^{Climate}_{i,t}$, which equals 1 if at least one conversation in the earnings call of firm i in quarter t is classified as climate change-related, and 0 otherwise. In Equation 6, the variables of interest are $ValueCall^{Climate}_{i,t}$ (and $ValuesCall^{Climate}_{i,t}$), which each equal 1 if at least one climate change question from the climate change conversation in the earnings call is classified as *value*-related (*values*-related). We consider earnings calls on the earnings announcement date or one day after (i.e., on days [0,+1]). The vector K includes firm-level characteristics that may affect turnover, including a measure of news released in the announcement, the scaled difference between the actual earnings and the consensus forecast, market cap, dispersion in analysts' forecasts, the stock price at the end of the announcement day (to control for transaction costs), and the market-adjusted cumulative return around the announcement. Some specifications add further firm characteristics. We estimate equations 5 and 6 using a sample that intersects data from IBES, CRSP, and Compustat. We cluster standard errors by firm.

We present our findings in Table 6. In Column 1, abnormal trading volume is positively associated with the degree of climate change discussions in earnings calls ($ConvCall^{Climate}_{i,t}$). This finding holds after controlling for additional firm fundamental variables in Column 3. When we consider the differential effects of *value* and *values*-related climate conversations in Columns 2 and 4, we find that both increase abnormal trading volumes. This suggests that climate change is a source of investor disagreement that drives trading activity in the stock market. The coefficient on $ValueConv_{i,t}^{Climate}$ is about twice as large in magnitude as the coefficient on $ValuesConv_{i,t}^{Climate}$. This difference suggests that *value*, more than *values*, discussions drive the positive relation between climate discussions and trading volume.

Overall, these results imply that investors disagree more about the financial consequences of climate change than about the normative issues related to it. It also suggests that investors are more motivated by economic incentives (rather than moral preferences) when trading on climate change information. This finding is consistent with the literature that shows that investors are more sensitive to value-relevant information than to non-value-relevant information (Dhaliwal et al., 2011, 2012; Flammer, 2015).

7. Do Climate Change Analysts Specialize?

7.1. Defining Climate Change Analysts

Our findings provide some new perspective on analysts' role in incorporating climate change topics into earnings calls, and how this affects financial market outcomes related to investor disagreement. Further, the data do not support the notion that some analysts consistently address climate issues or have an innate predisposition toward comprehending the corporate repercussions of climate change. Hence, analysts do not appear to have fixed green styles. There has also been a shift over time regarding whether climate change conversations are about *value* or *values*. These insights imply that climate change inquiries, and the type of these questions, are driven by situational circumstances or specific professional goals rather than an individual's inherent interest or specialization in the subject.

While there may not be a persistent style for analysts, there could still be a possibility that some analysts specialize over time in whether and how they address climate change issues. This specialization could be a response to personal experiences or a strategy to cater to the interests of their investors. In this section, we, therefore, shift our analysis from the conversation level to the analyst level. We identify analysts with a high propensity in a given year to ask climate-related questions, and we also consider the propensity to raise *value* or *values* questions related to climate change.

A crucial task when creating variables that capture an analyst's frequency of asking climate change questions is to establish a relevant benchmark for comparison. Compared to other analysts, industry attributes, and macroeconomic events may create the appearance of differences regardless of whether the analyst has specialized in climate change. The variable $ClimateAnalyst_{a,t}$ aims to adjust for these differences, in order to reliably identify climate change "specialists." We construct the variable as an indicator that equals one if analyst a poses more climate change questions than the yearly industry average for their coverage portfolio in year t.[19] Two further variables reflect whether analysts additionally specialize in *value* or *values* questions in climate change conversations. $ValueClimateAnalyst$ equals one if analyst a is identified as a value climate change analyst in year t, and zero otherwise. A *value* climate change analyst poses more *value* climate change questions than the yearly industry average for their coverage portfolio in the year. $ValuesClimateAnalyst_{a,t}$ equals 1 if an analyst is identified as a *values* climate change analyst in a given year and 0 otherwise. Such an analyst poses more *values* climate change questions than the yearly industry average for their coverage portfolio in the year.

7.2. Questions from Climate Change Analysts

To validate and understand the three measures, we characterize the questions raised by climate change analysts. Specifically, we investigate whether the conversations that occur in a year where an analyst qualifies as a climate change "specialist" (e.g., where $ClimateAnalyst_{a,t} = 1$) exhibit distinct characteristics. Using the NER technique we introduced earlier, we substitute $ClimateConv_{a,i,t}$ in Equation 4 with $ClimateAnalyst_{a,t}$ and present the results in Table 7.[20]. As before, we focus only on climate change conversations in this analysis. In

[19] IA Section VI provides further details on the operationalization of this variable.

[20] Note that the regressions are still at conversation level, that is for the conversation with analyst a in the earnings call of firm i in *quarter* t, while the measure of analyst specialization is constructed for analysts a in *year* t.

Panel A, we first consider effects for the overall measure $ClimateAnalyst_{a,t}$, that is, we do not factor in whether analysts lean towards *value* or *values* in their questions.

In Column 1, $ClimateAnalyst_{a,t}$ is positively associated with the number of named entities ($NER_{a,i,t}$) mentioned during a conversation, suggesting that these analysts use specific and precise language when posing questions in climate change conversations. In particular, according to the remaining columns, climate change analysts use more named entities related to numbers (Column 4), locations (Column 6), organizations (Column 8), and nationalities (Column 9) in their questions. This finding is in line with such analysts collecting information on the dealings of specific (environmental) agencies and the geographical impact of climate change. The conclusion is that climate change analysts have different habits when asking questions, which helps to contrast them with non-climate change analysts: their specialization appears to allow them to query management on concrete climate change attributes.

In Panel B, we replace $ClimateAnalyst_{a,t}$ with independent variables that highlight the *value* and *values* content of questions by climate change analysts. Several distinctions arise between analysts with *value* or *values* specializations. *Value* analysts ask more climate change questions that contain named entities related to money (Column 2), numbers (Column 4), time (Column 5), and organizations (Column 8) compared to other analysts. Apart from named entities related to organizations, we do not observe such relations for *values* analysts. Such analysts instead ask *less* about numbers and more about locations and nationalities than other analysts. These differences highlight that our analyst classification reflects distinct differences between analysts that originate from the content of the conversations they initiate. This raises the question of whether this specialization is rewarded in the labor market.

7.3. Career Trajectories of Climate Change Analysts

Whether the type of climate change conversations initiated by financial analysts affects labor market outcomes can be inferred from analysts' LinkedIn profiles. Our LinkedIn dataset mirrors the structure of an analyst's CV, offering a year-by-year career record that allows us to construct proxies for analysts' career progressions. We limit the sample to the years after 2000 to have sufficiently detailed individual career records.[21] Our analysis is built around the three indicator variables that capture career progressions at the analyst-year level ($Promotion_{a,t+1}$, $NewCompany_{a,t+1}$, and $ESGJob_{a,t+1}$)

Before employing these measures, we delve deeper into the details of the LinkedIn-based variables. Table 8 provides insights into the careers of analysts across three different phases: i) before their debut in earnings calls, ii) during the period of active participation in earnings calls, and iii) after they cease to appear in earnings calls. On average, analysts begin their participation in calls approximately 7.5 years after their initial employment, as denoted by the average $YearsofWork$ in the initial period (before attending earnings calls). Having amassed substantial experience before partaking in earnings calls, their active engagement spans around 6.2 years. Subsequently, while no longer featuring in the earnings calls' participant lists, they continue to be listed on LinkedIn for 5.0 more years on average.[22]

Consistent with the notion that participation in earnings calls necessitates meaningful work experience, analysts tend to be more senior during the periods in which they attend calls, and this trend persists subsequently. As analysts ascend to higher ranks while participating in earnings calls, the pace of further career advancement slows down, aligning with a diminishing availability of promotional opportunities. Concurrently, the decreasing frequency of analysts transitioning between brokerages implies an intensifying preference to maintain their positions within their firms. This is consistent with analysts accumulating more brokerage-specific human capital and cultivating extensive professional networks.

Next, we consider whether asking climate change questions predicts career outcomes. For this purpose, we need to modify our measures of climate change analysts. We replace

[21] We provide details of how we infer the seniority and career trajectories of analysts from their job titles on LinkedIn in IA Section III.

[22] Our LinkedIn data ends in December 2022. Accordingly, the reported mean of five years on $YearsofWork$ after the period in which an analyst attends earnings calls may underestimate the length of the remainder of the career of these analysts.

$ClimateAnalyst_{a,t}$ with $ClimateAnalyst_{a,t}^{Profile}$, which represents the cumulative number of years that analyst a has been identified as a climate change analyst according to our data (measured up to year t). We scale this variable by $WorkExperience_{a,t}$, the total years since their first professional role per their LinkedIn profiles. We standardize $ClimateAnalyst_{a,t}^{Profile}$ to have zero mean and unit standard deviation. We perform similar adjustments for the measures of *value* and *values* climate change analysts.

To determine if the accrued relative experience as a climate change analyst influences career outcomes, we estimate the following regression model for analyst a and year t:

$$CareerProg_{a,t+1} = \delta_a + \delta_t + \alpha ClimateAnalyst_{a,t}^{Profile} + \zeta Z'_{a,t} + \epsilon_{a,t}, \tag{7}$$

where $CareerProg_{a,t+1}$ corresponds to $Promotion_{a,t+1}$, $NewCompany_{a,t+1}$, or $ESGJob_{a,t+1}$. δ_a represent analyst fixed effects, and δ_t year fixed effects. $Z'_{a,t}$ is a vector for analyst characteristics, such as holding a $BusinessDegree_{a,t}$ or a $PhD_{a,t}$, along with other previously introduced attributes. We can incorporate these additional variables in this analysis as LinkedIn provides analyst characteristics beyond what is available for the larger transcripts-based database. We estimate Equation 7 with a linear probability model and double-cluster standard errors at the analyst and broker level. Since we include analyst fixed effects, we identify effects from within-analyst variation in their status as a climate change analyst. One way to think about this choice is that we show how career progression benefits from accumulating a stronger climate change profile over time.

Table 9, Panel A, shows that $ClimateAnalyst_{a,t}^{Profile}$ is a significant predictor of career advancements. In Columns 1 and 2, which vary based on the definition of a promotion, climate change analysts have higher odds of being promoted (Column 2 uses the more refined seniority stratification to define a career step). In Column 2, an increase in the climate change analyst profile by one standard deviation raises the probability of receiving a promotion in the following year by 0.5 percent. This magnitude must be evaluated in the context of promotions being rare events, with a sample mean of 6.3 percent. In Column 3, the climate change analyst profile enhances the chances of moving to a new firm $NewCompany_{a,t+1}$, and in Column 4, it increases the probability of acquiring an $ESGJob_{a,t+1}$.

In Panel B, we bifurcate $ClimateAnalyst_{a,t}^{Profile}$ into two new variables, $ValueClimate-Analyst_{a,t}^{Profile}$ and $ValuesClimateAnalyst_{a,t}^{Profile}$, and then re-estimate Equation 7. We find that analysts who emphasize the *value*-related consequences of climate change in their questions are more likely to be promoted, and also more likely to transition to a new job. Having a *values* profile in a given year is not associated with promotion but raises the likelihood of obtaining a new position outside the current firm. Overall, these results suggest that there are tangible benefits for analysts to specialize in climate change issues, especially when related to the financial risks and returns of firms.

7.4. Coverage Discontinuation by Climate Change Analysts

So far, we have not estimated whether analyst specialization is related to firm outcomes. We turn to this question by examining whether analysts specializing in climate change are more or less likely to terminate coverage of specific firms (estimated compared to their peers who participate in the calls of these firms). The decision of an analyst to cover a firm is useful for two reasons. First, coverage decisions might serve as a proxy for green investors' decisions to sell shares of brown firms (exit) or to encourage brown firms to change (voice). The reason is that analyst coverage is in response to an information demand by either their own investment institutions (buy-side) or by other market participants that make investments based on their reports (sell-side). Continued coverage and posing climate questions, in turn, implies a choice for voice rather than exit, plausibly on behalf of investors (Broccardo et al., 2022). Second, coverage choices might explain *how* posing climate change questions predicts career outcomes. Analysts likely utilize information from their exchanges with management in calls to decide whether to continue covering the firm, affecting how well they meet their clients' demands and, thus, their promotion chances. To explore these issues, we employ the following specification for analysts a, covering firm i in year t:

$$DropCoverage_{a,i,t+1} = \delta_{i\times t} + \beta ClimateAnalyst_{a,t} + \lambda Y_j, t + \mu Z_{i,t} + \epsilon_{a,i,t} \tag{8}$$

where $DropCoverage_{a,i,t+1}$ equals one if analyst a ceases coverage of firm i in the next year $t+1$. $\delta_{i\times t}$ symbolizes a complete set of firm-by-year fixed effects. We estimate Equation 8 using a linear probability model with standard errors clustered by firm and analyst.

