Analysts' Perspectives on Climate Change: An Examination of Analyst Reports

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Abstract: I explore the nature of analysts' climate-related discussion in their reports. Focusing on industries most exposed to climate change, I find a minority of analysts (less than 11%) discuss climate-related topics. Analysts concentrate their discussion on electric utilities and electronic equipment manufacturers and frequently use more specific language to discuss solar and wind technologies relative to conference calls. Climate-related discussions exhibit a weak association with more pessimistic long-term growth forecast revisions but are associated with more optimistic target prices when long-term growth forecasts are not recently revised, suggesting the development of a long-term perspective shapes analysts' translation of climate-related topics into financial expectations. Discussions of solar-, emissions-, and automotive-related bigrams are associated with greater target price optimism. These findings highlight analysts' focus on climate-related assessments for firms where these issues are most salient (e.g., utilities) and how these assessments can differ based on the decision to revise long-term growth forecasts.

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I. INTRODUCTION

I explore how sell-side equity analysts integrate climate change issues into their perspectives by exploring the frequency, nature, and consequences of their climate-related discussions in analyst reports. The economic consequences of climate change are expected to be widespread, with insurer Swiss Re predicting it will reduce economic output 11%–14% by 2050 (Flavelle 2021). These consequences include physical risks and transition risks but also potential opportunities.[1] Physical risks represent the increased likelihood of economic losses from extreme weather, rising sea levels and temperatures, and increasing drought intensity (SASB 2021), while transition risks represent economic consequences arising from regulations and the possibility of accelerated obsolescence of already developed products and technologies. Potential opportunities include selling new products or services (e.g., electric vehicles) and enhanced resource efficiency (Coppola et al. 2019).

Reflecting an emerging link between climate change and firms' economic outcomes, recent research notes that climate-related issues relate to firms' financial outcomes and a variety of temporal, industry, geographic, and firm factors influence the relationship (Kirk et al. 2025), leading to wide variation across firms (Hugon and Law 2019; Addoum et al. 2023). This variation suggests information intermediaries (e.g., sell-side equity research analysts) may play a role in evaluating how climate change will impact firms' finances and in processing climate-related information (e.g., Griffin et al. 2020). Emerging academic research explores this role, finding analysts revise their earnings expectations following extreme temperature events (Addoum et al. 2023; Cuculiza et al. 2021) and ESG-related incidents (e.g., Park et al. 2025;

[1] The Taskforce on Climate-Related Financial Disclosures (TCFD) and the US Environmental Protection Agency (EPA) consider regulatory risks as a subcategory of transition risks (TCFD 2020; EPA 2025), as the effects of regulation can induce other transition risks for firms, e.g., the accelerated obsolescence of certain technologies.

Derrien et al. 2024; Li et al. 2025). Recent research also explores analysts' use of ESG- and climate-related disclosures (Dhaliwal et al. 2012; Ding et al. 2024). I contribute to this literature by examining the role of analyst reports as a setting to discuss climate-related issues and how these discussions translate to analysts' forecasts.

In initial analyses, I observe patterns suggesting climate-related financial consequences are concentrated in the set of industries Sautner et al. (2023) identify as most exposed to climate change.[2] I additionally search over 1 million analyst reports for the frequency of the top 100 climate-related bigrams from Sautner et al. (2023) and identify reports containing at least five of these bigrams as discussing climate-related topics. I observe that very few (less than 1%) analyst reports discuss climate-related topics, and, of the 1,163 reports that do, 946 (81%) relate to firms operating in the most exposed industries. These analyses imply analysts focus their climate-related discussion where the issues matter most. Motivated by this observation, I focus my remaining analyses on firms operating in these industries.

Next, I observe that, even among firms in the most exposed industries, climate-related discussion is infrequent, with a minority of analysts (less than 11%) and reports (less than 1.5% in any given year) discussing climate-related topics. Climate-related discussion is concentrated in two industries: 40% of climate-related reports come from utilities (SIC = 49), and 34% come from electronic and other electric equipment (SIC = 36). Climate-related discussion usually relates to regulation, opportunities, and transition-related topics, and a substantial minority of reports discuss specific technologies, including solar (27%) or wind (26%). Additionally, six of the top 10 most frequent bigrams appearing in analyst reports consist of specific solar- (e.g., "solar PV") or wind-related (e.g., "wind power") terms. This suggests analysts focus on specific

[2] Appendix B contains a list of these industries as identified by Sautner et al. (2023).

technologies when discussing climate-related topics in their reports. I also observe that climate-related discussion is positively associated with report length and the initiation of reports, implying climate-related discussion is often part of a deeper analysis. I likewise note that climate-related discussion is positively associated with firms' participation in the EPA Greenhouse Gas Reporting Program and a firm's Refinitiv environmental innovation score, consistent with research indicating analysts consume environmental-related information from many sources (Griffin et al.2020) and suggesting they are more likely to discuss climate-related topics for firms classified as environmental innovators.

Exploring how analysts translate climate-related views into financial expectations, I explore how their climate discussion relates to earnings, long-term growth, and target price forecasts. I observe that this discussion is associated with 10.8% more pessimistic long-term growth forecast revisions than the forecasts of non-climate-discussing peers, which represents an incremental 0.19 percentage points lower than non-climate-discussing analysts. I also observe that climate-related discussion is associated with more *optimistic* target price forecasts that are met for fewer days, implying at least some analysts view climate change as presenting opportunities. Taken together, these patterns appear puzzling and contradictory. However, research suggests only a few analysts publish long-term growth forecasts (Jung et al. 2012) and that the process of developing those forecasts requires effort but helps facilitate a long-term perspective. Thus, I partition the sample into reports matched with and without a long-term growth forecast, finding the link between climate-related discussion and target price optimism is concentrated among *unmatched* reports. This suggests that how analysts translate climate-related topics to expectations can differ based on whether they are also concurrently revisiting long-term growth and that at least some analysts view climate change as presenting opportunities.

When decomposing analysts' climate-related discussion into broader subtopics (e.g., transition, regulatory, physical, emissions, and opportunities) or more specific subtopics (e.g., solar, wind, emissions, or automotive), I observe weak evidence suggesting that the increased pessimism in long-term growth forecast revisions is concentrated in transition-related topics and that the increased ex ante optimism in target prices for reports unaccompanied by a long-term growth forecast is concentrated among discussions of solar-, emissions-, and automotive-related topics.

Together, these analyses offer a few insights. First, the concentration of climate-discussing analyst reports in two industries suggests analysts prioritize the assessment of climate issues in settings where these issues matter most (e.g., utilities). Second, analysts discuss climate-related topics in greater specificity and detail in their reports than in earnings conference calls, as explored by Sautner et al. (2023), frequently discussing the specifics of solar- and wind-related technologies. Third, climate discussions exhibit some association with more pessimistic long-term growth forecast revisions and more optimistic target prices among reports not also accompanied by a long-term growth forecast. This suggests that the longer horizon perspective used to assess long-term growth can shape how analysts view climate change, particularly their assessment of transition-related topics, and that the processing of climate-related information into forecasts can differ based on analysts' decisions to explicitly forecast long-term growth.

My findings add to the growing literature on the relationship between climate change, its financial consequences, and how market participants process information about these consequences. By examining analysts' narratives about climate-related topics, I build upon work studying the corporate consequences of climate change (Hugon and Law 2019) and analysts' responses to climate shocks (Cuculiza et al. 2021; Addoum et al. 2023; Faralli 2024). My findings that only a minority of analysts focused on the most exposed industries discuss climate-related topics but discuss more specific solar- and wind-related terms suggests analyst reports offer a venue for deeper explorations of how climate issues shape firm outcomes. This finding adds to Sautner et al. (2023) by identifying how market participants' language surrounding climate change differs based on the discussion setting and adds to research studying how analysts respond to negative ESG incidents (Park et al. 2025; Li et al. 2024). My findings also highlight analysts' efforts to focus their climate-related discussion on firms facing the greatest exposure, building on Kirk et al.'s (2025) observation that analysts may not fully incorporate the earnings consequences of weather-related fluctuations.

This study also relates to a broader literature studying analysts' and investors' information processing costs (e.g., Griffin et al. 2020; Blankespoor et al. 2020) by suggesting that processing climate-related topics can be costly for analysts and that analysts thus focus on firms where these issues matter most, consistent with their information gathering costs impacting their processing decisions (e.g., Plumlee 2003; Jennings et al. 2017). My findings also suggest some analysts are willing to incur these high processing costs for firms where climate-related issues are particularly important (e.g., utilities) and highlight how unique issues in the climate change setting, notably climate change's wide reaching and multi-faceted effects, can interact with analysts' time orientations to inform differing perspectives.

II. MOTIVATION AND RESEARCH QUESTIONS

II.1. Climate change-related topics in analyst reports

I begin by exploring the frequency and nature of climate change-related discussion in analyst reports. To the extent analysts view climate change as having financial consequences (e.g., Hugon and Law 2019; Painter 2020) for their coverage portfolios, written reports can serve as a way for them to highlight their perspectives about climate-related issues. As climate change and its effects increasingly impact firms' financial and operational outcomes (e.g., Ramkumar 2023; Emont 2024), research finds that analysts are considering these issues, as studies observe extreme weather impacts analysts' forecasting (Bourveau and Law 2021; Cuculiza et al. 2021; Faralli 2024) and that analysts respond to negative ESG incidents by downgrading forecasts (e.g., Derrien et al. 2024; Park et al. 2025). Most related to my research question is the work of Sautner et al. (2023), who develop a firm-year level measure of climate change exposure based on climate change discussions during earnings conference calls and show this measure relates to real firm outcomes, including job creation and patenting. As part of their study, Sautner et al. (2023) also develop a dictionary of climate change-related bigrams following the approach of King et al. (2017), which enables the use of these validated bigrams to explore the frequency and nature of analysts' climate-related discussion in analyst reports. I build upon Sautner et al. (2023) by exploring how analysts' use of these terms differs in the report setting.