Results are reported in Table 10. In Column 1, a lower likelihood of discontinuing coverage is observed for climate change analysts ($ClimateAnalyst_{a,t}$), with the effect being estimated in comparison to their non-specialized peers. In Column 2, we partition $ClimateAnalyst_{a,t}$ and evaluate whether analysts who lean towards *value* or *values*-centric questions make distinctive coverage decisions compared to others. We find that both *Value-ClimateAnalyst* and $ValuesClimateAnalyst$ are negatively associated with $DropCoverage_{a,t}$. Nonetheless, the coefficient estimated for $ValueClimateAnalyst_{a,t}$ is significantly larger in absolute terms, suggesting that analysts who manifest a propensity for asking *value*-centric questions are more likely to sustain coverage of the firms in their portfolio for extended periods (the test for a difference in coefficients has a p-value of 0.05). Together, these findings suggest that climate change analysts are more likely to exercise voice over exit compared to their non-climate change counterparts. These results align with the theory presented by Broccardo et al. (2022), indicating that climate change analysts—particularly those posing value-centric questions—terminate their firm coverage less frequently than non-climate change analysts, which is consistent with a preference for voice over exit. This interpretation is in line with Broccardo et al. (2022)'s argument that voice is a more effective strategy for achieving ESG-related outcomes.

8. Conclusions

We investigate whether financial analysts play a role in the discovery of *value*- and *values*-related information in conversations about climate change during earnings calls. Demand for climate change information in such calls might reflect both price and values concerns, in line with the broader market trend in sustainable investing that also features these two dimensions. Whereas some analysts may intrinsically care about the environmental footprint of a firm, others might make *value*-related cost/benefit trade-offs to assess whether such *values* are costly to hold. Still others might believe green values have a moral component.

Analyzing over 310,000 earnings call transcripts spanning two decades, we use a fine-tuned LLM to identify whether conversations between individual analysts and management in earnings calls are about climate change and whether such climate change discussions focus on *value* or *values* aspects. We notice a steady increase in the intensity of climate-related conversations post-2012. While increasing, the values discovery remains stable over time, whereas analysts appear to increase their probing of climate change implications for the firm in *value* terms. This pattern reflects the rising relevance of climate considerations in corporate disclosures, firm policies, and investment strategies, denoting a substantive shift in the focus of financial analysts and firms. It also underscores that the traditional price discovery framework of financial analysis dominates the questions they ask in earnings calls.

Abnormal trading volume around earnings announcements is positively associated with the degree of climate change discussions in earnings calls. Investors disagree more about the financial consequences of climate change (*value*) than about the normative issues related to it (*values*). This result also suggests that investors are more motivated by economic incentives (rather than moral preferences) when trading on climate change information.

Climate change conversations are driven equally by firm and analyst-related factors. In both cases, the economically significant determinants are not fixed over time. Indeed, analysts' interest in "green" topics is situational, mirroring market demands rather than persistent individual traits. Compared with non-climate discussions between management and analysts, climate change conversations tend to feature more values-centered language (at the cost of questions about the *value* implications). We validate these findings by comparing the linguistic content of *value*-centered and *values*-centered conversations, finding marked differences in the language used.

The conversation features that we identify have tangible consequences for financial analysts. Notably, we find a correlation between an analyst's profile in earnings calls and favorable subsequent career trajectories, with climate-centric analysts, particularly those focusing on *value*, experiencing heightened job mobility and promotion opportunities. This indicates that labor markets recognize such competencies in analysts, signaling a broader market trend of rewarding focused attention on climate change.

Based on their coverage decisions, we infer that climate change analysts use voice, rather than exit, to ask (brown) firms to change. In particular, those climate change analysts with a raised profile of posing value-related questions continue their coverage longer, compared to *values*-centric analysts who have a higher propensity to drop coverage.

Methodologically, we provide solutions to two empirical challenges. First, we use a LLM fine-tuned to climate change discussions within financial disclosures, to reliably classify short text snippets (i.e., questions and answers) into climate and non-climate related. Second, we introduce a scalable, tested algorithm developed in the computational behavioral sciences to sub-categorize these conversations further based on their focus on *value* and *values.*

Finally, we provide a comprehensive, publicly accessible analyst-conversation level database, aspiring to be a resourceful asset for future research in climate finance. We envisage this research assisting analysts, firms, and investors in aligning their strategies with green priorities and integrating climate considerations into financial analysis and corporate strategy.

Appendix. Variable Definitions

Variable	Years	Definition
$ClimateConv_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one question that is classified as climate-related in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. Source: Self-constructed.
$ClimateConvIntensity_{a,i,t}$	2003-2021	Ratio between climate-related questions and the total number of questions asked by analyst a in a conversation in the earnings call of firm i at quarter t. Source: Self-constructed.
$ValueConv_{a,i,t}$	2003-2021	Indicator variable that equals 1 if a analyst a asks at least one *value* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *value* question is defined as a question that contains at least one valuation keyword shown in Table IA.II. Source: Self-constructed.
$ValueConv^{Climate}_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one climate change question that is a *value* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *value* question is defined as a question that contains at least one of the valuation keywords shown in Table IA.II. Source: Self-constructed.
$ValueConv^{NonClimate}_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one non-climate change question that is also a *value* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *value* question is defined as a question that contains at least one of the valuation keywords shown in Table IA.II. Source: Self-constructed.
$ValuesConv_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one question that is also a *values* question in the earnings call of firm i at quarter t, and 0 otherwise. A *values* question is defined as a question with an eMFD score ranking in the top decile of the whole sample. Source: Self-constructed.
$ValuesConv^{Climate}_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one climate change question that is also a *values* question in the earnings call of firm i at quarter t, and 0 otherwise. A *values* question is defined as a question with an eMFD score ranking in the top decile of the whole sample. Source: Self-constructed.
$ValuesConv^{NonClimate}_{a,i,t}$	2003-2021	Indicator variable that equals 1 if analyst a asks at least one non-climate change question that is also a *values* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *values* question is defined as a question with an eMFD score ranking in the top decile of the whole sample. Source: Self-constructed.
$Call^{Climate}_{i,t}$	2003-2021	Indicator variable that equals 1 if at least one conversation in an earnings call of firm i in quarter t is classified as climate change-related, and 0 otherwise.
$ValueCall^{Climate}_{i,t}$	2003-2021	Indicator variable that equals 1 if at least one climate change question from the climate change conversation in the earnings call of firm i in quarter t is classified as *value*-related, and 0 otherwise. Source: Self-constructed.
$ValuesCall^{Climate}_{i,t}$	2003-2021	Indicator variable that equals 1 if at least one climate change question from the climate change conversation in the earnings call of firm i in quarter t is classified as *values*-related, and 0 otherwise. Source: Self-constructed.
$ClimateAnalyst_{a,t}$	2003-2021	Indicator variable that equals 1 if analyst a is identified as a climate change analyst in year t, and 0 otherwise. A climate change analyst poses more climate change questions than the yearly industry average for their coverage portfolio in a year. Details about the variable construction are in Internet Appendix Section VI. Source: Self-constructed.
$ValueClimateAnalyst_{a,t}$	2003-2021	Indicator variable that equals 1 if analyst a is identified as a *value* climate change analyst in year t, and 0 otherwise. A *value* climate change analyst poses more *value* climate change questions than the yearly industry average for their coverage portfolio in a year. Source: Self-constructed.

$ValuesClimateAnalyst_{a,t}$	2003-2021	Indicator variable that equals 1 if analyst a is identified as a *values* climate change analyst in year t, and 0 otherwise. A *values* climate change analyst poses more *values* climate change questions than the yearly industry average for their coverage portfolio in a year. Source: Self-constructed.
$ClimateAnalyst_{a,t}^{Profile}$	2000-2022	Cumulative sum of years that analyst a has been identified as a climate change analyst. Measured in year t and scaled by the $WorkExperience_{a,t}$ of the analyst in the year. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed from LinkedIn profiles.
$ValueClimateAnalyst_{a,t}^{Profile}$	2000-2022	Cumulative sum of years that analyst a has been identified as a *value* climate change analyst. Measured in year t and scaled by the $WorkExperience_{a,t}$ of the analyst in the year. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed from LinkedIn profiles.
$\#Questions_{a,i,t}$	2003-2021	Number of questions asked by analyst a in a conversation in the earnings call of firm i in quarter t. Winsorized at the 1% level. Source: Self-constructed.
$Buyside_{a,t}$	2003-2021	Indicator variable that equals 1 if the affiliation of analyst a is classified as buy-side at quarter t, and 0 otherwise. Please refer to Internet Appendix Section II for details on buy-side classification. Source: Self-constructed.
$\#FirmCoverage_{a,t}$	2003-2021	Number of distinct firms that analyst a covers in year t. Winsorized at the 1% level. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed.
$\#IndustryCoverage_{a,t}$	2003-2021	Number of unique industries that analyst a covers in year t. Winsorized at the 1% level. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed.
$\#CallsAttended_{a,t}$	2003-2021	Number of earnings calls that analyst a attended in year t. Winsorized at the 1% level. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed.
$Experience_{a,t}$	2003-2021	Number of years since analyst a first attends an earnings call, measured in quarter t. Winsorized at the 1% level. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed.
$FirmExperience_{a,i,t}$	2003-2021	Number of years since analyst a first attends an earnings call of firm i, measured in quarter t. Winsorized at the 1% level. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Source: Self-constructed.
$SpecializedIndustry_{a,i,t}$	2003-2021	Indicator variable that equals 1 if firm i is in the SIC2 industry in which analyst a specialized in year t, and 0 otherwise. In a year, an analyst specializes in one SIC2 industry if the majority of the analyst coverage is in this SIC2 industry and there are at least five firms that the analyst covers in this SIC2 industry. Source: Self-constructed.
$\#NER_{a,i,t}$	2003-2021	Number of named entities identified from all questions in a conversation of analyst a in the earnings call of firm i at quarter t. We construct the variable for different types of named entities including quantities, monetary values, time, locations, organizations, regulations, events, and nationalities (indicated accordingly). Source: Self-constructed.
$\#Words_{a,i,t}$	2003-2021	Number of words from all questions in a conversation of analyst a in the earnings call of firm i at quarter t. $\#Words_{a,i,t}^{Climate}$ and $\#Words_{a,i,t}^{NonClimate}$ denotes the number of words from climate change questions and non-climate change questions in a conversation of analyst a in the earnings call of firm i at quarter t respectively. Source: Self-constructed.
$MarketCap_{i,t}$	2003-2021	Market value of equity (in \$ millions) of firm i at the end of quarter t, computed as the market price (Compustat item PRCCQ) times number of shares outstanding (CSHOQ). Winsorized at the 1% level. Source: Compustat NA/Global