To the extent analysts' written reports have informational value (e.g., Asquith et al. 2005; Twedt and Rees 2012; Huang et al. 2014; Huang et al. 2018), climate-related discussion in them could reflect analysts' perspectives on which industries, firms, and types of climate-related issues are most closely linked to financial outcomes. This leads to my first research question:

RQ1: How frequently do analysts discuss climate-related topics in their analyst reports and on which industries, firms, and climate-related issues do these discussions focus?

II.2. The determinants of climate-related discussion in analyst reports

Besides exploring the frequency of climate-related discussion in analyst reports, I also explore the potential determinants of analysts' decisions to discuss climate-related topics. Recent studies suggest personal exposure to extreme weather impacts analysts' forecasting (e.g., Bourveau and Law 2021; Cuculiza et al. 2021; Faralli 2024) and that personal and firm characteristics can influence the relationship between climate-related events and forecasting outcomes (Faralli 2024; Li et al. 2024). Other recent work highlights the firm and industry implications of climate change (Kirk et al. 2025) and the availability of environmental information (Griffin et al. 2020), suggesting firm characteristics relate to the likelihood of climate-related discussion. De Franco et al. (2015) observe several analyst characteristics that impact report readability, including analyst experience and forecasting frequency, suggesting these forces could also impact climate-related discussions. Other studies note that analysts' access to environmental disclosures can impact their forecasting (e.g., Ioannou and Serafeim 2015; Dhaliwal et al. 2012; Griffin et al. 2020), suggesting the climate-related information environment could influence climate discussions in analyst reports. Finally, research suggests that brokerage resources, as proxied by brokerage size, can influence forecasting outcomes, implying resources and access to internal expertise (e.g., Hugon et al. 2016) along with resource constraints (i.e., time constraints, as highlighted by Driskill et al. 2020) can influence climate-related discussion. Together, these insights from prior research motivate my second research question:

RQ2: What report, analyst, and firm characteristics are associated with climate-related discussion in analyst reports?

II.3. Climate-related discussion and forecasting

Next, I explore how analysts process climate-related issues and translate them into expectations by exploring whether climate-related discussion in analyst reports is associated with forecasting consequences. Recent research (e.g., Addoum et al. 2023; Bourveau and Law 2021; Faralli 2024) suggests physical climate change-related events impact analysts' forecasting, and other studies highlight analysts' processing of environmental disclosures and ratings (Griffin et al. 2020). However, Ben-Amar et al. (2024) find that firms' disclosures highlighting climate change-related transition risk "are not associated with financial analyst forecast properties." To the extent that analyst report discussion about climate-related topics reflects analysts' efforts to link climate-related issues to firms' financial outcomes, climate discussion could be associated with differences in earnings, long-term growth, and target price forecasts. This would reflect analysts' attempts to process climate-related insights into perspectives on firms' prospects, consistent with Griffin et al. (2020). Climate-related discussion in analyst reports can translate to forecasts in two broad ways. First, to the extent that analysts develop climate-related insights for their reports, they could also use these insights to inform their forecasts. This could occur through assessments of how climate-related issues (e.g., extreme weather, shifting consumer preferences, or regulation) could impact firms' ability to generate revenues (e.g., increased sales from selling electric vehicles), shift their expenses (e.g., increased compliance costs with new regulations), or growth in either of these line items. As a result, analysts' forecasts of earnings, long-term growth rates, and target prices could be associated with climate-related discussion in reports. Second, if analysts perceive climate-related issues as altering the riskiness or volatility of firms' future financial outcomes, analysts may apply climate-related insights to valuations by shifting discount rates (consistent with Park et al. 2025), resulting in changing target prices.

Alternatively, discussion in reports about climate-related topics may not relate to forecast properties. To the extent analysts' discussion of climate-related issues in their reports is primarily meant to inform clients about potential topics to consider and analysts do not translate these insights into forecasts and valuations, climate-related discussion in analyst reports may not be associated with shifts in forecast properties (e.g., Ben-Amar et al. 2024). This leads to my third research question:

RQ3: Does climate-related discussion in analyst reports relate to differences in earnings, long-term growth, and/or target price forecasts?

III. RESEARCH DESIGN AND SAMPLE SELECTION

III.1. Research design for frequency and determinants of climate-related discussion

III.1.1. Measurement of climate-related discussion in analyst reports

Two challenges exist with exploring the frequency and determinants of climate-related discussion in analyst reports. The first is identifying which analyst reports contain climate-related discussion. The second is identifying the types of climate-related topics discussed. To address the first, I apply Sautner et al.'s (2023) list of the top 100 bigrams associated with their climate change exposure measure, presented in their Table 2. Sautner et al. (2023) developed this list of bigrams using the supervised machine learning approach of King et al. (2017) and applied it to the full transcript of earnings conference calls to identify climate change-related bigrams or pairs of words. I count the frequency each of the top 100 climate change-related bigrams from Sautner et al.'s (2023) Table 2 in each report. I aggregate the frequencies of all climate-related bigrams at the report level. To mitigate the concern this approach generates false positives, I require a report contain more than five occurrences of climate change bigrams before classifying it as an individual analyst report that discusses climate-related topics.[3]

To address the second challenge of identifying the types of climate-related discussion, I conduct three sets of analyses. First, I tabulate the frequency counts of the Sautner et al. (2023)

[3] To test the validity of this approach and explore the possibility of false positives (Bingler et al. 2022), I randomly select 100 analyst reports with more than five climate-related bigrams and read each on my own. I find 86% of individual reports discuss climate-related topics.

climate-related bigrams across the sample of 946 climate-related analyst reports for firms in the most exposed industries. This tabulation helps assess whether the language analysts use in their reports to discuss climate-related topics correlates with the language used during conference calls. Second, I group the Sautner et al. (2023) bigrams into subcategories based on the technologies mentioned in the bigrams and explore patterns in these subcategories. Third, leveraging recent advancements in large language model-based textual analysis techniques (e.g., de Kok 2025), I worked with LyraText, an external analytics firm, to present each climate-discussing report identified under the bigram search approach to four different large language models and prompt each model to identify whether each discusses physical risks (e.g., extreme weather exposure), carbon emissions, transition risks (e.g., shifting consumer preferences for low emissions products), regulatory risks (e.g., new renewable energy mandates), or opportunities (e.g., new product lines) related to climate change, noting that a single report can discuss multiple topics.[4,5]

Specifically, I presented each analyst report classified as discussing climate-related topics using the bigram count approach to each of four LLMs in early March 2025: Anthropic's Claude 3.5 Haiku, Google's Gemini 2.0 Flash, Google's Gemini 2.0 Flash Lite, and OpenAI's GPT 4o-mini and prompted each LLM to identify whether each report discussed each of the topical areas detailed above. An individual analyst report can contain multiple categories of discussion, and

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[4] I also evaluated the possibility of applying a Latent Dirichlet allocation (LDA) model to these reports to identify sub-topical areas. However, in an initial application of a model fitted with 130 topics, while some topics appeared to contain climate-related terms, these subtopics primarily related to industry specific terminology, such as "utilities infrastructure" or "oil and gas" and suggested climate-related issues are more often discussed not as a standalone topic but as part of a broader, integrated discussion about the business.

[5] In identifying these topical areas, I started with the broad TCFD classifications of physical and transition risks. The TCFD, EPA, and CDP all acknowledge climate change may present economic opportunities, and I include a subtopic area for opportunities. The CDP asks explicit questions about regulatory issues, motivating the decision to sub-divide transition risk into separate transition and regulatory categories. Given the CDP focus on carbon emissions and the capital market implications of carbon emissions data (Matsumura et al. 2014; Griffin et al. 2017), I add an additional subtopic for emissions.

often an individual report will discuss a variety of climate-related topics. For each report, I classify the report as discussing a particular climate-related subtopic only if all four LLMs agreed the report discussed that subtopic.[6] In general, the models agreed with each other fairly frequently, making the same classifications roughly 70%–79% of the time. The inter-rater Cohen's Kappa statistics exhibited variation, ranging between 0.18 and 0.74, depending on the topic and the LLMs used for comparison. Across the models overall, the Cohen's Kappa statistics averaged between 0.3334 (physical topics) and 0.6904 (regulatory topics), suggesting fair to substantial agreement between the LLMs but some level of disagreement, depending on the specific LLM pairings and subtopics. This highlights how, even with an LLM-based approach, different models reading the same report can reach different conclusions on whether a report contains a particular subtopic, indicating climate-related discussion can be nuanced and open to interpretation.[7]

III.1.2. Empirical approach

To explore RQ2, I apply a determinants model and include a series of report, analyst, and firm characteristics to explore whether these factors are associated with climate-related discussion in analyst reports. I use the following determinants model, labeled equation 1:

$$CLIMATE-RELATED_{i,j,k,t} = ReportCharacteristics_{i,j,k,t} + AnalystCharacteristics_{j,t} + FirmCharacteristics_{k,t} + YearFE + \varepsilon_{i,j,k,t}, \qquad [1]$$

[6] A small number of reports could not be processed by two of the LLMs: Claude 3.5 Haiku (7 reports) and GPT-4o mini (25 reports). Reports that could not be sub-classified by either of these LLMs (27 reports) were set to missing and excluded from analyses.