Variable	Years	Definition
$Book\text{-}to\text{-}Market_{i,t}$	2003-2021	Book value of equity (Compustat item CEQQ) of firm i divided by market value of equity (in $ millions) at the end of quarter t. Winsorized at the 1% level. Source: Compustat NA/Global
$Leverage_{i,t}$	2003-2021	Sum of the book value of long-term debt (Compustat data item DLTTQ) and the book value of current liabilities (DLCQ) of firm i divided by total assets (Compustat data item ATQ) at the end of quarter t. Winsorized at the 1% level. Source: Compustat NA/Global.
$Cash_{i,t}$	2003-2021	Cash and short-term investments (Compustat data item CHEQ) of firm i divided by total assets (Compustat data item ATQ) at the end of quarter t. Winsorized at the 1% level. Source: Compustat NA/Global.
$Investment_{i,t}$	2003-2021	Changes in property, plant, and equipment (Compustat data item PPENTQ minus lagged PPENTQ) of firm i divided by lagged total assets (Compustat data item ATQ) at the end of quarter t. Winsorized at the 1% level. Source: Compustat NA/Global.
$ROA_{i,t}$	2003-2021	Net income (Compustat data item NIQ) of firm i divided by lagged total assets (Compustat data item ATQ) at the end of quarter t. Winsorized at the 1% level. Source: Compustat NA/Global.
$EarningsGrowth_{i,t}$	2003-2021	Year-on-year growth of net income (Compustat data item NIQ) of firm i. Winsorized at the 1% level. Source: Compustat NA/Global.
$SalesGrowth_{i,t}$	2003-2021	Year-on-year growth of net income (Compustat data item SALEQ) of form i. Winsorized at the 1% level. Source: Compustat NA/Global.
$CCExposure_{i,t}^{Pres}$	2003-2021	Relative frequency with which bigrams related to climate change occur in the presentation part of the earnings call of firm i in quarter t. We count the number of such bigrams and divide by the total number of bigrams. Source: Sautner et al. (2023).
$LogAbnVol_{i,t}$	2003-2021	Daily average of the shares turnover (i.e., volume divided by the number of shares outstanding) in the (-1,+1) window around the earnings announcement day net of the daily average of the shares turnover in the (-40, -11) window. Winsorized at the 1% level. Source: CRSP.
$Dispersion_{i,t}$	2003-2021	Standard deviation of analysts' forecast of the earnings of firm i in quarter t scaled by the closing stock price at the fiscal quarter end. Winsorized at the 1% level. Source: IBES.
$UE_{i,t}$	2003-2021	Difference between the actual earnings and the median of analysts' forecasts of the earnings of firm i in quarter t, divided by the closing stock price at the fiscal quarter end. Winsorized at the 1% level. Source: IBES.
$LogPrice_{i,t}$	2003-2021	Natural logarithm of the closing stock price on the earnings announcement date. Winsorized at the 1% level. Source: CRSP.
$CAR_{i,t}^{EA}$	2003-2021	Market-adjusted cumulative return in the (-1,+1) window around the earnings announcement day. Winsorized at the 1% level. Source: CRSP.
$Promotion_{a,t+1}$	2000-2022	Indicator variable that equals 1 if the job title of the analyst is more senior than the current one over the next year ($t+1$), and 0 otherwise. Please refer to Internet Appendix III for details about seniority classification. Source: Self-constructed from LinkedIn profiles.
$NewCompany_{a,t+1}$	2000-2022	Indicator variable that equals 1 if the analyst moves to a different company over the next year ($t+1$), and 0 otherwise. Source: Self-constructed from LinkedIn profiles.
$ESGJob_{a,t+1}$	2000-2022	Indicator variable that equals 1 if the job title or work experience description of the analyst over the next year ($t+1$) mentioned ESG, sustainability, climate, or CSR, and 0 otherwise. Source: Self-constructed from LinkedIn profiles.

Variable	Years	Definition
$AttendingCalls_{a,t}$	2000-2022	Indicator variable that equals 1 if analyst a attends at least one earnings call in year t, and 0 otherwise. Source: Self-constructed from LinkedIn profiles and conference call transcripts.
$PostAttendingCalls_{a,t}$	2000-2022	Indicator variable that equals 1 for years after the last time when the analyst a attended an earnings call, and 0 otherwise. Source: Self-constructed from LinkedIn profiles and conference call transcripts.
$YearsofWork_{a,t}$	2000-2022	Number of years the analyst a has worked counted in three periods respectively: before her first appearance in an earnings call, during the period of attending earnings calls, and after her last attendance to an earnings call.
$Mid_{a,t}$	2000-2022	Indicator variable that equals 1 if the job title of analyst a in year t is classified as mid-level, such as VP and portfolio manager, and 0 otherwise. Source: Self-constructed from LinkedIn profiles.
$Mid\text{-}Senior_{a,t}$	2000-2022	Indicator variable that equals 1 if the job title of analyst a in year t is classified as mid-senior-level, such as Director and Head of Research, and 0 otherwise. Source: self-constructed from LinkedIn profiles.
$Senior_{a,t}$	2000-2022	Indicator variable that equals 1 if the job title of analyst a in year t is classified as senior-level, such as Managing Director, Managing Partner, and Chief Investment Officer, and 0 otherwise. Source: Self-constructed from LinkedIn profiles.
$Ph.D._{a,t}$	2000-2022	Indicator variable that equals 1 if analyst a earned a Ph.D. degree, and 0 otherwise. Indicator equals 1 from the year t in which the degree was acquired onward. Source: self-constructed from LinkedIn profiles.
$BusinessDegree_{a,t}$	2000-2022	Indicator variable that equals 1 if analyst a acquired a business education, including MBA, and 0 otherwise. Indicator equals 1 from the year t in which the degree was acquired onward. Source: Self-constructed from LinkedIn profiles.
$WorkExperience_{a,t}$	2000-2022	Number of years since analyst a starts the first job, measured in year t. Standardized by subtracting the mean and dividing the standard deviation (in regression analyses only). Winsorized at the 1% level. Source: Self-constructed from LinkedIn profiles.
$DropCoverage_{a,i,t+1}$	2003-2021	Indicator variable that equals 1 if the analyst a ends coverage of firm i in year t, and 0 otherwise. We define the end of coverage based on the time t of the last earnings call of firm i that the analyst a attends. If the analyst leaves the brokerage houses within 180 days after the last earnings call or the last earnings call is in the last half year of the sample (after July 1, 2021), we do not consider it as the end of coverage. Source: Self-constructed from conference call transcripts.

References

Bae, J., C. Y. Hung, and L. van Lent (2023). Mobilizing text as data. *European Accounting Review 6*, 1–22.

Bertrand, M. and A. Schoar (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 1169–1208.

Besley, T. and T. Persson (2023, 01). The Political Economics of Green Transitions. *The Quarterly Journal of Economics 138*(3), 1863–1906.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics 50*(2-3), 296–343.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of Financial Economics 142*(2), 517–549.

Bradshaw, M. T. (2011). Analysts' forecasts: what do we know after decades of work? *Working Paper, Boston College*.

Broccardo, E., O. Hart, and L. Zingales (2022). Exit versus voice. *Journal of Political Economy 130*(12), 3101–3145.

Cen, L., J. Chen, S. Dasgupta, and V. Ragunathan (2021). Do analysts and their employers value access to management? Evidence from earnings conference call participation. *Journal of Financial and Quantitative Analysis 56*(3), 745–787.

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Crowley, R. M., W. Huang, H. Lu, and W. Luo (2019). Do firms manage their csr reputation? Evidence from twitter. *Working Paper, Singapore Management University* (2022-149).

Dai, X., D. Ding, and C. Gao (2023). Do you have any questions? Revealing analyst attention to CSR. *Working Paper, Australian National University*.

Derrien, F., P. Krueger, A. Landier, and T. Yao (2023). Esg news, future cash flows, and firm value. *Working Paper, HEC Paris*.

Dhaliwal, D. S., O. Z. Li, A. Tsang, and Y. G. Yang (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review 86*(1), 59–100.

Dhaliwal, D. S., S. Radhakrishnan, A. Tsang, and Y. G. Yang (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review 87*(3), 723–759.

Finkel, J. R., T. Grenager, and C. D. Manning (2005). Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd annual meeting of the association for computational linguistics (ACL'05)*, pp. 363–370.

Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? a regression discontinuity approach. *Management science 61*(11), 2549–2568.

Groysberg, B., P. M. Healy, and D. A. Maber (2011). What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research 49*(4), 969–1000.

Harris, M. and A. Raviv (1993). Differences of opinion make a horse race. *The Review of Financial Studies 6*(3), 473–506.

Hassan, T. A., S. Hollander, L. van Lent, M. Schwedeler, and A. Tahoun (2023). Firm-level exposure to epidemic diseases: COVID-19, SARS, and H1N1. *The Review of Financial Studies*, forthcoming.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019, 08). Firm-Level Political Risk: Measurement and Effects. *The Quarterly Journal of Economics 134*(4), 2135–2202.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2023). The global impact of Brexit uncertainty. *The Journal of Finance*, forthcoming.

Heckman, J. J., B. Galaty, and H. Tian (2023). The economic approach to personality, character and virtue. Technical report, National Bureau of Economic Research.

Hinze, A.-K. and F. Sump (2019). Corporate social responsibility and financial analysts: A review of the literature. *Sustainability Accounting, Management and Policy Journal 10*(1), 183–207.

Holthausen, R. W. and R. E. Verrecchia (1990). The effect of informedness and consensus on price and volume behavior. *Accounting Review*, 191–208.

Hong, H. and J. D. Kubik (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance 58*(1), 313–351.

Hong, H. and J. C. Stein (2007, June). Disagreement and the stock market. *Journal of Economic Perspectives 21*(2), 109–128.

Hope, O.-K., D. Hu, and H. Lu (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies 21*, 1005–1045.

Hopp, F. R., J. T. Fisher, D. Cornell, R. Huskey, and R. Weber (2021). The extended moral foundations dictionary (emfd): Development and applications of a crowd-sourced approach to extracting moral intuitions from text. *Behavior Research Methods 53*, 232–246.

Huang, A. H., H. Wang, and Y. Yang (2023). Finbert: A large language model for extracting information from financial text. *Contemporary Accounting Research 40*(2), 806–841.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *Review of Financial Studies 34*(3), 1540–1571.

Jung, M. J., M. H. F. Wong, and X. F. Zhang (2018). Buy-side analysts and earnings conference calls. *Journal of Accounting Research 56*(3), 913–952.

Kandel, E. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy 103*(4), 831–872.

Kim, O. and R. E. Verrecchia (1991). Market reaction to anticipated announcements. *Journal of Financial Economics 30*(2), 273–309.

Kim, O. and R. E. Verrecchia (1997). Pre-announcement and event-period private information. *Journal of accounting and economics 24*(3), 395–419.

Kothari, S., E. So, and R. Verdi (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics 8*(1), 197–219.

Krueger, P., Z. Sautner, and L. Starks (2020). The importance of climate risks for institutional investors. *Review of Financial Studies*, 1067–1111.

Li, K., F. Mai, G. Wong, C. Yang, and T. Zhang (2023). Female equity analysts and corporate environmental and social performance. *Working Paper, University of British Columbia*.

Mayew, W. J. (2008). Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research 46*(3), 627–659.

Mayew, W. J., M. Sethuraman, and M. Venkatachalam (2020). Individual analysts' stock recommendations, earnings forecasts, and the informativeness of conference call question and answer sessions. *The Accounting Review 95*(6), 311–337.

Park, M., A. Yoon, and T. Zach (2022). Sell-side analysts' assessment of operational risk: Evidence from negative ESG incidents. *Working Paper, University of Kansas*.

Ramnath, S., S. Rock, and P. B. Shane (2008). Financial analysts' forecasts and stock recommendations: A review of the research. *Foundations and Trends in Finance 2*(4), 311–421.

Rennekamp, K. M., M. Sethuraman, and B. A. Steenhoven (2022). Engagement in earnings conference calls. *Journal of Accounting and Economics 74*(1), 101498.

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Schipper, K. (1991). Analysts' forecasts. *Accounting Horizons 5*(4), 105–121.

Starks, L. T. (2023). Presidential address: Sustainable finance and esg issues—value versus values. *The Journal of Finance 78*(4), 1837–1872.

Webersinke, N., M. Kraus, J. A. Bingler, and M. Leippold (2021). ClimateBERT: A pretrained language model for climate-related text. *Working Paper, University of Zurich*.

Wu, J. S. and A. Y. Zang (2009). What determine financial analysts' career outcomes during mergers? *Journal of Accounting and Economics 47*(1), 59–86.

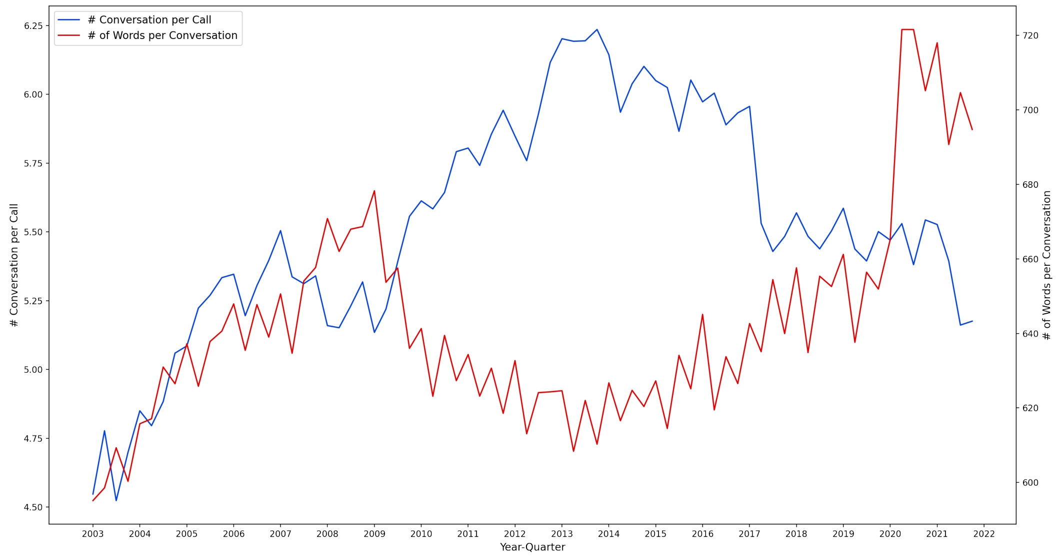


Figure 1. Trends in Earnings Call Conversations

This figure describes the quarterly time series variations of earnings call conversation characteristics. The figure plots the number of conversations per earnings call (blue line, left axis), and the number of words per conversation (red line, right axis).