[7] For comparison purposes, I alternatively recruited two undergraduate or graduate business school research assistants at a large university to independently read each report and identify, based on their assessment, whether each report discussed each subtopic. I did not override these classifications. Comparing the two independently classified results, I observe Cohen's Kappa statistics of between approximately 0.20 and 0.44 between the humans, suggesting human readers exhibited fair to moderate agreement in subtopic classification and highlighting how, under either approach, there can be differences in interpretation of climate-related discussion.

where CLIMATE-RELATED is an indicator equal to 1 if analyst report *i* issued by analyst *j* covering firm *k* on date *t* has more than five climate-related bigrams. *ReportCharacteristics* include a series of report characteristics that could relate to the presence of climate-related discussion. These include length (LN_REPORT LENGTH) and whether the report is an initiation report (INITIATING), intended to capture whether climate-related discussion relates to analysts' decision to produce more complex analyses, as research suggests processing environmental information is costly (Griffin et al. 2020) and thus analysts may be more (or less) likely to incur these costs when already making a substantial investment in information processing. I additionally include the number of other reports issued by the analyst on the same day (REPORTS ISSUED SAME DAY) and whether the report is issued within three days following an earnings announcement for the firm (WITHIN 3 DAYS OF AN EA) or another firm in the analyst's coverage portfolio (WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM) to capture the possibility that attention constraints (Driskill et al. 2020) impact climate-related discussion.

I additionally include *AnalystCharacteristics*, which reflects individual analyst characteristics that research has shown to be associated with forecast properties. Specifically, I include analysts' general experience (LN_GENERAL EXPERIENCE) and firm coverage experience (LN_FIRM SPECIFIC EXPERIENCE) to explore whether expertise (Clement 1999) impacts climate-related discussion. Like Clement (1999), I include the number of firms covered (LN_NUMBER OF COVERED FIRMS), industries covered (LN_NUMBER OF COVERED INDUSTRIES), and the number of forecasts the analyst previously issued for the firm (LN_NUMBER OF ANNUAL FORECASTS) as well as the number of reports the analyst issues during the year (NUMBER OF REPORTS ISSUED DURING THE YEAR). To proxy for resource availability following Clement (1999), I include brokerage size (LN_BROKER SIZE).

Li et al. (2024) note that female analysts are more likely to discuss ESG issues, so I additionally include FEMALE.[8] To the extent analyst expertise in a highly exposed industry or the availability of environmental disclosures make climate-related issues more salient (Griffin et al. 2020), I include an indicator for whether the analyst primarily covers most exposed firms (PRIMARILY COVERS EXPOSED INDUSTRIES) and the number of firms in the analyst's coverage portfolio disclosing to CDP (NUMBER OF PORTFOLIO FIRMS IN CDP). Di Giuli and Kostovetsky (2014) and Jiang et al. (2016) note that partisanship can influence views on ESG issues and analysts' forecasting, and I include POLITICAL SPECTRUM, a measure of analysts' political beliefs following Jiang et al. (2016).

FirmCharacteristics capture a series of firm characteristics that could relate to analysts' decisions to discuss climate-related topics. Following de Franco et al. (2015) and Huang et al. (2014), I include general firm controls, including book-to-market ratio (BOOK-TO-MARKET) and the market value of equity to proxy for firm size (FIRM SIZE). To measure the role of the information environment in shaping analysts' decisions to discuss climate-related topics (Griffin et al. 2020), I include analyst coverage (LN_FOLLOWING) and firm age (LN_FIRM_AGE) (Hamers et al. 2016). As institutional investors increasingly seek climate-related disclosures from firms, a firm's institutional ownership (INSTITUTIONAL OWNERSHIP %) could also relate to analysts' decision to discuss climate-related topics (Krueger et al. 2020; Flammer et al. 2021). I include leverage (LEVERAGE) and return on assets (ROA) to explore whether capital structure or financial performance is associated with climate-related discussion. I additionally explore firm environmental characteristics that may influence climate-related discussion, as Griffin et al.

[8] I measure gender by submitting each analyst's name to Gender-API.com, "the biggest platform on the internet to determine gender by a first name, a full name, or an email address." Recent research (e.g., Ballestero and Chan 2025) finds this approach is reasonably accurate.

(2020) highlight the role this plays in shaping analysts' information processing costs. These include whether the firm participates in CDP (FIRM COMPLETES CDP) or the EPA Greenhouse Gas Reporting Program[9] (FIRM PARTICIPATES IN EPA GHG REPORTING PROGRAM), whether it had an environmental offense reported to Violation Tracker last year (FIRM RECEIVED ENVIRONMENTAL PENALTY LAST YEAR), as well as the three environmental subcomponents of Refintiv's ESG scores, motivated by research suggesting CSR and ESG ratings factor into analysts' assessments (e.g., Ioannou and Serafeim 2015). Appendix A defines all variables.

III.1.3. Sample selection

Table 1 Panel A presents the sample selection process for the descriptive analyses. The sample begins with 1,026,478 analyst reports in ThomsonOne for S&P 500 member firms between January 1, 2009, and October 1, 2020. I downloaded these reports between October and December 2020. I match these reports to IBES broker and analyst identifiers, matching 701,562 reports. I then match each report to an outstanding IBES recommendation, resulting in 526,740 reports for 876 firms issued by 2,627 analysts working for 109 brokers. I then screen for nonmissing report, analyst, and firm characteristics, leaving a sample of 415,531 reports for 651 firms issued by 2,062 analysts working for 97 brokerages. If I further screen for only reports issued for firms operating in the most exposed industries, as defined by Sautner et al. (2023) in their Table 3, this leaves a sample of 107,578 reports for 191 firms issued by 995 analysts working for 85 brokerages. Report-level variables come from ThomsonOne, while analyst variables come from IBES and firm variables come from Compustat, CRSP, or Thomson

[9] The EPA GHG Reporting Program is a mandatory reporting regime where the EPA requires facilities producing large amounts of greenhouse gas emissions to report emissions from these facilities to the EPA, which makes the data publicly available each October. Tomar (2023) discusses this program.

Reuters. Data on analysts' position along the political spectrum come from Federal Election Comission (FEC) contribution filings during the 2010–2020 election cycles, following Jiang et al. (2016). Data on firms' environmental characteristics, including their participation in the Carbon Disclosure Project (CDP) and the EPA Greenhouse Gas Reporting Program, come from each organization, while Violation Tracker provides data on regulatory violations and Refinitiv provides ESG environmental-related category scores (resource use, emissions, and environmental innovation scores). [10]

III.2. Research design for climate-related discussion and forecast properties

III.2.1. Empirical approach

To explore whether climate-related discussion in analyst reports is associated with forecast properties, I use the following OLS regression labeled equation 2:

$$FORECAST\_OUTCOME_{i,j,k,t} = \beta_1 CLIMATE - RELATED_{i,j,k,t} + ReportCharacteristics_{i,j,k,t} + AnalystCharacteristics_{j,t} + \beta_{14} HORIZON_{i,j,k,t} + Fixed\ Effects\ + + \varepsilon_{i,j,k,t}, \quad [2]$$

where FORECAST_OUTCOME represents one of several forecast-level outcomes, including earnings forecast revisions (REVISION), signed forecast error (SCALED_FE), absolute forecast error (SCALED_AFE), outstanding long-term growth forecasts (LONG-TERM GROWTH), long-term growth forecast revisions (LONG-TERM GROWTH FORECAST REVISIONS), target price forecast optimism (TARGET PRICE AS % OF SHARE PRICE), and target price

[10] Recent research suggests changes to the IBES database during 2018–2021 may be potentially problematic for this study. Law (2023) notes that, during this period, WRDS published a research note claiming that IBES anonymized many brokerage and analyst identifiers, making it challenging to identify individual analysts. Law (2023) documents that this issue is largely concentrated among non-US firms and that IBES reversed this reshuffling in March 2020. For this study, I use IBES earnings forecast data downloaded outside of this reshuffling window and focus on US firms, making the IBES anonymization and reversal a less significant concern. Despite the timing appearing not to represent a major concern, I acknowledge that any remaining reshuffling of identifiers is a potential drawback of this study.

accuracy measures (TARGET PRICE MET NUMBER OF DAYS).[11] The control variables include the time-varying report and analyst characteristics from equation 1 plus a control for the time between forecast issuance and the actual earnings announcement date for the earnings forecast (HORIZON), consistent with research suggesting the forecast horizon relates to forecasting properties (Raedy et al. 2006).[12]

III.2.2. Sample selection

Table 1 Panels B–D present the sample selection process for tests of equation 2. In Panel B, I match reports with earnings forecasts in year *t*,[13] beginning with the 130,301 analyst reports for 251 firms authored by 1,192 analysts employed by 98 brokers matched to an outstanding recommendation for firms operating in the most exposed industries. Next, I screen for non-missing report and analyst variables, resulting in 117,968 reports for 232 firms authored by 1,020 analysts employed at 86 brokers. From here, I match these reports to earnings forecasts (Panel B), long-term growth forecasts (Panel C), or target prices (Panel D) issued within 90 days of report issuance[14], resulting in 110,399 (earnings forecasts), 16,914 (long-term growth forecasts), or 86,443 (target price forecasts) reports.[15] For earnings and long-term growth forecasts, I also explore revisions, where I subsequently screen for non-initiation reports with non-missing earnings (long-term growth) forecast revision data, which requires the presence of a new and an

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[11] For forecast revisions, this requires the presence of two forecasts. I construct revisions first within IBES for each analyst-firm-fiscal year (for earnings) or analyst-firm (for long-term growth) prior to merging with the reports and when merging, merge in the corresponding constructed values for forecast values, revisions, errors, and target price measures.

[12] HORIZON is not included as a control variable for tests of long-term growth and target price forecasts.

[13] I also explore earnings forecasts for *t+1* and *t+2* and note that the samples for these tests are smaller due to attrition in the number of analysts that provide these values to IBES.

[14] In additional untabulated analyses, I match using a narrower +/- 60-day window and draw similar inferences.

[15] The median number of days between the report date and the matched forecast issuance date is 1 day for earnings forecasts in year *t*, 9 days for long-term growth forecasts, and 8 for target price forecasts.

old forecast to construct revisions. This reduces the sample in these tests to 78,744 and 14,685 reports for earnings and long-term growth forecasts, respectively.

IV. MAIN RESULTS

IV.1. Summary statistics

Table 2 presents summary statistics for variables used throughout the study. I present summary statistics for the full sample of 415,531 reports in columns 1 and 2 and the subsample of 107,578 (307,953) reports for firms (not) operating in the most exposed industries in columns 3 and 4 (5 and 6). I highlight several observations from Table 2. First, the percentage of reports with climate-related discussion is extremely low at approximately 0.2% of the full sample. Climate-related discussion is concentrated among the most exposed firms, representing 0.7% of all reports in these industries versus nearly zero outside these industries. Second, reports for the most exposed firms differ along a few analyst-level dimensions. Specifically, these reports come from analysts working at larger brokerages (82.73 analysts versus 79.68 for non-exposed industries) and analysts who issue fewer reports during the calendar year (82.03 reports versus 87.20 for non-exposed industries). Third, firms in the most exposed industries are more likely to participate in the CDP (53.6% versus 51.3%) and the EPA Greenhouse Gas Reporting Program (9.6% versus 0.1%) and are more likely to have reported an environmental offense in the prior year (34.1% versus 17.1%) but have higher environmental subscores assigned by Refinitiv, particularly for environmental innovation (0.439 vs. 0.253). Taken together, the summary statistics suggest that climate-related discussion is concentrated among most exposed industries and that, outside these industries, there is little climate-related discussion.

IV.2. Focus on most exposed industries

I focus the remaining analyses on the subsample of firms in the most exposed industries identified by Sautner et al. (2023). This comprises a list of 20 industries with the highest industry-wide average values on various permutations of their *CCExposure* score, tabulated in Appendix B.[16] I focus on this group of industries for several reasons. First, from Table 2, I observe climate-related discussion is concentrated in this group of firms and is nearly nonexistent outside of these industries. Second, in untabulated preliminary analyses, I observe the association between climate risk exposure (proxied by the number of climate-related risks reported to CDP) and firm financial performance (proxied by ROA) is concentrated in these industries. Specifically, I find a negative and significant association between the number of climate-related risks and ROA in the years following CDP data release but only in industries most exposed to climate change. Decomposing a firm's disclosed climate-related risks into separate physical and transition risk components suggests the link between climate-related risks and financial performance is driven by transition risk (coeff. = -0.007, $p < 0.05$ in year t+1).

These findings collectively motivate the decision to focus only on firms operating in the most exposed industries, where the link between climate change and financial outcomes strengthens and where analysts' discussion of climate-related topics is concentrated. Additionally, 81% of analyst reports with climate-related discussions come from this group of highly exposed industries.[17] Thus, for the remainder of the study, I focus on the subsample of firms operating in Sautner et al.'s (2023) list of the most exposed industries.

IV.3. Prevalence and determinants of climate-related discussion

[16] The list in Appendix B is simplified compared to Sautner et al.'s (2023) Table 3, as I remove duplicate appearances of industries in Appendix B.

[17] As part of the report classification process, I classified 1,163 reports as discussing climate-related topics (i.e., CLIMATE-RELATED = 1). Of these 1,163 reports, 946 (81%) are for firms operating in the most exposed industries identified by Sautner et al. (2023), suggesting climate-related discussion in analyst reports is concentrated in these industries.

Next, I conduct a series of descriptive analyses to explore the characteristics of climate-related reports. In Figure 1, I plot the percentage of analyst reports (Panel A) and unique analysts who issue at least one climate-related report (Panel B) for firms in the most exposed industries. First, although 81% of climate-related reports address these firms, climate-related reports represent a very small percentage (between 0.4% and 1.4% in any given year) of overall reports for these firms, though this percentage has grown since 2014. Second, approximately 4%–11% of unique analysts discuss climate-related topics at least once each year, suggesting only a minority of analysts covering highly exposed firms discuss climate-related topics in their reports. This suggests that discussing climate issues may require substantial effort and attention. Third, both the percentage of reports and unique analysts discussing climate-related topics decline from the start of the sample period in 2009 until 2014 and rebounding. Both rebound after 2019, as public opinion about prioritizing environmental issues spikes (Gallup 2025).

To explore why the trend in climate-related discussion changes beginning in 2014, I retrieve all 90 reports discussing climate-related topics in 2014 and 2015 and read each. First, I observe the EPA proposed the Clean Power Plan on June 2, 2014, which entailed new regulations around carbon emissions from power generating facilities (English 2014).[18] These proposed rules appeared in several analyst reports for utilities. Second, the onset of revised hot water heater efficiency standards in 2015[19] also appeared as a topic of interest for impacted firms (e.g., A.O. Smith Corporation). Third, some analyst reports during 2014 and 2015 noted the impending reduction in the solar Investment Tax Credit (ITC) from 30% of eligible costs to 10%, which was

[18] The EPA Clean Power Plan was initially proposed in 2014 and finalized in 2015. However, the Supreme Court in 2016 stayed implementation (EPA 2017), and the EPA withdrew the plan in 2017 (Puko 2017).
[19] This presentation by the American Council for an Energy-Efficient Economy highlights the impact of this rule on hot water heater manufacturers:
https://www.aceee.org/sites/default/files/files/pdf/conferences/hwf/2016/Trant_Session6D_HWF16_2.23.pdf

expected to occur beginning in 2017.[20] Together, these anecdotal observations suggest that the shifting regulatory and policy landscape beginning in 2014 could have stimulated climate-related discussion.

In Figure 2, I examine the industry composition of the 946 analyst reports discussing climate-related topics to determine whether these reports are further concentrated in specific industries. In Panel A, I observe that most reports (approximately 74%) come from two industries: electric, gas, and sanitary services (SIC code = 49) and electronic and other equipment (SIC code = 36). Firms in these industries include power utilities (e.g., Eversource and Exelon) and electric equipment companies (e.g., General Electric, Intel, and NVIDIA). This implies that, even within highly exposed industries, climate-related discussion is concentrated in two sectors where climate issues are particularly salient. In Panel B, I present the LLM-based summary of the relative frequency of each subcategory discussed using the approach outlined in section III.1.1. Across the categories, this approach suggests climate-related discussion covers regulation, opportunities, and transition-related topics most frequently.

Next, I tabulate the frequency of the Sautner et al. (2023) bigrams in this sample of 946 analyst reports. Table 3 presents the frequency of the bigrams in rank order of appearance in the sample of analyst reports along with their frequency and rank order of appearance in Sautner et al.'s (2023) sample of earnings conference calls. From Table 3, I make two observations. First, the top 10 bigrams appearing in the sample of analyst reports pertain primarily to renewable energy topics, including renewable energy, clean energy, solar, and wind power. This is consistent with the high concentration of these reports among electric utilities and other electrical

[20] Chan and Fischer (2025) explore the Investment Tax Credit (ITC) and its consequences for electric utilities.

equipment companies (e.g., General Electric).[21] Second, the correlation between a particular bigram's frequency rank order in the analyst reports and in Sautner et al.'s (2023) set of conference calls is 0.53 (untabulated), indicating there are some distinct differences in frequency ranks between the two settings. For example, "solar PV," "solar farm," and "scale solar" appear among the top 10 bigrams appearing in the analyst reports but are ranked much lower in Sautner et al.'s (2023) conference call data. In contrast, the reports contain far fewer discussions of less specific terms, like "eco friendly" or "sustainability goal," suggesting analysts are focused on specific topics closely linked to the underlying business.[22]

To further explore this notion, I group each of the Sautner et al. (2023) bigrams into a few broad categories, depicted in Table 4, first focusing on specific technologies or topics (solar, wind, emissions, automotive, regulatory, physical related issues, and combustion and gas) and then grouping bigrams discussing renewable energy generally into a renewables category and the remaining terms into a general climate change category (e.g., climate change). I then create a series of indicators to mark whether an analyst report contains any bigrams from each of these subcategories. In Table 4, I observe the gap in average rank order of appearance between analyst reports and conference calls in Sautner et al. (2023) is starkest for solar-related bigrams (average rank order of 15.67 in analyst reports versus 50 in conference calls), suggesting analysts discuss solar more extensively in reports than during conference calls. [23]

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[21] In additional untabulated analyses, I count the number of climate-related reports by firm and observe the five firms with the most climate-related reports are General Electric (154 reports), First Solar (103 reports), NextEra Energy (74 reports), Public Service Enterprise Group (42 reports), and SunEdison (42 reports).
[22] I thank an anonymous reviewer for highlighting this point.
[23] Interestingly, the mix of topics also evolves. In an untabulated analysis, I observe declines in solar-related discussion and increases in automotive-related and general renewables discussion over time. Additionally, the mix of companies with the most climate-related reports also evolves, with First Solar being the most common firm covered by climate-related reports in earlier years and General Electric the most common more recently. Over time, there are also some firms that frequently have a small number of climate-related reports (e.g., Southern Company). This suggests that while there may be some patterns consistent with analysts herding climate-related discussion into a few companies (e.g., General Electric and First Solar), there are also cases where climate-related discussion appears

Figure 2 Panel C highlights the percentage of climate-related reports discussing each of the subtopics depicted in Table 4. Most reports (71%) contain at least some discussion of general renewable terms like "clean energy," with fewer reports (38%) discussing general climate change terms. Consistent with the notion that analysts discuss solar extensively, solar-specific bigrams are the third most frequent category, with 27% of reports containing at least one. In untabulated tests, I also observe that, conditional on discussing solar-related topics, analysts discuss them extensively, using on average 7.16 bigrams. Compared with the unconditional mean of using 10.54 bigrams (untabulated) to discuss climate-related topics overall, this implies extensive and detailed solar discussion when it occurs.