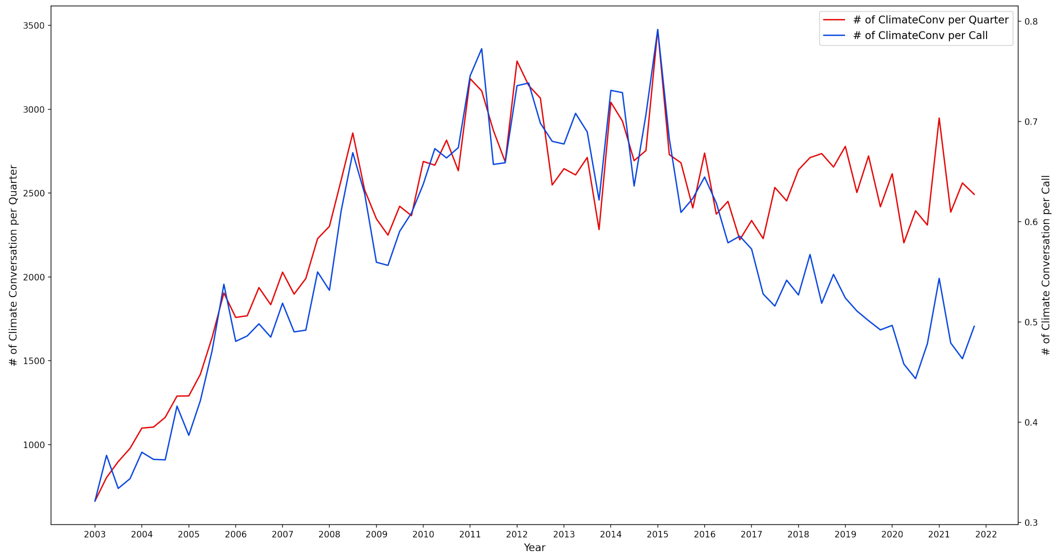


Figure 2. Trends in Climate Change Conversations

This figure describes the quarterly time series variations of the total number of earnings call conversations with climate change questions (red line, left axis), and the average number of conversations with climate change questions per earnings call (blue line, right axis).

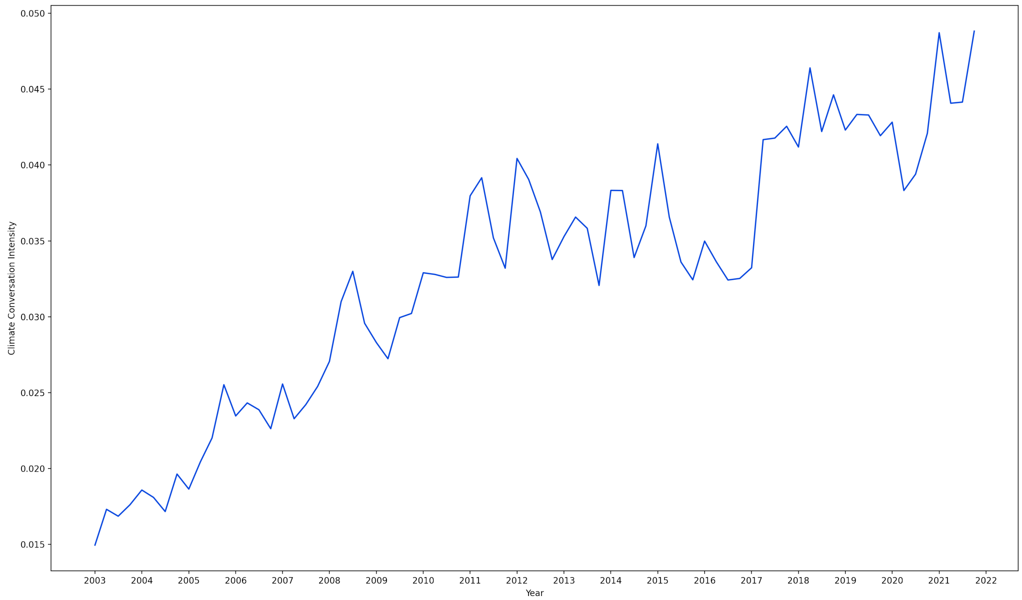


Figure 3. Trends in the Climate Change Conversations Intensity

This figure describes the quarterly time series variation of the average climate change conversation intensity, $ClimateConvIntensity$, across earnings calls. $ClimateConvIntensity$ is the ratio between climate-change-related questions and the total number of questions asked by an analyst in the earnings call conversation.

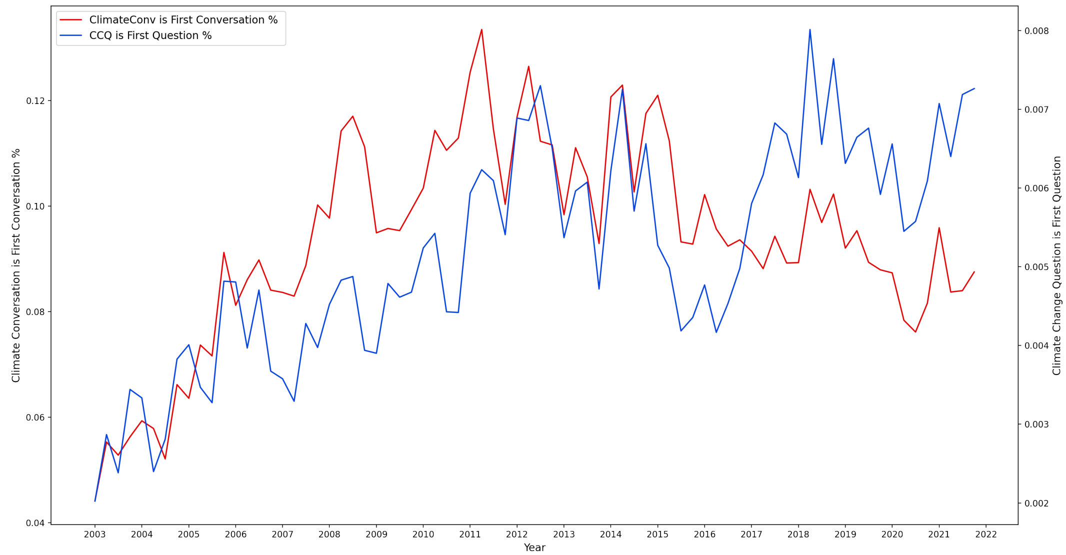
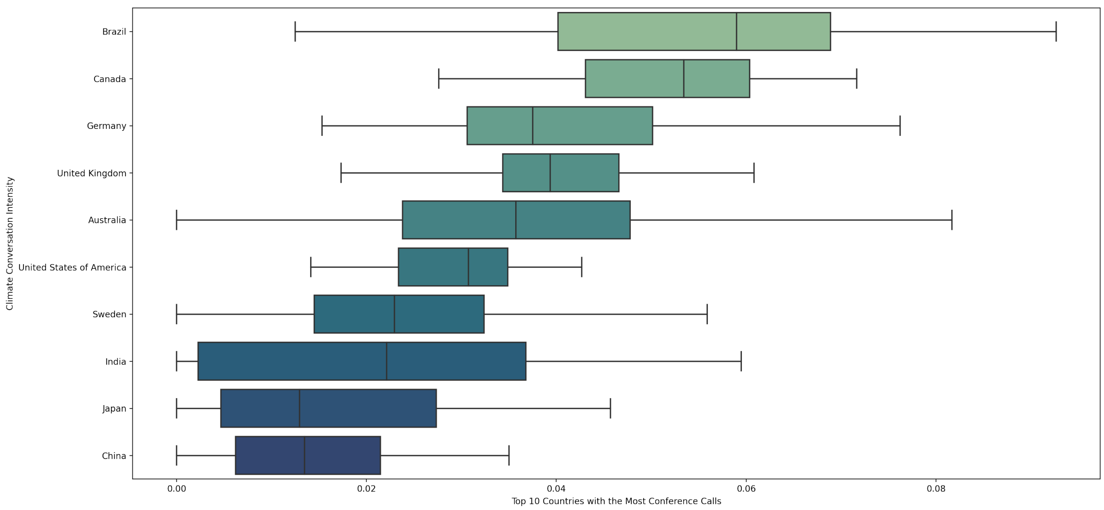
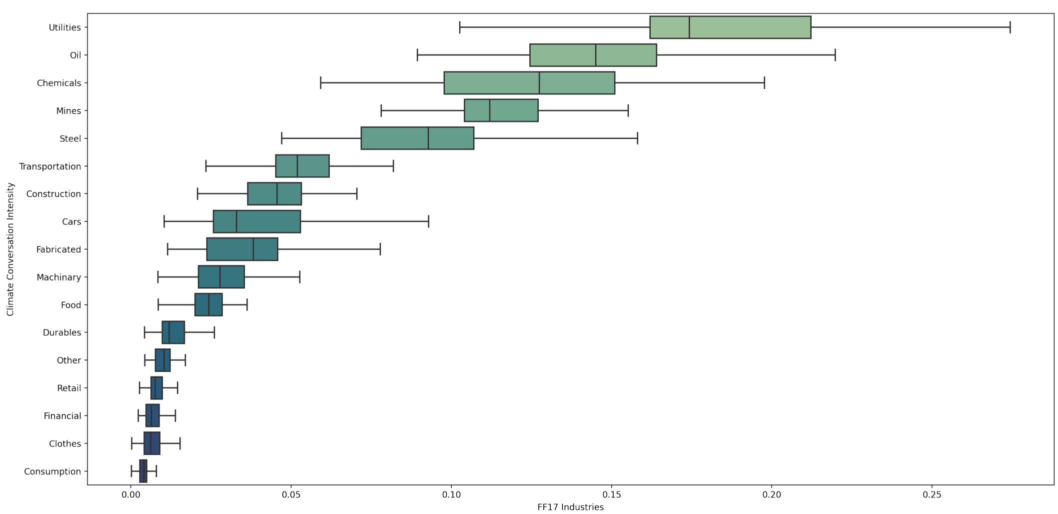


Figure 4. Trends in the First Conversation/First Question on Climate Change

This figure describes the quarterly time series variation of the average frequency of earnings calls that commence with a climate change conversation (red line, left axis), and the average frequency of conversations that raise a climate change question as the first question within a conversation (blue line, right axis).



(a) $ClimateConvIntensity$ across countries



(b) $ClimateConvIntensity$ across sectors

Figure 5. Climate Change Conversation Intensity Across Countries and Sectors

This figure shows the distribution of climate change conversation intensity ($ClimateConvIntensity$) across countries and sectors. We concentrate on the ten sample countries with the largest number of earnings calls. The boxes in the figure draw from the 25th to 75th percentile of the variable $ClimateConvIntensity$, and the bar inside the boxes denotes the median value. The whiskers have 1.5 times interquartile range values (i.e., the distance between the 25th to 75th percentile). We rank countries and sectors based on average values of $ClimateConvIntensity$. $ClimateConvIntensity$ is the ratio between climate change-related questions and the total number of questions asked by an analyst in the earnings call conversation.

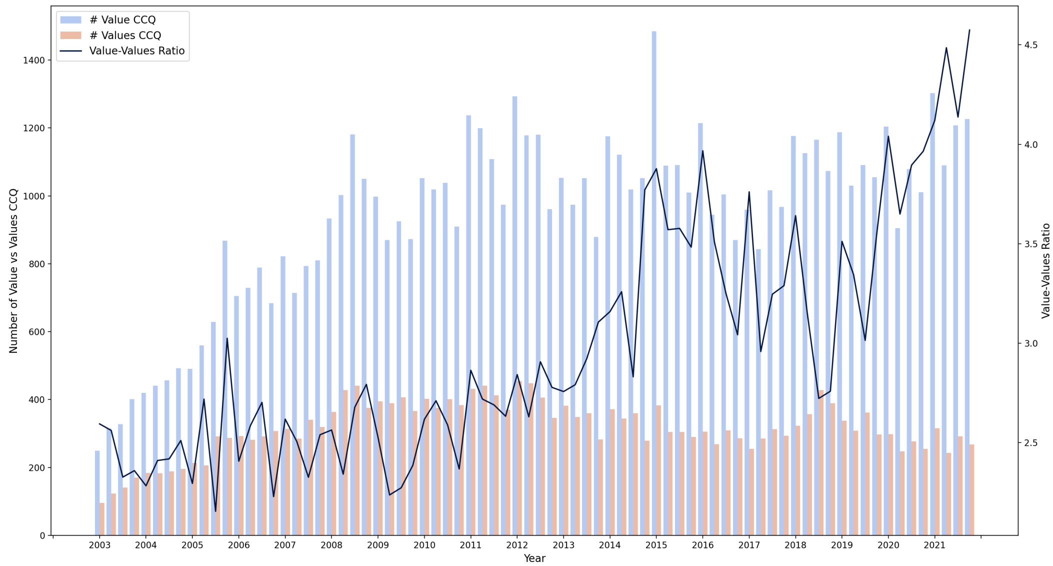


Figure 6. Trends in *Value*- and *Values*-related Climate Change Questions

This figure describes the quarterly time series variation of *value*- and *values*-related climate change questions. The bar plot shows the quarterly counts of *value*- and *values*-centric climate change questions, respectively (*value*-related questions in blue, *values*-related question in red, left axis). The black line depicts the ratio between the number of *value*-related climate change questions and the number of *values*-related climate change questions (right axis).