Table 5 presents results of the determinants analysis conducted using equation 1. Columns 1–4 explore report, analyst, firm, or firm environmental characteristics alone, while Column 5 combines both firm and firm environmental characteristics and Column 6 explores all these characteristics together. Generally, across the columns, I observe that climate-related discussions are positively associated with report length and initiation reports, suggesting that analysts are more likely to include climate-related topics as part of a deeper investigation into the firm. I also observe analysts are less likely to discuss climate-related topics in the three days following an earnings announcement (WITHIN 3 DAYS OF AN EA) for the firm, suggesting analysts deprioritize climate-related topics during busy periods (e.g., Driskill et al. 2020) and processing climate-related information is costly (e.g., Plumlee 2003). I also observe that firms'

somewhat idiosyncratic, not inconsistent with some analysts expressing 'boldness' in discussion (e.g., Clement and Tse 2005). I leave the more direct exploration of herding-like behavior for climate-related discussion to future research.

participation in the EPA Greenhouse Gas Reporting Program and their environmental innovation scores are positively associated with climate-related discussion.[24]

Taken together, these descriptive analyses highlight a few insights. First, analysts are more likely to discuss specific technologies, particularly solar-related topics, in their reports relative to conference calls. Second, analysts discuss solar-related topics more extensively than other types of climate topics. Third, these detailed discussions are more likely to occur as part of deep analyses of the firm and less likely to occur when analysts are attention constrained.

IV.4. Climate-related discussion and forecast properties

IV.4.1. Earnings forecasts

To explore RQ3 and how climate-related discussion in analyst reports relates to forecast properties, I begin by exploring whether that discussion is associated with earnings forecasts. This analysis can also provide insight into how climate-discussing analysts translate their discussions into earnings expectations. I take each analyst report and match it to the closest earnings forecast issued for the analyst-firm pair within 90 days of the report date. I study earnings forecast revisions and errors for the current fiscal year *t*, the next fiscal year *t+1*, and the following fiscal year *t+2*. Table 6 Columns 1–3 presents analyses of forecast revisions, while Columns 4–6 present analyses of forecast optimism (signed forecast errors), and Columns 7–9 present analyses of forecast accuracy (absolute forecast errors). In all regressions, I use analyst and firm-fiscal year fixed effects to control for analyst-specific, time-invariant factors or firm-year specific factors. I also control for the time-varying analyst and report characteristics from equation 1 and the forecast horizon. Across the columns, I observe little evidence that climate-

[24] According to Refinitiv (2021), this score captures "a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed products." In a more recent update of Refinitiv's ESG scoring methodology, this category retains a similar definition (LSEG 2024).

related discussion is associated with EPS forecast revisions, optimism, or accuracy across the upcoming three fiscal years.

This suggests that, to the extent climate-discussing analysts translate their climate insights into expectations about firms' financial performance, they appear not to be doing so through earnings forecasts, on average.[25] If analysts expect the economic consequences of climate change to manifest in later years, climate-related discussion may be associated with long-term growth and target price forecasts, which are more likely to incorporate analysts' assessments of longer-term factors impacting the firm. I explore this possibility next.

IV.4.2. Long-term growth and target price forecasts

In Table 7, I explore whether climate-related discussion is associated with long-term growth and target price forecasts using the equation 2 framework previously applied to earnings forecasts. In Columns 1 and 2, I explore long-term growth forecast levels (column 1) and long-term growth forecast revisions (column 2). Given research indicates that developing a long-term growth forecast is costly and difficult for analysts (Jung et al. 2012), the number of observations available to study long-term growth forecasts is lower, comprising 16,914 reports issued for 200 firms by 404 analysts employed by 52 brokerages.[26] Jung et al. (2012) note that long-term growth forecasts are an outcome of a process where analysts explicitly take a long-term (3-5 years, based on IBES definitions and Décaire and Guenzel 2025) view, and thus to the extent analysts view climate change as a long-run issue, they could translate these views into long-term growth forecasts. In Table 7 Columns 1 and 2, while I observe little evidence of a statistically

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[25] In additional untabulated tests decomposing the earnings forecast regressions into sub-topical areas, I observe some evidence regulatory-related (emissions-related) discussions are associated with negative (positive) earnings forecast revisions in year *t* while solar- and physical-related (gas-related) topics are associated with negative (positive) revisions in year *t+1* and emissions and general climate-related (general renewables-related) discussion are negatively (positively) associated with forecast revisions in year *t+2*.

[26] The exact number of observations used in the regression analyses in Table 7 is slightly lower due to the removal of singleton observations induced by the analyst and firm-year fixed effects structure.

significant association between climate discussion and long-term growth forecast levels (Column 1), I observe a negative and statistically significant association between climate-related discussion and long-term growth forecast revisions (coeff. = -0.108, $p < .05$), suggesting climate-discussing analysts revise their long-term growth forecasts 10.8% lower than other analysts covering the same firm-fiscal year. Benchmarked against the sample median long-term growth rate of 9% (untabulated) and the median long-term growth forecast revision of –1.77% (untabulated), this implies climate-discussing analysts revise their long-term growth forecasts, on average, approximately an incremental 0.19 percentage points (-1.77% times 0.108) lower than other analysts covering the same firm-fiscal year or 2.12% of the median long-term growth rate. For comparison purposes, Dechow et al. (2000) observe affiliated analysts forecast long-term growth more optimistically than unaffiliated ones, with differences in long-term growth rates approximately between three to seven percentage points higher for affiliated analysts, depending on the comparison group. Lin and McNichols (1998) document narrower differences in growth rates between affiliated and unaffiliated analysts, observing differences between approximately 27 and 56 basis points, depending on the comparison group. Compared to both studies, Table 7 Columns 1 and 2 suggest the effects of climate-related discussion are of somewhat smaller economic magnitude than affiliation with the lead underwriter.[27]

[27] In supplemental back-of-the-envelope type calculations, I consider two hypothetical analysts, one discussing climate-related topics and one not discussing climate-related topics, forecasting for the same firm and exhibiting similar forecast properties prior to revising long-term growth forecasts. In these analyses, I simulate how a long-term growth forecast revision for each analyst impacts their revised valuations. Given concurrent research noting long-term growth forecasts focus on the 3–5-year window (Décaire and Guenzel 2025), I model five years of EPS forecasts and the impact of climate-related discussion on one analyst's earnings forecasts in this window. Broadly, I observe the more pessimistic long-term growth forecast revisions associated with climate-related discussion translate to an approximately 0.46-0.48% lower valuation relative to the non-climate-discussing analyst, holding all other inputs constant (e.g., discount rate, pre-revision long-term growth forecast, terminal growth rate, and current year EPS forecast). For the median firm in the sample with an approximately $11 billion market capitalization prior to revision (untabulated), this translates into an approximately $51.8 million lower total valuation for climate-discussing analysts relative to non-climate discussing analysts covering the same firm and holding other inputs constant. I note these calculations are very broad and intended only to provide a rough order of magnitude effect and leave the more detailed exploration of how climate-related issues translate to valuations to future work.

In addition to long-term growth rates and because only a small subsample of analysts publish long-term growth forecasts, I explore the association between climate-related discussion and target price forecasts to understand whether climate-discussing analysts translate climate issues into valuations. In Table 7 Column 3, I observe weak evidence that these analysts issue marginally more *optimistic* target price forecasts (coeff. = 0.016, $p < .10$), with their forecasts being roughly 1.6 percentage points higher than those of other analysts covering the same firm-fiscal year. This is approximately 17.86% of the sample mean target price optimism of 8.9% above the outstanding share price three days prior to target price issuance. In terms of economic significance, Roger (2024) finds that analysts issue higher target prices with higher E, S, and G scores, noting that a one standard deviation change in E score is associated with an approximately two percentage point increase in target price optimism, suggesting climate-related discussion has a slightly smaller economic effect on target prices than one standard deviation changes in third-party ESG ratings. In Column 4, I observe evidence suggesting climate-discussing analysts' target prices are met for fewer days (coeff. = -0.270, $p < .01$) in the 12 months following target price issuance, which translates to target prices being met for approximately $1 - \exp(-0.270) = 23.6\%$ fewer days. Compared with the sample mean for TPMETDAYS of 124.10, this implies climate-related discussion is associated with target prices being met for $124.10 \times 23.6\%$ = approximately 29.29 fewer days.