Table 1 Summary Statistics

This table reports in Panels A summary statistics for conversation characteristics at the conversation level. A conversation is the collection of questions an analyst a poses during the earnings call of firm i in quarter t. The sample includes 1,738,571 conversations including 21,431 analysts in 313,380 earnings calls of 11,855 unique firms over the period 2003 to 2021. Panel B reports summary statistics for conversation characteristics in climate change conversations (i,e., we condition on $ClimateConv$=1) at the conversation level. The sample includes 177,369 climate change conversations. Panel C reports summary statistics for analyst characteristics at the conversation level. The sample is the same as in Panel A. Panel D contains summary statistics for the trading volume tests at the firm-quarter level. Panel E contains summary statistics of analyst career records constructed based on LinkedIn profiles at the analyst-year level. The sample covers 1,848 analysts with matched data in LinkedIn. Panel F reports summary statistics of firm characteristics at the firm-quarter level. For indicator variables, we only report the mean. The Appendix provides detailed variable definitions.

	N	Mean	STD	25%	Median	75%
Panel A: Conversation Characteristics (Conversation Level)						
$ClimateConv_{a,i,t}$	1,738,571	0.102	-	-	-	-
$ClimateConvIntensity_{a,i,t}$	1,738,571	0.034	0.126	0	0	0
$ValueConv_{a,i,t}$	1,738,571	0.725	-	-	-	-
$ValuesConv_{a,i,t}$	1,738,571	0.294	-	-	-	-
$ValueConv_{a,i,t}^{NonClimate}$	1,738,571	0.707	-	-	-	-
$ValuesConv_{a,i,t}^{NonClimate}$	1,738,571	0.286	-	-	-	-
$ValueConv_{a,i,t}^{Climate}$	1,738,571	0.041	-	-	-	-
$ValuesConv_{a,i,t}^{Climate}$	1,738,571	0.014	-	-	-	-
$\#Questions_{a,i,t}$	1,738,571	4.225	2.899	2	4	5
$\#Words_{a,i,t}$	1,738,571	185.274	103.286	112	164	233
$\#Words_{a,i,t}^{NonClimate}$	1,738,571	176.890	103.539	105	157	226
Panel B: Climate Change Conversation Characteristics (if $ClimateConv$=1) (Conversation Level)						
$ValueConv_{a,i,t}^{Climate}$	177,369	0.403	-	-	-	-
$ValuesConv_{a,i,t}^{Climate}$	177,369	0.136	-	-	-	-
$\#Words_{a,i,t}^{Climate}$	177,369	75.911	41.425	44	65	105
$\#NER_{a,i,t}^{Climate}$	177,369	4.180	3.972	1	3	6
$\#Money_{a,i,t}^{Climate}$	177,369	0.205	0.694	0	0	0
$\#Law_{a,i,t}^{Climate}$	177,369	0.005	0.082	0	0	0
$\#Number_{a,i,t}^{Climate}$	177,369	0.700	1.211	0	0	1
$\#Time_{a,i,t}^{Climate}$	177,369	1.327	1.711	0	1	2
$\#Location_{a,i,t}^{Climate}$	177,369	0.706	1.267	0	0	1
$\#Event_{a,i,t}^{Climate}$	177,369	0.009	0.109	0	0	0
$\#Org_{a,i,t}^{Climate}$	177,369	0.516	1.038	0	0	1
$\#Nationality_{a,i,t}^{Climate}$	177,369	0.074	0.338	0	0	0
Panel C: Analyst Characteristics (Conversation Level)						
$ClimateAnalyst_{a,t}$	1,738,571	0.299	-	-	-	-
$ValueClimateAnalyst_{a,t}$	1,738,571	0.253	-	-	-	-
$ValuesClimateAnalyst_{a,t}$	1,738,571	0.168	-	-	-	-
$Buyside_{a,i,t}$	1,738,571	0.050	-	-	-	-
$\#FirmCoverage_{a,t}$	1,738,571	12.036	6.865	7	11	16
$\#IndustryCoverage_{a,t}$	1,738,571	3.572	2.363	2	3	5

Table 1 (Continued)

	N	Mean	STD	25%	Median	75%
$\#CallsAttended_{a,t}$	1,738,571	28.777	19.414	13	26	42
$Experience_{a,t}$	1,738,571	5.798	4.265	2	5	9
$FirmExperience_{a,i,t}$	1,738,571	2.583	2.953	0	2	4
$SpecializedIndustry_{a,i,t}$	1,738,571	0.449	-	-	-	-
Panel D: Trading Volume Tests (Firm-Quarter Level)						
$LogAbnVol_{i,t}$	128,488	1.786	1.209	1.020	1.840	2.609
$Call_{i,t}^{Climate}$	128,488	0.303	-	-	-	-
$ValueCall_{i,t}^{Climate}$	128,488	0.164	-	-	-	-
$ValuesCall_{i,t}^{Climate}$	128,488	0.076	-	-	-	-
$Dispersion_{i,t}$	128,488	0.007	0.029	0.000	0.001	0.003
$UE_{i,t}$	128,488	-0.001	0.033	0.000	0.001	0.002
$LogPrice_{i,t}$	128,488	3.266	0.939	2.678	3.334	3.902
$CAR_{i,t}^{EA}$	128,488	0.000	0.084	-0.042	0.000	0.044
Panel E: Analyst Career Characteristics (Analyst-Year Level)						
$ClimateAnalystProfile_{a,t}$	34,317	0.053	0.106	0	0	0.071
$ValueClimateAnalystProfile_{a,t}$	34,317	0.035	0.081	0	0	0.038
$ValuesClimateAnalystProfile_{a,t}$	34,317	0.018	0.059	0	0	0
$Promotion_{a,t+1}$	34,317	0.062	-	-	-	-
$Promotion_{a,t+1}^{Refine}$	34,317	0.068	-	-	-	-
$NewCompany_{a,t+1}$	34,317	0.174	-	-	-	-
$ESGJob_{a,t+1}$	34,317	0.008	-	-	-	-
$AttendingCalls_{a,t}$	34,317	0.346	-	-	-	-
$PostAttendingCalls_{a,t}$	34,317	0.320	-	-	-	-
$Mid_{a,t}$	34,317	0.160	-	-	-	-
$MidSenior_{a,t}$	34,317	0.207	-	-	-	-
$Senior_{a,t}$	34,317	0.203	-	-	-	-
$BusinessDegree_{a,t}$	34,317	0.339	-	-	-	-
$Ph.D._{a,t}$	34,317	0.025	-	-	-	-
$WorkExperience_{a,t}$	34,317	13.048	8.301	7	12	19
Panel F: Firm Fundamentals (Firm-Quarter Level)						
$MarketCap_{i,t}$	263,805	8.440	4.362	6.067	7.366	8.919
$Book\text{-}to\text{-}Market_{i,t}$	261,271	0.516	0.487	0.193	0.417	0.720
$Leverage_{i,t}$	246,322	0.257	0.220	0.066	0.226	0.389
$Cash_{i,t}$	266,393	0.177	0.208	0.032	0.091	0.238
$Investment_{i,t}$	251,134	0.005	0.023	-0.002	0.000	0.006
$ROA_{i,t}$	265,349	0.001	0.043	-0.002	0.008	0.019
$EarningsGrowth_{i,t}$	266,039	-0.107	4.139	-0.723	-0.028	0.432
$SalesGrowth_{i,t}$	263,504	0.146	0.430	-0.034	0.071	0.217
$CCExposure_{i,t}^{Pres}$	269,046	0.001	0.003	0	0	0.001

Table 2 Variance Decomposition

This table provides a variance decomposition of the climate change-related conversation measures. Regressions are estimated at the conversation level. $ClimateConv_{a,i,t}$ equals 1 if analyst a asks at least one question classified as climate change-related in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. $ClimateConvIntensity_{a,i,t}$ is the ratio between climate change-related questions and the total number of questions asked by analyst a in a conversation in the earnings call of firm i at quarter t.

	$ClimateConv_{a,i,t}$	$ClimateConv$ $Intensity_{a,i,t}$
Panel A: Time, Country, Sector, and Firm-level Variations		
Year-Quarter FE	0.2%	0.4%
Industry FE	16.7%	13.4%
Industry × Year-Quarter FE	0.8%	1.2%
Country FE	0.2%	0.3%
Firm FE	10.1%	10.1%
Firm × Year-Quarter FE	14.2%	13.9%
Sum Panel A	42.3%	39.2%
Panel B: Analyst-Related Variations		
Analyst FE	2.6%	3.1%
Analyst × Year-Quarter FE	15.7%	17.3%
Analyst × Industry FE	3.0%	3.2%
Analyst × Firm FE	7.3%	8.1%
Analyst × Industry × Year-Quarter FE	10.5%	10.1%
Sum Panel B	39.1%	41.8%
"Unexplained"	18.7%	19.0%
Sum	100.0%	100.0%

Table 3 Determinants of Climate Change Question Conversation

This table reports regressions that relate whether a conversation contains a climate change question to firm, analyst, and conference call characteristics. Regressions are estimated at the conversation level. $ClimateConv_{a,i,t}$ equals 1 if analyst a asks at least one question classified as climate change-related in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. Standard errors, three-way clustered at the analyst, firm, and year-quarter level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

	$ClimateConv_{a,i,t}$	
	(1)	(2)
$\#Questions_{a,i,t}$	0.012***	0.014***
	(0.000)	(0.001)
$Buyside_{a,t}$	-0.007***	-0.008**
	(0.002)	(0.004)
$\#FirmCoverage_{a,t}$	-0.002	0.002
	(0.001)	(0.003)
$\#IndustryCoverage_{a,t}$	-0.001	0.005***
	(0.001)	(0.002)
$\#CallsAttended_{a,t}$	0.002	-0.001
	(0.001)	(0.002)
$Experience_{a,t}$	-0.001	-0.003***
	(0.001)	(0.001)
$FirmExperience_{a,i,t}$	-0.000	-0.002**
	(0.000)	(0.001)
$SpecializedIndustry_{a,i,t}$	0.003***	-0.001
	(0.001)	(0.002)
$Market\,Cap_{i,t}$		0.001
		(0.000)
$Book\text{-}to\text{-}Market_{i,t}$		0.010***
		(0.003)
$Leverage_{i,t}$		0.008
		(0.006)
$Cash_{i,t}$		-0.097***
		(0.008)
$Investment_{i,t}$		0.280***
		(0.037)
$ROA_{i,t}$		0.129***
		(0.026)
$EarningsGrowth_{i,t}$		0.000
		(0.000)
$SalesGrowth_{i,t}$		-0.001
		(0.002)
$CCExposure^{Pres}_{i,t}$		0.041***
		(0.002)
Industry × Quarter FE	Y	Y
Firm × Quarter FE	Y	N
N	1,710,656	1,340,754
adj. R-sq	0.304	0.210

Table 4 ***Value*** and ***Values*** Questions

This table reports regressions that relate conversations that contain *value*- or *values*-centric questions to whether the conversation is classified as a climate change conversation or not. Regressions are estimated at the conversation level. $ValueConv_{a,i,t}$ equals 1 if analyst a asks at least one *value* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *value* question is defined as a question that contains at least one valuation keyword shown in Table IA.II. $ValueConv_{a,i,t}^{NonClimate}$ equals 1 if analyst a asks at least one non-climate change question that is also a *value* question in the conversation with managers in the earnings call, and 0 otherwise. $ValuesConv_{a,i,t}$ equals 1 if analyst a asks at least one question that is also a *values* question in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. A *values* question is defined as a question with an eMFD score ranking in the top decile of the whole sample. $ValuesConv_{a,i,t}^{NonClimate}$ equals 1 if analyst a asks at least one non-climate change question that is also a *value* question in the conversation with managers in the earnings call, and 0 otherwise. $ClimateConv_{a,i,t}$ equals 1 if analyst a asks at least one question classified as climate change-related in a conversation in the earnings call of firm i at quarter t, and 0 otherwise. Standard errors, three-way clustered at the analyst, firm, and year-quarter level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

	$ValueConv_{a,i,t}$	$ValueConv_{a,i,t}^{NonClimate}$	$ValuesConv_{a,i,t}$	$ValuesConv_{a,i,t}^{NonClimate}$
	(1)	(2)	(3)	(4)
$ClimateConv_{a,i,t}$	-0.038***	-0.210***	0.014***	-0.065***
	(0.002)	(0.006)	(0.002)	(0.001)
$\#Questions_{a,i,t}$	0.038***	0.041***	0.068***	0.069***
	(0.001)	(0.001)	(0.001)	(0.001)
$Buyside_{a,i,t}$	-0.012***	-0.012***	0.017***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
$\#FirmCoverage_{a,i,t}$	-0.012***	-0.011***	-0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
$\#IndustryCoverage_{a,i,t}$	-0.003**	-0.003**	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
$\#CallsAttended_{a,i,t}$	0.024***	0.024***	-0.006***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
$Experience_{a,t}$	-0.003***	-0.003***	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
$FirmExperience_{a,i,t}$	0.007***	0.007***	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$SpecializedIndustry_{a,i,t}$	0.006***	0.006***	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Industry × Quarter FE	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y
N	1,710,656	1,710,656	1,710,656	1,710,656
adj. R-sq	0.121	0.139	0.210	0.211

Table 5 Characterizing Content of *Value*- and *Values*-centric Climate Change Questions

This table reports regressions that relate the content (or specificity) of climate change conversations to whether the climate change conversation is classified as *value*- (or *values-)* related or not. Regressions are estimated at the conversation level. The sample in this table includes only climate change conversations (i.e., we require $ClimateConv_{a,i,t} = 1$). The dependent variables are the numbers of different kinds of named entities in climate change conversations. $ValueConv_{a,i,t}^{Climate}$ ($ValuesConv_{a,i,t}^{Climate}$) equals 1 when at least one climate change question from the climate change conversation is classified as *value*-related (*values*-related). The regressions control for $\#Questions$, $Buyside_{a,i,t}$, $\#FirmCoverage_{a,t}$, $\#IndustryCoverage_{a,t}$, $\#CallsAttended_{a,t}$, $Experience_{a,t}$, $FirmExperience_{a,i,t}$, $SpecializedIndustry_{a,i,t}$, $Log\#Words_{a,i,t}^{Climate}$ (not reported). Standard errors, three-way clustered at the analyst, firm, and year-quarter level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

	$\#NER_{a,i,t}^{Climate}$	$\#Money_{a,i,t}^{Climate}$	$\#Law_{a,i,t}^{Climate}$	$\#Number_{a,i,t}^{Climate}$	$\#Time_{a,i,t}^{Climate}$	$\#Location_{a,i,t}^{Climate}$	$\#Event_{a,i,t}^{Climate}$	$\#Org_{a,i,t}^{Climate}$	$\#Nat_{a,i,t}^{Climate}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ValueConv_{a,i,t}^{Climate}$	0.009*	0.768***	-0.244**	-0.060***	0.095***	-0.239***	-0.173**	0.015	-0.278***
	(0.006)	(0.029)	(0.109)	(0.013)	(0.010)	(0.013)	(0.083)	(0.016)	(0.036)
$ValuesConv_{a,i,t}^{Climate}$	-0.020***	0.002	0.452***	-0.040**	-0.088***	0.024	0.068	0.082***	0.116***
	(0.006)	(0.027)	(0.145)	(0.016)	(0.012)	(0.015)	(0.121)	(0.015)	(0.042)
Difference (*p*-value)	0.002	0.000	0.000	0.307	0.000	0.000	0.131	0.004	0.000
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	133,019	51,284	2,526	105,748	123,266	97,896	3,589	89,930	27,645
pseudo R-sq	0.364	0.237	0.107	0.230	0.253	0.222	0.105	0.212	0.143

Table 6 Climate Change Conversations and Abnormal Trading Volumne

This table reports regressions that relate trading volumes around the earnings announcement date to whether the earnings call held contains climate change conversations or not. Regressions are estimated at the firm-quarter level. $LogAbnVol_{i,t}$ is the natural logarithm of the average daily share turnover (i.e., trading volume divided by the number of shares outstanding) for firm i in quarter t over the [-1,+1]-day window around the earnings announcement day, net of the average daily share turnover in the [-40,-11]-days window. $Call_{i,t}^{Climate}$ equals 1 if at least one conversation in an earnings call of firm i in quarter t is classified as climate change-related, and 0 otherwise. $ValueCall_{i,t}^{Climate}$ ($ValuesCall_{i,t}^{Climate}$) equals 1 if at least one climate change question from the climate change conversation in the earnings call of firm i in quarter t is classified as *value*-related (*values*-related). We consider earnings calls on the earnings announcement date or one day after. In Columns 3 and 4, we additionally control for $Book\text{-}to\text{-}Market_{i,t}$, $Leverage_{i,t}$, $Cash_{i,t}$, $Investment_{i,t}$, $ROA_{i,t}$, $EarningsGrowth_{i,t}$, and $SalesGrowth_{i,t}$ (not reported). Standard errors, clustered at the firm level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

	$LogAbnVol_{i,t}$			
	(1)	(2)	(3)	(4)
$Call_{i,t}^{Climate}$	0.015*		0.020**	
	(0.009)		(0.009)	
$ValueCall_{i,t}^{Climate}$		0.039***		0.043***
		(0.009)		(0.010)
$ValuesCall_{i,t}^{Climate}$		0.024**		0.022*
		(0.012)		(0.012)
$MarketCap_{i,t}$	0.060***	0.059***	0.078***	0.077***
	(0.019)	(0.019)	(0.020)	(0.020)
$Dispersion_{i,t}$	0.512*	0.510*	0.272	0.271
	(0.297)	(0.297)	(0.306)	(0.306)
$UE_{i,t}$	0.296**	0.297**	0.187	0.187
	(0.137)	(0.137)	(0.148)	(0.148)
$LogPrice_{i,t}$	-0.004	-0.003	-0.023	-0.023
	(0.020)	(0.020)	(0.021)	(0.021)
$CAR_{i,t}^{EA}$	-0.815***	-0.815***	-0.861***	-0.861***
	(0.041)	(0.041)	(0.042)	(0.042)
Additional Controls	N	N	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
N	128,151	128,151	115,962	115,962
adj. R-sq	0.407	0.407	0.409	0.409

Table 7 Characterizing Questions from Climate Change Analysts

This table reports regressions explaining whether the numbers of named entities in climate change conversations differ between climate change analysts and other analysts. Regressions are estimated at the conversation level. The sample in this table includes only climate change conversations (i.e., we require $ClimateConv_{a,i,t} = 1$). The dependent variables are the numbers of different kinds of named entities in climate change conversations. Panel A focuses on comparing $ClimateAnalyst_{a,t}$ with other analysts. $ClimateAnalyst_{a,t}$ equals 1 if analyst a is identified as a climate change analyst in year t, and 0 otherwise. A climate change analyst poses more climate change questions than the yearly industry average for their coverage portfolio in a year. Panel B explores whether $ValueClimateAnalyst_{a,t}$ and $ValuesClimateAnalyst_{a,t}$ compose climate change questions differently. $ValueClimateAnalyst_{a,t}$ equals 1 if the analyst is identified as a *value* climate change analyst in a given year, and 0 otherwise. A *value* climate change analyst poses more *value* climate change questions than the yearly industry average for their coverage portfolio in a specific year. $ValuesClimateAnalyst_{a,t}$ equals 1 if the analyst is identified as a *values* climate change analyst in a given year, and 0 otherwise. A *values* climate change analyst poses more *values* climate change questions than the yearly industry average for their coverage portfolio in a specific year. The regressions control for $\#Questions_{a,i,t}$, $\#FirmCoverage_{a,t}$, $\#IndustryCoverage_{a,t}$, $\#CallsAttended_{a,t}$, $Experience_{a,t}$, $FirmExperience_{a,i,t}$, $SpecializedIndustry_{a,i,t}$, $Log\#Words^{Climate}_{a,i,t}$ (not reported). Standard errors, three-way clustered at the analyst, firm, and year-quarter level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Climate Change Questions from Climate Change Analysts

	$\#NER^{Climate}_{a,i,t}$	$\#Money^{Climate}_{a,i,t}$	$\#Law^{Climate}_{a,i,t}$	$\#Number^{Climate}_{a,i,t}$	$\#Time^{Climate}_{a,i,t}$	$\#Location^{Climate}_{a,i,t}$	$\#Event^{Climate}_{a,i,t}$	$\#Org^{Climate}_{a,i,t}$	$\#Nat^{Climate}_{a,i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ClimateAnalyst_{a,t}$	0.052***	0.034	0.165	0.043***	0.006	0.172***	0.100	0.086***	0.137***
	(0.007)	(0.034)	(0.152)	(0.014)	(0.013)	(0.020)	(0.108)	(0.015)	(0.037)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	133,733	89,361	4,270	127,989	133,134	115,478	7,500	117,612	41019
pseudo R-sq	0.393	0.301	0.102	0.288	0.307	0.236	0.109	0.236	0.145

Panel B: Climate Change Questions from Value and Values Climate Change Analysts

	$\#NER^{Climate}_{a,i,t}$	$\#Money^{Climate}_{a,i,t}$	$\#Law^{Climate}_{a,i,t}$	$\#Number^{Climate}_{a,i,t}$	$\#Time^{Climate}_{a,i,t}$	$\#Location^{Climate}_{a,i,t}$	$\#Event^{Climate}_{a,i,t}$	$\#Org^{Climate}_{a,i,t}$	$\#Nat^{Climate}_{a,i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ValueClimateAnalyst_{a,t}$	0.048***	0.315***	0.081	0.025*	0.065***	0.021	0.128	0.060***	-0.026
	(0.007)	(0.030)	(0.123)	(0.015)	(0.010)	(0.015)	(0.091)	(0.014)	(0.032)
$ValuesClimateAnalyst_{a,t}$	0.018***	0.008	0.047	0.007	-0.024**	0.099***	0.019	0.060***	0.127***
	(0.007)	(0.023)	(0.113)	(0.014)	(0.010)	(0.014)	(0.100)	(0.016)	(0.032)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	133,019	51,284	2,526	105,748	123,266	97,896	3,589	89,930	27,645
pseudo R-sq	0.364	0.222	0.103	0.230	0.252	0.220	0.104	0.212	0.141
Difference (p-value)	0.003	0.000	0.865	0.341	0.000	0.000	0.484	0.997	0.001

Table 8 Career Trajectories of Analysts: Summary Statistics

This table tabulates the statistics of analysts' years of work, seniority, and career progress in three periods: before, during, and after attending earnings calls. $YearsofWork$ is calculated as the number of years the analyst a has worked before her first appearance in an earnings call, during the period of attending earnings calls, and after her last attendance to an earnings call. $Mid_{a,t}$, $MidSeniord_{a,t}$, and $Seniord_{a,t}$ are indicator variables measuring the seniority of the analysts in the period and equal to 1. $Promotion_{a,t+1}$ equals 1 if the analyst moves to a new job title with higher seniority over the next year, and 0 otherwise. $Promotion^{Refined}$ is defined similarly to $Promotiond_{a,t+1}$ but with a more granular definition of seniority. We refine the senior classification based on the prefix of job titles within the mid, mid-senior, and senior brackets. For example, changing the title from "associate director" to "director" is now considered a promotion as well. $NewCompany_{a,t+1}$ equals 1 if the analyst moves to a different company over the next year, and 0 otherwise. $ESGJob_{a,t+1}$ equals 1 if the analyst has an ESG job in the year. We aggregate all these variables by analyst in each of the three periods by taking maximum values of Mid, $Mid\text{-}Senior$, $Senior$, and $ESGJob$ and summing the values of $Promotion_{a,t+1}$, $Promotion^{Refined}_{a,t+1}$, and $NewCompany_{a,t+1}$. Then we report the mean of all the variables across analysts before, during, and after attending earnings calls. The Appendix defines all variables in detail.