Taken together with the long-term growth forecast revision results, this appears puzzling and contradictory, as I observe some evidence in Column 2 that climate-related discussion is associated with more pessimistic long-term growth forecast revisions. Jung et al. (2012) note that long-term growth forecasts reflect taking a long-term view, suggesting this process could influence how analysts translate climate-related issues into expectations to the extent climate change is a long-term issue (e.g., Painter 2020). To explore this possibility, in Columns 5–8, I split the sample of reports matched to a target price forecast into those also attached to a long-term growth forecast (Columns 5 and 7) and those not attached to a long-term growth forecast (Columns 6 and 8). In these tests, I find the association between climate-related discussion and target price optimism is concentrated among reports not linked to a long-term growth forecast (e.g., Column 6, coeff. = 0.019, $p < .05$). Similarly, the observation climate-related discussion is associated with fewer days of meeting the target price is concentrated among reports not matched to a long-term growth forecast (Column 8, coeff. = -0.304, $p < .01$). This suggests climate-related discussion in an analyst report is associated with target prices being met for 1 – exp(-0.304) = 26.2% fewer days for the reports not also connected to a long-term growth forecast. In terms of economic significance, this appears consistent with recent studies exploring how policy uncertainty impacts analysts' forecasts. Specifically, Chourou et al. (2021) find a 10% increase in general economic policy uncertainty relates to a 14% increase in earnings forecast errors and a 24% increase in earnings forecast dispersion. Similarly, Baloria and Mamo (2017) note that periods of high economic policy uncertainty are associated with 7% below average earnings forecast accuracy while Biswas (2019) notes "a doubling of economic policy uncertainty is associated with a 4.29 percentage point increase in earnings forecast errors", suggesting the effects of climate-related discussion are of similar economic magnitude to the effects of economic policy uncertainty on analyst earnings forecasts. In contrast, for the subsample of reports attached to both a long-term growth and target price forecast, I observe little evidence of statistically significant patterns. These findings build upon Sautner et al. (2023), who focus on studying the firm-level consequences of climate-related discussion during earnings conference calls by exploring how climate-related discussion translates to long-term growth and target price forecasts, along with how the decision to forecast long-term growth can relate to how the analyst interprets and processes climate-related issues.

Taken together, these analyses suggest two insights. First, how analysts translate climate-related topics to future earnings and valuation expectations can differ based on whether analysts are concurrently also explicitly revisiting their perspectives on long-term growth. Climate-related issues can present unique challenges for analysts to incorporate, as climate change and its financial impact entails a wide range of uncertainties about the nature, frequency, timing, and magnitude of its financial impact. These multiple unknowns suggest analysts could differ widely in their interpretations of these topics and suggest that assessments of climate change and its financial impact may differ depending on the observer. I examine this implication in section IV.5.

IV.5. Decomposition of climate-related discussion into subtopics

I next explore whether specific subtopics of analysts' climate-related discussion relate to forecasting outcomes. In earlier descriptive analyses, I highlight that analysts' climate-related discussions tend to cover regulation, opportunities, and transition topics most frequently. I also observe that climate-related discussion in analyst reports (relative to conference calls) is more likely to address specific technologies, particularly those related to solar, and that, when analysts discuss solar, they tend to do so extensively. These descriptive findings imply that analysts' more pessimistic long-term growth forecast revisions and more optimistic target prices (when not accompanied by a long-term growth forecast) could be concentrated among specific subtopics. In Table 8, I examine this possibility by decomposing the CLIMATE-RELATED indicator for climate-related discussion into 1) indicators for subcategories as agreed upon by all four LLMs (e.g., transition, regulatory, physical, emissions, and opportunities) and 2) indicators for each of the subgroupings of the Sautner et al. (2023) bigrams based on the categorizations presented in Table 4 (e.g., solar, wind, emissions, and automotive).

In Table 8 Columns 1 and 2, I observe weak evidence that the increased pessimism in long-term growth forecast revisions is primarily concentrated in transition-related discussion (TRANS_ALL, coeff. = -0.256, $p < .10$)[28] and in emissions- and gas-related bigrams. Interestingly, I also observe some evidence solar-, automotive-, and regulatory-related bigrams associate with more optimistic long-term growth forecast revisions, highlighting the multi-faceted nature of climate-related issues. In Columns 3 and 4, focusing on the target price forecasts without an associated long-term growth forecast, I observe the increased optimism in target price forecasts at initial issuance is driven by discussion about solar-, emissions-, and automotive-related topics (Column 4) and the reduced number of days a target price is met over the 12 months following issuance is driven by transition-related discussion (Column 5, DISCUSSES TRANSITION (LLM), coeff. = -0.588, $p < .01$) and emissions-related discussion (Column 6, EMISSIONS, coeff = -0.421, $p < .10$).

Taken together, this decomposition indicates transition-related topics (i.e., how the transition to a low carbon economy has implications for firms) relate both to increased pessimism among analyst reports attached to a long-term growth forecast and increased optimism for analyst reports attached to a target price but not a long-term growth forecast,

[28] From an economic impact perspective, this finding suggests transition-related discussion is associated with an incrementally pessimistic 0.45 percentage point long-term growth forecast revision for climate-discussing analysts, approximately 5% of the sample median long-term growth forecast of 9%. Benchmarked against Chouru et al. (2021) who find a 10% increase in general economic policy uncertainty associates with a 14% increase in earnings forecast errors and Baloria and Mamo (2017) who find periods of high economic policy uncertainty are associated with 7% lower-than-average earnings forecast accuracy, this suggests the economic impact of transition-related climate discussion is somewhat smaller than the economic impact of increases in economic policy uncertainty on analysts' earnings forecasts.

suggesting analysts' long-term orientation can influence their views on transition-related topics.[29] This decomposition analysis also suggests discussion of solar- and automotive-related topics are particularly associated with target price optimism and implies some analysts view these areas as presenting future opportunities. These insights also highlight the context dependence of climate-related issues and how analysts can differ in their processing of climate-related issues, along with the potential unique challenges of climate change more generally, which is expected to have wide-reaching consequences across the economy (e.g., Flavelle 2021) along many dimensions. These patterns also suggest processing climate-related information into financial expectations can be challenging for analysts, as translating climate-related information to direct financial outcomes requires holistic perspectives on the nature, timing, and magnitude of climate-related financial consequences, which presents opportunities for analysts to develop unique perspectives, but requires careful consideration of how climate-related issues will impact firms differently across the economy along multiple dimensions.[30] Together, these findings build upon Sautner et al. (2023) by studying how climate-related discussion shapes individual analysts' forecasting

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[29] In additional untabulated analyses, I observe somewhat similar patterns when using human-coded classifications, although I note findings under that approach are sensitive to specific readers' interpretations, highlighting how climate-related discussion can be open to interpretation and judgement. I encourage future research exploring these differences in judgment. In other untabulated analyses, I also explore regressions with each sub-category of discussion independently explored and find evidence suggesting emissions- and gas-related discussion are negatively associated with long-term growth forecast revisions. I also observe several sub-topical areas (solar, wind, emissions, automotive, and gas) are associated with ex ante target price optimism among analysts without a long-term growth forecast.

[30] In additional untabulated analyses, I explore potential cross-sectional variation in the results and observe some evidence suggesting the pessimism over long-term growth forecasts concentrates among smaller firms, non-utilities, and in the earlier half (2009-2014) of the sample period. This suggests analysts' view on climate-related issues may be evolving over time, and I encourage further research studying this possibility. Additionally, I explore whether the state-level regulatory environment impacts analysts' views, as concurrent research (Korganbekova 2025) notes these state-level regulations can impact firms' emissions and risk disclosures. Applying her setting here, I observe the pessimism in long-term growth forecasts concentrates among firms headquartered in states with a Greenhouse Gas (GHG) reduction target enacted, using headquarters location data for firms from Gao et al. (2021). I additionally observe some evidence ex ante target price optimism concentrates among firms headquartered in states *without* a GHG reduction target enacted, suggesting the state-level regulatory environment can shape analysts' climate-related perspectives.

behavior, adding to their exploration of firm-level consequences from climate-related discussion on earnings conference calls.

V. ADDITIONAL ANALYSES

V.1. Climate-related discussion and market outcomes

In additional analyses, I further explore whether analysts' climate-related discussion in their reports has market-related consequences. In other words, do financial markets react differently to climate-discussing reports compared with other reports? I explore this notion in Table 9 by examining whether climate-related discussion is associated with market reactions to the analyst report over the [0,1] window following report issuance (Columns 1–6) and average turnover over the [0,1] window (Columns 7–12). In each test, I partition the sample into reports matched to a long-term growth forecast and those not matched to a long-term growth forecast, given the divergence in patterns observed in the previous analyses. I also explore the decomposition into the LLM- and bigrams-based subtopics.

In Table 9, I find weak evidence climate-related discussion is associated with negative abnormal returns over the [0,1] window for reports attached to a long-term growth forecast. However, the decompositions provide little incremental insight into the specific topics driving this weakly negative association. This finding may suggest markets find analysts' relatively pessimistic long-term growth forecasts informative and react accordingly, although I caution this statistical association is weak. What's more, the decompositions cannot reveal whether a particular subtopic drives this reaction, which may suggest an area for further research.

Across the remaining columns, I observe some evidence suggesting both physical- and transition-related discussion in reports matched to a long-term growth forecast are associated with lower turnover (Column 8, coeff = -0.129 and -0.128, respectively, $p < .10$), though this somewhat conflicts with physical-related bigrams generating more trading activity in Column 9 (PHYSICAL, coeff = 0.586, $p < .01$). Taken together, these patterns suggest that climate-related discussion in analyst reports can be complex, nuanced, and take time for market participants to digest. This interpretation would be consistent with Miller's (2010) finding that reporting complexity is negatively associated with trading.[31,32]

VI. CONCLUSION

This study explores the prevalence and nature of climate-related discussion in analyst reports and how analysts translate this discussion into earnings expectations for firms. Examining a large sample of analyst reports using a list of climate-related bigrams identified by Sautner et al. (2023), I observe that even firms operating in the industries most exposed to climate change generate very few analyst reports (less than 1.5%) and that even their analysts seldom discuss climate-related topics (less than 11%). Analyst discussion is concentrated in two industries: utilities and electronic equipment manufacturers, and analysts are more likely to discuss specific technologies, particular solar-related topics, in reports than they are conference calls. When discussing solar, analysts do so extensively, using on average 7.16 solar-related bigrams per report. I observe climate-related discussion is positively (negatively) associated with report length and initiations (busy periods), suggesting analysts (do not) incorporate climate-

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[31] In additional untabulated analyses, I also explore whether climate-related discussion in analyst reports relates to changes in information asymmetry, as proxied by bid-ask spreads (Peterson et al. 2015), and find little evidence climate-related discussion is associated with differences in bid-ask spreads over the [0,1] window following report issuance for the main CLIMATE-RELATED measure. However, I observe some evidence suggesting physical-related discussion is associated with greater average bid-ask spreads over the [0,1] window for reports matched to a long-term growth forecast, suggesting these topics could relate to uncertainty in how these topics will translate to financial consequences for the covered firm.

[32] In additional untabulated analyses, I also explore a longer [0,5] window and observe some weak evidence of automotive and regulatory-related discussion associate with lower turnover ($p < .10$), some evidence regulatory related discussion associates with lower bid-ask spreads ($p < .05$), and physical related discussion associates with higher bid-ask spreads ($p < .10$). I leave the more detailed exploration of long-run market consequences to future research.

related topics when conducting deeper investigations of the firm (they are attention constrained). This suggests processing climate information is costly. Some evidence also suggests that analysts are more likely to discuss climate-related topics for firms with stronger environmental innovation scores. Although these discussions appear not to translate to differences in earnings forecasts, I observe some evidence that climate-related discussion is associated with more pessimistic long-term growth forecast revisions and more optimistic target prices among reports not attached to a long-term growth forecast. This implies that the process of developing a long-term growth forecast also shapes analysts' interpretation and processing of climate-related information.

Overall, these findings highlight how the processing of climate-related topics in analyst reports is nascent and concentrated among firms and settings where these issues are most salient. Relative to the conference calls explored by Sautner et al. (2023), climate-discussing analyst reports are more likely to discuss specific technologies, particularly solar-related ones, consistent with the analyst report format enabling more detailed discussion and analysis. Building on Sautner et al. (2023), my findings highlight the differences in language used in analyst reports versus conference calls to discuss climate-related topics and provide an initial exploration of how climate-related discussion relates to earnings, long-term growth, and target price forecasts. Additionally, my findings also suggest that analysts' long-term orientation, as proxied by whether the analyst is concurrently issuing a long-term growth forecast, can shape their views on how climate-related issues translate to financial outcomes for the firm, adding to the information-processing literature exploring how analysts process and consume environmental information (e.g., Griffin et al. 2020). These findings also suggest analysts' information processing of climate-related issues relates to analysts' forecasting choices (i.e., the decision to issue a long-term growth forecast), building upon recent research finding life events outside of work shape analysts' information processing behavior (e.g., Bourveau and Law 2021).

However, these analyses are subject to several limitations that present opportunities for future research. First, to the extent analysts discuss climate-related topics using different terminology in analyst reports than during conference calls, I may have under-identified the true number of reports discussing climate topics. Second, to the extent analysts and brokerages provide insights into climate-related topics outside of reports (e.g., sustainability thematic conferences) or through other parties (e.g., dedicated sustainability research teams), I may have also under-identified the extent of brokerage houses' insights. Third, to the extent identifying climate-related discussion involves judgment and discretion on the part of a human- or LLM-based reader, differences of opinion in interpreting and processing climate-related discussion may relate to differences in how readers of analyst reports interpret and process analysts' climate-related discussions. Exploring how the development of dedicated sustainability expertise interacts with traditional sell-side equity research and how shifting opinions on climate change-related issues and their importance to financial markets both offer future research opportunities.

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Appendix A: Variable Definitions

Variable	Description
$AUTOS_{i,j,k,t}$ / GAS / COAL / $COMBUSTION_{i,j,k,t}$ / GENERAL $CLIMATE\text{-}RELATED_{i,j,k,t}$ / $EMISSIONS_{i,j,k,t}$ / $REGULATORY_{i,j,k,t}$ / GENERAL $RENEWABLES_{i,j,k,t}$ / $PHYSICAL_{i,j,k,t}$ / $SOLAR_{i,j,k,t}$ / $WIND_{i,j,k,t}$	An indicator equal to 1 (0 otherwise) if analyst report *i* issued by analyst *j* for firm *k* on date *t* contains at least one automotive related bigram from the automotive sub-category presented in Table 4. This indicator is constructed similarly for the other sub-topical areas (solar, wind, emissions, gas / coal / combustion, general renewables, physical, regulatory, and general climate change bigrams) from grouping the Sautner et al. (2023) bigrams as in Table 4. Source: ThomsonOne
$BOOK\text{-}TO\text{-}MARKET_{i,t}$ / LN_BOOK-$TO\text{-}MARKET_{i,t}$	CEQ divided by (CSHO*PRCC_F) for BOOK-TO-MARKET or the natural log of (CEQ / (CSHO*PRCC_F)) for LN_BOOK-TO-MARKET. Source: Compustat
BROKER $SIZE_{i,t}$ / LN_BROKER $SIZE_{i,t}$	The number of analysts employed by analyst *i*'s employer as of the beginning of year *t* (BROKER SIZE) or the natural log of 1 plus this value (LN_BROKER SIZE). Source: IBES
$CAR[0,1]_{i,j,k,t}$	Cumulative abnormal returns beginning the day *t* of issuance for analyst report *i* issued by analyst *j* for firm *k* on date *t* and ending 1 trading day after report *i* is issued. Abnormal returns are computed as delisting and size adjusted returns minus benchmark returns computed following Daniel et al. (1997). Source: CRSP
$CLIMATE\text{-}RELATED_{i,j,k,t}$ / CLIMATE-RELATED $(SCALED)_{i,j,k,t}$	An indicator equal to 1 if analyst report *i* issued by analyst *j* for firm *k* on date *t* contains more than five climate-related bigrams and 0 otherwise (CLIMATE-RELATED). This value is multiplied by 100 to create CLIMATE-RELATED (SCALED). Source: ThomsonOne
DISCUSSES EMISSIONS $(LLM)_{i,j,k,t}$ / DISCUSSES OPPORTUNITIES $(LLM)_{i,j,k,t}$ / DISCUSSES PHYSICAL $(LLM)_{i,j,k,t}$ / DISCUSSES REGULATORY $(LLM)_{i,j,k,t}$ / DISCUSSES TRANSITION $(LLM)_{i,j,k,t}$	An indicator equal to 1 (0 otherwise) if analyst report *i* issued by analyst *j* for firm *k* on date *t* discusses emissions related topical areas as identified by four different large language models. All four large language models must agree the report discusses emissions related topics to receive a value of 1. This indicator is constructed similarly for the other sub-topical areas identified using the LLM-based approach (opportunities-, physical-, regulatory-, and transition-related topical areas). Source: ThomsonOne
EMISSIONS $SCORE_{j,t-1}$ / ENVIRONMENTAL INNOVATION $SCORE_{j,t-1}$ / RESOURCE USE $SCORE_{j,t-1}$	The Emissions (or Innovation or Resource Use) sub-score for firm *j* in year *t-1* as assigned by Refinitiv when assigning ESG ratings. Source: Refinitiv (now LSEG)
$FEMALE_i$	An indicator equal to 1 if analyst *i* is classified as a female by Gender-API.com's name classification system; 0 otherwise. Source: ThomsonOne, Gender-API.com
FIRM $AGE_{j,t}$ / LN_FIRM $AGE_{j,t}$	The number of (natural log of 1 plus the number of) years firm *j* has appeared in Compustat as of the beginning of year *t*. Source: Compustat
FIRM COMPLETES $CDP_{i,t}$	An indicator equal to 1 if firm *i* completes and returns the climate risk portion of the CDP survey during year *t* and 0 otherwise. Source: CDP
FIRM PARTICIPATES IN EPA GHG REPORTING $PROGRAM_{j,t-1}$	An indicator equal to 1 (0 otherwise) if firm *j* participated in the EPA Greenhouse Gas Reporting Program during year *t-1*. Source: EPA
FIRM RECEIVED ENVIRONMENTAL PENALTY LAST $YEAR_{j,t-1}$	An indicator equal to 1 (0 otherwise) if firm *j* is identified as having paid a monetary penalty for an environmental related form of misconduct or regulatory violation in Violation Tracker's database. Source: Violation Tracker
FIRM-SPECIFIC $EXPERIENCE_{i,j,t}$ / LN_FIRM-SPECIFIC $EXPERIENCE_{i,j,t}$	The number of years analyst *i* is listed as producing earnings forecasts for firm *j* in IBES as of the beginning of year *t* (FIRM-SPECIFIC EXPERIENCE) or the natural log of 1 plus this value (LN_FIRM-SPECIFIC EXPERIENCE). Source: IBES
$FOLLOWING_{j,t}$ / $LN\_FOLLOWING_{j,t}$	The number of (natural log of 1 plus the number of) analysts following firm *j* as of the beginning of year *t*. Source: IBES
$FUTURE\_ROA_{i,t+n}$	Future ROA (IB / AT) for firm *i* in year *t*, *t+1*, *t+2* or the three-year average. Source: Compustat