Mean	Before Attending Earnings Calls	While Attending Earnings Calls	After Attending Earnings Calls
$Years\,of\,Work_{a,t}$	7.541	6.177	5.060
$Mid_{a,t}$	0.320	0.303	0.298
$Mid\text{-}Senior_{a,t}$	0.309	0.486	0.508
$Seniorb_{a,t}$	0.148	0.246	0.345
$NewCompany_{a,t+1}$	1.783	1.154	0.844
$Promotion_{a,t+1}$	0.528	0.506	0.313
$Promotion^{Refine}_{a,t+1}$	0.567	0.546	0.355
$ESGJob_{a,t+1}$	0.008	0.012	0.027

Table 9 Climate Analyst Career Trajectories

This table reports regressions that relate the career trajectories of analysts to their records of posing climate questions in the earnings calls. Regressions are estimated at the analyst-year level. $ClimateAnalyst_{a,t}^{Profile}$ is the cumulative sum of years that analyst a in year t has been identified as a climate change analyst scaled by the $WorkExperience_{a,t}$ of the analyst a in year t. $WorkExperience$ is calculated as the number of years since the analyst's first job was reported in the LinkedIn profile. $ValueClimateAnalyst_{a,t}^{Profile}$ and $ValuesClimateAnalyst_{a,t}^{Profile}$ are defined accordingly but based on *value*- and *values*-centric climate change questions. $Promotion_{a,t+1}$ equals 1 if the analyst moves to a new job title with higher seniority over the next year, and 0 otherwise. $Promotion_{a,t}^{Refined}$ is defined similarly to $Promotion_{a,t+1}$ but with a more granular definition of seniority. Panel A focuses on the career path of climate change analysts and Panel B bifurcates climate change analysts into *value* and *values* climate change analysts. Column 1 reports regression results on $Promotion_{a,t+1}$ defined by this seniority measure. We further refine the senior classification based on the prefix of job titles within the mid, mid-senior, and senior brackets. For example, changing the title from "associate vice president" to "director" is now considered a promotion as well. Column 2 repeats the analyses in the first column with the refined measure $Promotion_{a,t+1}^{Refined}$ measure. $NewCompany_{a,t+1}$ equals 1 if the analyst moves to a different company over the next year, and 0 otherwise. $ESGJob_{a,t+1}$ equals 1 if the analyst takes an ESG job over the next year. The regressions control for $AttendingCalls_{a,t}$, $PostAttendingCalls_{a,t}$, $Mid_{a,t}$, $Mid\text{-}Senior_{a,t}$, $Senior_{a,t}$, $BusinessDegree_{a,t}$, $PhD_{a,t}$, and $WorkExperience_{a,t}$ (not reported). Standard errors, double-clustered at the analyst and broker level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Climate Change Analysts

	$Promotion_{a,t+1}$	$Promotion_{a,t+1}^{Refined}$	$NewCompany_{a,t+1}$	$ESGJob_{a,t+1}$
	(1)	(2)	(3)	(4)
$ClimateAnalyst_{a,t}^{Profile}$	0.005**	0.005**	0.016***	0.003**
	(0.003)	(0.003)	(0.003)	(0.002)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Analyst FE	Y	Y	Y	Y
N	34,317	34,317	34,317	34,317
adj. R-sq	0.063	0.058	0.058	0.356

Panel B: Value and Values Climate Change Analysts

	$Promotion_{a,t+1}$	$Promotion_{a,t+1}^{Refined}$	$NewCompany_{a,t+1}$	$ESGJob_{a,t+1}$
	(1)	(2)	(3)	(4)
$ValueClimateAnalyst_{a,t}^{Profile}$	0.005*	0.005*	0.010***	0.002
	(0.003)	(0.003)	(0.004)	(0.002)
$ValuesClimateAnalyst_{a,t}^{Profile}$	-0.001	-0.001	0.006*	0.002
	(0.003)	(0.003)	(0.003)	(0.001)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Analyst FE	Y	Y	Y	Y
N	34,317	34,317	34,317	34,317
adj. R-sq	0.063	0.057	0.058	0.356

Table 10 Analyst Coverage Discontinuation

This table reports regressions that relate the discontinuation of coverage to whether the analyst is classified as a climate change analyst or not. Regressions are estimated at the analyst-firm-year level. $DropCoveragea, i, t+1$ equals one if analyst a drops coverage of firm i over the upcoming year $t+1$. $ClimateAnalyst_{a,t}$ equals 1 if analyst a is identified as a climate change analyst in year t, and 0 otherwise. A climate change analyst poses more climate change questions than the yearly industry average for their coverage portfolio in a year. Column (2) explores whether $ValueClimateAnalyst_{a,t}$ and $ValuesClimateAnalyst_{a,t}$ compose climate change questions differently. $ValueClimateAnalyst_{a,t}$ equals 1 if the analyst is identified as a *value* climate change analyst in a given year, and 0 otherwise. A *value* climate change analyst poses more *value* climate change questions than the yearly industry average for their coverage portfolio in a specific year. $ValuesClimateAnalyst_{a,t}$ equals 1 if the analyst is identified as a *values* climate change analyst in a given year, and 0 otherwise. A *values* climate change analyst poses more *values* climate change questions than the yearly industry average for their coverage portfolio in a specific year. Regressions are estimated using a linear probability model. Standard errors, clustered at the firm and analyst level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

	$DropCoverage_{a,i,t+1}$	
	(1)	(2)
$ClimateAnalyst_{a,t}$	-0.008***	
	(0.002)	
$ValueClimateAnalyst_{a,i,t}$		-0.009***
		(0.002)
$ValuesClimateAnalyst_{a,i,t}$		-0.004*
		(0.002)
$Buyside_{a,i,t}$	0.094***	0.094***
	(0.004)	(0.004)
$\#FirmCoverage_{a,i,t}$	0.039***	0.039***
	(0.002)	(0.002)
$\#IndustryCoverage_{a,i,t}$	0.013***	0.014***
	(0.001)	(0.001)
$Experience_{a,t}$	0.009***	0.009***
	(0.001)	(0.001)
$FirmExperience_{a,i,t}$	-0.018***	-0.018***
	(0.001)	(0.001)
$\#CallAttended_{a,i,t}$	-0.077***	-0.076***
	(0.002)	(0.002)
$\#Questions_{a,i,t}$	-0.003***	-0.003***
	(0.000)	(0.000)
$SpecializedIndustry_{a,i,t}$	-0.035***	-0.035***
	(0.002)	(0.002)
Firm × Year FE	Y	Y
N	838,268	838,268
adjpseudo R-sq	0.093	0.093

Internet Appendix

for

Climate *Value* and *Values* Discovery in Earnings Calls

ZACHARIAS SAUTNER, LAURENCE VAN LENT, GRIGORY VILKOV,

and RUISHEN ZHANG*

This Internet Appendix provides additional tables and figures supporting the main text. Section I explains the procedures of parsing analyst Q&A data from earnings call transcripts. Section II discusses how to identify buy-side analysts in earnings calls. Section III provides details about the rules classifying the seniority of analysts' job titles. Section IV and V contains the technical details on fine-tuning the BERT model and named entity recognition. Section VI describes the definition of climate change analysts. Section VII provides additional tables.

*Citation format: Zacharias Sautner, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, Internet Appendix for "Analysts' Value and *Values* Discovery in Earnings Calls".

I. Parsing Q&As and Identifying Analysts from Earnings Call Transcripts

The earnings conference call transcripts contain three sections: participants' information, the management presentations, and the questions & answers (Q&A) sessions. We parse the Q&A sessions into discrete questions and answers. These are then mapped to the respective participants. Questions from individual analysts and their corresponding answers are grouped together, preserving the original sequence of each question and answer.

Transcripts are sourced from Eikon and contain detailed participant information in the header. We extract names, affiliations, and job titles for corporate participants—namely, managers—and we do the same for the other earnings call participants such as analysts. We subsequently align the participants' details from the header with the speaker details in the Q&A portion of the transcripts. Consequently, we transform the Q&A transcript text into a table format. Each row of the table encompasses the text of a continuous speech by a participant, an indicator identifying the speech as either a question or an answer, and the associated speaker's details. This method not only preserves the original order of speeches during the earnings call, but it also omits any speech by operators. We categorize a continuous speech from an analyst as a *question* (or *query*). Any subsequent management responses, up until the next question, are classified as an *answer*. The collective of all questions posed by an individual analyst, along with the responses to them during a single earnings call, is referred to as a *conversation*.

Next, we strive to identify individual analysts across multiple earnings calls. Unlike structured databases such as IBES—where researchers can utilize a unique analyst identifier to seamlessly connect the forecasts of a singular analyst across different firms or time spans—earnings call transcripts present as unstructured texts, devoid of an immediately accessible identifier for call participants. Nevertheless, the information regarding analysts embedded within the transcripts can serve as a foundation to formulate a distinct identifier for each analyst (misspellings, abbreviations, and aliases occasionally mar the analyst names and affiliations in these transcripts).

We extract all analyst names in the transcripts and generate a TF-IDF vector for each, using sequences of two contiguous characters. Subsequently, we compute the cosine similarity among these names. This approach allows us to pinpoint names that are potentially misspelled or abbreviated. Utilizing these harmonized names, we craft a unique identifier for the analysts. This methodology is replicated for analyst affiliations, producing a unique brokerage identifier. We acknowledge that our methodology might not capture every nuance in name variations and might occasionally misidentify the conversations of analyst A_i as those of analyst A_j. To mitigate potential inaccuracies, our sample criteria dictate that an analyst must participate in at least 10 calls, and a brokerage must be represented in at least 50 calls. This restriction helps exclude erroneously attributed conversations.

Our empirical tests draw from a sample of 313,380 transcripts. This sample comprises 11,855 distinct firms and 21,431 individual analysts, representing 1,907 brokers and various other institutions.

II. Buy-side Classification

We employ ChatGPT to distinguish between buy-side and sell-side analysts. Initially, we provide ChatGPT 4.0 with the 1,907 unique affiliations of the analysts. We then instruct it with the following prompt:

> *From the provided list, please categorize the firms into buy-side and sell-side based on their primary operations. Recognize buy-side firms as those primarily managing investments on behalf of clients, including but not limited to mutual funds, pension funds, private equity funds, hedge funds, insurance firms, family offices, asset management, venture capital, wealth management, and capital management. Classify sell-side firms as those like investment banks, market makers, broker-dealers, financial advisors, and equity research providers. If a firm, such as JP Morgan, Goldman Sachs, or UBS, is primarily an investment bank but has divisions explicitly named as buy-side operations, for instance, "Goldman Sachs Asset Management," then classify it as buy-side. Otherwise, treat it as sell-side. Firms purely offering financial research, like Autonomous Research LLC, or rating/service providers, including Morningstar and Standard & Poor's, should not be placed in either category.*

Following ChatGPT's classification, we review the separated buy-side and sell-side firm lists, rectifying any errors based on internet searches. We further refine the categorization by designating a firm as buy-side if its name includes terms like "asset management" or "investment management" or if the analyst's designation reads as "fund manager" or "portfolio manager." Our analysis identifies 617 distinct buy-side firms and 4,876 buy-side analysts. These figures align well with the findings of Jung et al. (2018), given our sample constraints.

III. Seniority of Analysts

We infer the seniority of analysts from the job titles disclosed in their LinkedIn profiles. We rely on the observation that most analysts work in the financial industry throughout their careers and develop rules tailored to the norm of the financial industry to classify job titles into junior, mid, mid-senior, and senior categories. The mid category includes "vice president" and variations such as "assistant or senior vice president" and "manager." The mid-senior category mainly consists of directors, principals, and heads of teams. Managing directors, founders, board members, presidents, and C-suite officers are classified in the senior category. The following table depicts the keywords we used to assign seniority to the job titles. A job title with at least one of the keywords will be classified into the corresponding seniority category. When a job title matches more than one keyword, we take the most senior category. If the job title matches with no keywords, it is classified in the junior category.

Seniority	Keywords in Job Titles
Mid	'vp', 'vice president', 'vicepresident', 'manager', 'fund manager', 'portfolio manager', 'svp', 'senior vp', 'sr vp', 'sr vice president', 'senior vice president'
Mid-Senior	'director', 'executive director', 'principal', 'partner', 'head'
Senior	'md', 'managing director', 'managing partner', 'cio', 'chief investment officer', 'founder', 'ceo', 'cfo', 'coo', 'chief executive officer', 'chief financial officer', 'chief operating officer' , 'board' , 'chairman', 'managing member', 'chief of staff'

We further refine the stratification of seniority by further comparing the prefixes of job titles, such as "associate" and "executive." Specifically, we list the hierarchy of five prefixes and no-prefix as follows: assistant < associate < no prefix < executive or senior < managing. We impose the prefix rule within the three seniority categories to capture that an executive director should be more senior than an associate director.

IV. Fine-tuning the FinBERT Model for Climate Change Text Classification

As with most large-scale transformer-based models, the application of BERT consists of two critical stages: pre-training and fine-tuning. During pre-training, the model is trained on a vast corpus of unlabeled data, learning representations via tasks like masked language modeling and next-sentence prediction. Once this base model is established, it is further refined or fine-tuned on domain-specific *labeled* data to adapt it to specific downstream tasks—here, text classification.

For our task of classifying questions and answers in earnings calls, we opt for FinBERT, a domain-adapted version of BERT. The reasons are as follows. Firstly, considering the nuance in earnings call transcripts—where an average question spans 42 words—a misinterpretation, such as conflating "economic climate" with "physical climate," could skew classification outcomes. Unlike traditional methods, like bag-of-words or even deep learning models such as LSTM, transformer-based models, particularly BERT, are adept at capturing contextual semantics, ensuring robustness in our classification. Secondly, FinBERT, having been pre-trained on financial documents—including corporate filings, analyst reports, and earnings call transcripts—naturally offers a semantic edge. It grasps finance-specific jargon more efficiently, making the fine-tuning process more streamlined and effective.[1]

Building on the dataset from Sautner et al. (2023), we curated an enhanced set of labeled snippets, resulting in roughly 2400 snippets derived from a randomized subset of earnings call transcripts. For the fine-tuning stage, we allocate 81 percent of this dataset for training FinBERT on climate content detection. The residual data is segmented for validation (9 percent) and testing (10 percent). The training regimen is executed over ten epochs at a $5e^{-5}$ learning rate. This approach yields commendable results, with F1 scores of 96 percent for the validation set and 94 percent for the test set.

V. Named Entity Recognition (NER)

Named Entity Recognition (NER) is a fundamental task in natural language processing (NLP). It seeks to locate and classify named entities in text into predefined categories such as persons, locations, monetary values, and more. We utilize the built-in transformer-based large language model from SpaCy to recognize named entities within earnings call Q&As.

SpaCy's default named entity types are enumerated as follows:

Entity Type	Definition
PERSON	People, including fictional.
NORP	Nationalities, religious or political groups.
FAC	Buildings, airports, highways, bridges, etc.
ORG	Companies, agencies, institutions, etc.
GPE	Countries, cities, states.
LOC	Non-GPE locations, mountain ranges, bodies of water.
PRODUCT	Objects, vehicles, foods (excluding services).
EVENT	Named hurricanes, battles, wars, sports events, etc.
WORK_OF_ART	Titles of books, songs, etc.
LAW	Named legal documents.
LANGUAGE	Any named language.
DATE	Absolute or relative dates or periods.
TIME	Times within a day.
PERCENT	Percentages, including "%."
MONEY	Monetary values, including units.
QUANTITY	Measurements, e.g., weight or distance.
ORDINAL	"first," "second," etc.
CARDINAL	Numerals not classified elsewhere.

For the purpose of our analysis, we group the NER types into specific categories:

[1]When models are pre-trained on generic corpora, domain-specific terms might be treated as anomalies, affecting the model's efficacy in specialized tasks. Thus, a generic BERT model would necessitate an additional step: first adapting it to the financial domain using a masked language modeling task before the climate change-focused fine-tuning.

Variable	Constituent NER Types
Law	LAW
Location	GPE, LOC, FAC
Number	QUANTITY, PERCENT, ORDINAL, CARDINAL
Money	MONEY
Time	DATE, TIME
Event	EVENT
Nationality	NORP
Organization	ORG

We demonstrate the usage of named entities in the climate change questions with ten real excerpts from the earnings call transcripts in Table IA.III. The named entities are in **bold** and followed by the named entity type in brackets.

VI. Identifying Climate Change Analyst

We create the variable $ClimateAnalyst_{a,t}$ to capture an analyst's emphasis on climate change questions relative to their peers covering the same sectors during the same period. We first count the number of earnings calls, $\#Call_{a,s,t}$, attended by analyst a during year t for each SIC2 industry s and the number of climate questions, $\#CCQ_{a,t}$, posed by analyst a in year t. We then calculate the average number of climate questions in a conversation, $\overline{\#CCQ}_{s,t}$, for each SIC2 industry s in year t. Then the benchmark number of climate change questions, $\widehat{\#CCQ}_{a,t}$, for analyst a in year t is calculated as $\Sigma_s \overline{\#CCQ}_{s,t} \times \#Call_{a,s,t}$.

Finally, $ClimateAnalyst_{a,t}$ is constructed as an indicator variable that equals 1 if $\#CCQa,t > \widehat{\#CCQ}_{a,t}$, and 0 otherwise. The construction procedures take account into that some industry attributes and macroeconomic events may stimulate climate change questions unrelated to analysts' emphasis on climate change. For example, analysts covering energy sectors naturally ask questions about oil production and alternative energy, which are considered climate change-related. However, we cannot simply classify every energy analyst as climate analyst.

VII. Additional Tables

Table IA. I Climate Change Questions and Answers

This table reports the interplay between (non-)climate change questions and answers in conversations.

	Climate Answer = 0	Climate Answer = 1	Total
Climate Question = 0	1,451,777	109,425	1,561,202
Climate Question = 1	73,466	103,903	177,369
Total	1,525,243	213,328	1,738,571

Table IA. II Value Keywords

This table lists the keywords used to identify valuation content in questions. We also use the plurals of these keywords when applicable.

earning	asset	inventory
profit	debt	receivable
eps	liability	payable
revenue	capex	equity
sales	tax	investment
margin	dividend	roa
income	interest rate	roe
ebit	loan	roi
ebitda	depreciation	cogs
cash	amortization	intangible
expenditure	bond	ppe
expense	stock	property, plant, and equipment
cost	capital gain	sg&a
loss	net worth	sga
working capital	overhead	

Table IA. III Named Entities in Climate Change Questions

This table demonstrates the usage of named entities in the climate change questions with ten real excerpts from the earnings call transcripts. The named entities are in **bold** and followed by the type of the named entity in a bracket.

Company	Quarter	Analyst	Affiliation	Question
E.ON AG	2009Q4	Martin Young	Nomura	... and are you holding back in any particular way for the possible outcomes of the **Copenhagen summit** [***EVENT***], which may or may not put upward pressure on the carbon price, post the end of this year? thank you.
Grupo Bimbo	2015Q4	Alex Robarts	Citigroup	....it seems pretty well documented that we've got **El Nino** [***EVENT***] coming through and with the dryness that is expected to bring in **Oceania** [***LOC***], particularly the wheat outlook from **Australia** [***GPE***] has pressured the global wheat prices... So, tell us or could you walk us through how you are just thinking about the wheat price on average **next year** [***DATE***]...
Scania AB	2010Q4	Chris Youl	MainFirst Bank	... I just wanted to follow up on some of the comments you made this morning around the **Euro 6** [***LAW***] transition, which I think is on **January 1, 2014** [***DATE***]. I appreciate it's a long way off, but you mentioned there was talk of incentives in **Europe** [***LOC***] already...
Enel Green Power	2015Q3	Cosma Panzacchi	Sanford C. Bernstein & Co	... my second question again is on additional opportunities in **Italy** [***GPE***]. So we have seen that you have started investing in biomass. if I read the **draft green act** [***LAW***] by the (inaudible) government right now, there is clearly an additional opportunity for formal sugar refineries to be converted in biomass power plants...
Volvo	2010Q3	Arndt Ellinghorst	Credit Suisse	... on the **Euro 6** [***LAW***], obviously we talk a lot about **EPA** [***ORG***] '10. we know that these engines are roughly **$8,000** [***MONEY***] to **$10,000** [***MONEY***] more expensive...and then just more strategically maybe comparing **Volvo's** [***ORG***] truck business to **Daimler** [***ORG***], I think it's fair to say that your businesses are relatively similar at least from a global footprint in size. ...
Petroleo	2019Q1	Vicente Falanga Neto	Banco Bradesco	...with **the energy council** [***ORG***] possibly setting the date for the auction today. now from Petrobras' standpoint, does the company see **bill 78** [***LAW***] in the **senate** [***ORG***] as a prerequisite to sign this contract...
Titan Cement	2019Q1	Iakovos Kourtesis	Piraeus Securities	...if you could identify for us what is the price increases you took in **Florida** [***GPE***], and the plant price increases that would be applied to **mid-Atlantic** [***GPE***]? if you're covered on co2 emission rights for **2019** [***TIME***] in your markets?
Centrica PLC	2014Q1	Mark Freshney	Credit Suisse	...firstly on the impact of the **polar vortex** [***EVENT***] in **north America** [***GPE***], the **$70 million** [***MONEY***] to **$80 million** [***MONEY***]...
Endesa SA	2011Q4	Javier Suarez	Nomura	...the question could be if you could give us a flavor of which could be the result from **Chile** [***GPE***] in normalized weather conditions? ... I would like if you could give us quantify the effect that the implementation of the **domestic coal decree** [***LAW***] has on the numbers of Endesa so far this year. many thanks.
HELLA	2019Q2	Julian Radlinger	UBS	okay. great. and then my second question relates to the **European Union** [***ORG***] co2 targets in **2020** [***DATE***] and **2021** [***DATE***] . I think what's pretty clear is that many **OEMs** [***ORG***], especially the **European** [***NORP***] ones, are going to launch **48** [***CARDINAL***] miles hybrid models and plug-in hybrid models quite aggressively, starting basically now and well into the **next 2 years** [***DATE***]...

Table IA. IV Characterizing Content of Conversation with and without Climate Change Questions

This table reports regressions that relate the content (or specificity) of questions to whether the conversation is classified as $ClimateConv = 1$ or not. Panel A includes all the questions from the conversations. Panel B omits climate change-related questions from the conversations. Regressions are estimated at the conversation level. The regressions control for $\#Questions_{a,i,t}$, $\#FirmCoverage_{a,t}$, $\#IndustryCoverage_{a,t}$, $\#CallAttended_{a,t}$, $Experience_{a,t}$, $FirmExperience_{a,i,t}$, $SpecializedIndustry_{a,i,t}$, $Length_{a,i,t}$ (not reported). Standard errors, three-way clustered at the analyst, firm, and year-quarter level, are in parentheses. The Appendix defines all variables in detail. *p<0.1; **p<0.05; ***p<0.01.

Panel A: Named Entities in Questions

	$\#NER_{a,i,t}$	$\#Money_{a,i,t}$	$\#Law_{a,i,t}$	$\#Number_{a,i,t}$	$\#Time_{a,i,t}$	$\#Location_{a,i,t}$	$\#Event_{a,i,t}$	$\#Org_{a,i,t}$	$\#Nat_{a,i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ClimateConv_{a,i,t}$	0.004	-0.130***	0.239***	-0.026***	-0.076***	0.317***	0.270***	0.101***	0.283***
	(0.003)	(0.010)	(0.054)	(0.005)	(0.004)	(0.008)	(0.057)	(0.007)	(0.016)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,710,579	1,285,705	66,023	1,693,511	1,708,545	1,374,318	165,933	1,632,405	522,491
pseudo R-sq	0.361	0.278	0.099	0.246	0.262	0.245	0.108	0.211	0.141

Panel B: Named Entities - Non-Climate-Related Questions

	$\#NER_{a,i,t}$	$\#Money_{a,i,t}$	$\#Law_{a,i,t}$	$\#Number_{a,i,t}$	$\#Time_{a,i,t}$	$\#Location_{a,i,t}$	$\#Event_{a,i,t}$	$\#Org_{a,i,t}$	$\#Nat_{a,i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ClimateConv_{a,i,t}$	-0.050***	-0.027**	-0.117*	-0.010**	-0.059***	-0.045***	-0.019	-0.049***	-0.031**
	(0.003)	(0.011)	(0.064)	(0.005)	(0.004)	(0.006)	(0.037)	(0.006)	(0.015)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,710,281	1,269,647	61,095	1,689,114	1,707,619	1,352,655	157,609	1,620,410	491,767
pseudo R-sq	0.383	0.284	0.104	0.258	0.278	0.244	0.111	0.221	0.144

Swiss Finance Institute

Swiss Finance Institute (SFI) is the national center for fundamental research, doctoral training, knowledge exchange, and continuing education in the fields of banking and finance. SFI's mission is to grow knowledge capital for the Swiss financial marketplace. Created in 2006 as a public–private partnership, SFI is a common initiative of the Swiss finance industry, leading Swiss universities, and the Swiss Confederation.

swiss:finance:institute

c/o University of Geneva, Bd. Du Pont d'Arve 42, CH-1211 Geneva 4
T +41 22 379 84 71, rps@sfi.ch, www.sfi.ch