GENERAL EXPERIENCE$_{i,t}$ / LN_GENERAL EXPERIENCE$_{i,t}$	The number of years analyst *i* is listed as producing earnings forecasts in IBES as of the beginning of year *t* (GENERAL EXPERIENCE) or the natural log of 1 plus this value (LN_GENERAL EXPERIENCE). Source: IBES
HORIZON$_{i,j,t}$	The number of days between analyst *i*'s forecast issued for firm *j* on date *t* and the actual earnings announcement date. Source: IBES
INITIATING$_{i,j,k,t}$	An indicator equal to 1 if analyst report *i* issued by analyst *j* for firm *k* on date *t* is flagged as an initiation report by ThomsonOne. Source: ThomsonOne
INSTITUTIONAL OWNERSHIP %$_{i,t}$	Percentage of firm *i*'s common shares held by institutional investors at the beginning of year *t*. Source: Thomson Reuters
LEVERAGE$_{i,t}$	Total Liabilities (LT) divided by Total Assets (AT) for firm *i* as of the beginning of year *t*. Source: Compustat
LN_MKT_CAP$_{i,t}$ / FIRM SIZE$_{i,t}$	The natural log of (1+(PRC*SHROUT)) for firm *i* as of the end of fiscal year *t* (LN_MKT_CAP) or calendar year *t* (FIRM SIZE). Source: Compustat (LN_MKT_CAP); CRSP (FIRM SIZE)
LONG-TERM GROWTH FORECAST REVISIONS$_{i,j,k,t}$	The long-term growth forecast revision matched with report *i* issued by analyst *j* covering firm *k* and issuing and analyst report on date *t.* The long-term growth forecast revision represents the long-term growth forecast matched to the report minus the long-term growth forecast prior to that, scaled by the prior long-term growth forecast: (LONG-TERM GROWTH – Old LONG-TERM GROWTH) / Old LONG-TERM GROWTH, where LONG-TERM GROWTH is the closest in absolute days long-term growth forecast +/- 90 days from the report date. Source: IBES
LONG-TERM GROWTH$_{i,j,k,t}$	The long-term growth forecast matched with report *i* issued by analyst *j* covering firm *k* and issuing an analyst report on date *t.* The long-term growth forecast matched is the closest in absolute days long-term growth forecast issued +/- 90 days from the report date. Source: IBES
NUM_PHYSICAL_RISKS$_{i,t}$ / LN_PHYSICAL_RISKS$_{i,t}$	The number of climate risks classified as physical risks firm *i* discloses to CDP when completing the year *t* survey. Source: CDP
NUM_TRANSITION_RISKS$_{i,t}$ / LN_TRANSITION_RISKS$_{i,t}$	The number of climate risks classified as transition risks firm *i* discloses to CDP when completing the year *t* survey. Source: CDP
NUMBER OF ANNUAL FORECASTS$_{i,j,t-1}$ / LN_NUMBER OF ANNUAL FORECASTS$_{i,j,t-1}$	The number of annual earnings forecasts analyst *i* issues for firm *j* during year *t-1* or the natural logarithm of 1 plus this value (LN_NUMBER OF ANNUAL FORECASTS). Source: IBES
NUMBER OF COVERED FIRMS$_{i,t}$ / LN_NUMBER OF COVERED FIRMS$_{i,t}$	The number of firms analyst *i* covers as of the beginning of year *t* (NUMBER OF COVERED FIRMS) or the natural logarithm of 1 plus this value (LN_NUMBER OF COVERED FIRMS). Source: IBES
NUMBER OF COVERED INDUSTRIES$_{i,t-1}$ / LN_NUMBER OF COVERED INDUSTRIES	The number of 2-digit SIC industries analyst *i* covers as of the end of year *t-1* (NUMBER OF COVERED INDUSTRIES) or the natural logarithm of 1 plus this value (LN_NUMBER OF COVERED INDUSTRIES). Source: IBES, Compustat
NUMBER OF PORTFOLIO FIRMS IN CDP$_{i,t}$	The number of firms in analyst *i*'s coverage portfolio during year *t* identified as disclosing climate-related risks to CDP. Source: CDP, IBES
NUMBER OF REPORTS ISSUED DURING THE YEAR$_{i,t}$	The number of analyst reports issued by analyst *i* during calendar year *t* across all firms. Source: ThomsonOne
POLITICAL SPECTRUM$_{i}$	An indicator equal to -1 (1) if an analyst is identified as contributing exclusively to Democratic (Republican) political campaigns as reported to the Federal Election Commission during the 2010-2020 election cycles and 0 otherwise. Source: Federal Election Commission
PRIMARILY COVERS EXPOSED INDUSTRIES$_{i,t}$	An indicator equal to 1 if the industry representing the largest percentage of analyst *i*'s coverage portfolio in year *t* is an exposed industry as defined by Sautner et al. (2023). Source: IBES, ThomsonOne

REPORT $LENGTH_{i,j,k,t}$	The natural log of 1 plus the total word count of analyst report *i* issued by analyst *j* for firm *k* on date *t.* The total word count of the report excludes common stop words as defined by Loughran and McDonald (2016) and posted to their website. Source: ThomsonOne
REPORTS ISSUED SAME $DAY_{i,t}$	The number of analyst reports issued by analyst *i* on the same date *t* as the analyst report observation. Source: ThomsonOne
$REVISION_{i,j,k,t}$	The earnings forecast revision matched to analyst report *i* issued by analyst *j* for firm *k* on report date *t.* The earnings forecast revision is defined as the earnings forecast for the current fiscal period issued within 90 days of report date *t* closest in absolute days minus the prior earnings forecast issued by the analyst for the firm-fiscal year scaled by the share price three days prior to the earnings announcement date: $Revision = \frac{New\ Value - Old\ Value}{Share\ Price\ Three\ Days\ Prior\ to\ Earnings\ Announcement}$ Forecast revisions for other forecast horizons computed similarly. Source: IBES
$ROA_{j,t}$	Income Before Extraordinary Items / Total Assets for firm *i* in year *t-1*. (IB / AT) Source: Compustat
$SCALED\_AFE_{i,j,k,t}$ / $SCALED\_FE_{i,j,k,t}$	The absolute (signed) forecast error, defined as actual EPS minus the forecasted EPS scaled by the share price three days prior to the earnings announcement, of the forecast matched to analyst report *i* issued by analyst *j* for firm *k* on report date *t.* I match the closest earnings forecast issued +/- 90 days from report date *t.* Source: IBES
TARGET PRICE AS % OF SHARE $PRICE_{i,j,k,t}$	The target price matched to report *i* issued by analyst *j* for firm *k* on date *t* divided by the share price from three trading days prior to target price issuance. I match reports to target prices based on the closest target price issued +/- 90 days from report date issuance. Source: IBES, CRSP
TARGET PRICE MET NUMBER OF $DAYS_{i,j,t}$	The natural log of 1 plus the number of trading days over the next calendar year that firm *j*'s share price meets or exceeds analyst *i*'s target price issued on date *t.* Source: IBES, CRSP
$TOTAL\_RISKS_{i,t}$ / $LN\_TOTAL\_RISKS_{i,t}$	The sum of the number of physical risks and the number of transition risks disclosed by firm i for CDP survey year t. Source: CDP
$TURNOVER[0,1]_{i,j,k,t}$	The average of logged turnover across days [0,1] beginning on report issuance date *t*. Logged turnover is constructed as the natural log of (trading volume / (shares outstanding * 1,000))+ 0.00000255), computed following Loh and Stulz (2011). Source: CRSP
WITHIN 3 DAYS OF AN $EA_{i,j,t}$ / WITHIN 3 DAYS OF AN EA FOR ANOTHER $FIRM_{i,j,t}$	An indicator equal to 1 if report *i* issued by analyst *j* on date *t* falls within three calendar days following an earnings announcement for the covered firm (WITHIN 3 DAYS OF AN EA) or a different firm (WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM) in analyst *j*'s coverage portfolio. Source: ThomsonOne, IBES

Appendix B: List of Industries Most Exposed to Climate Change

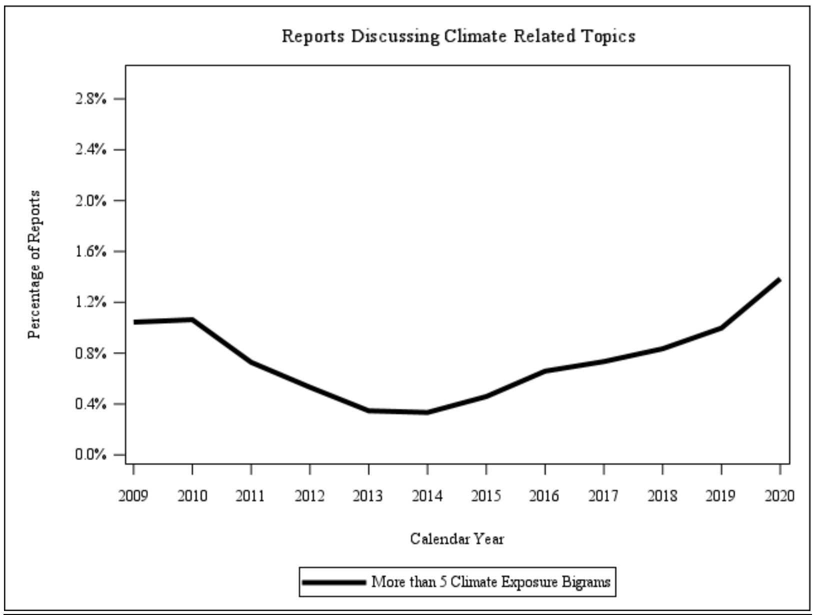
This table lists the unique 2-digit SIC codes identified by Sautner et al. (2023) as being most exposed to climate change, climate change opportunities, regulatory shocks related to climate change, or physical shocks related to climate change. I consolidate duplicate industry appearances across the panels presented by Sautner et al. (2023) in their Table III and present the industries in their order of first unique appearance in Sautner et al. (2023) Table III.

SIC 2-Digit Code	Industry
49	Electric, Gas, & Sanitary Services
16	Heavy Construction, Except Building
17	Construction
37	Transportation Equipment
36	Electronic & Other Electric Equipment
12	Coal Mining
29	Petroleum Refining
41	Local & Suburban Transit
55	Automotive Dealers & Service Stations
33	Primary Metal
35	Industrial Machinery & Equipment
75	Auto Repair, Services, & Parking
87	Engineering & Accounting & Research
32	Stone Clay Glass Products
10	Metal Mining
24	Lumber & Wood
26	Paper & Allied Products
14	Mining & Quarrying
64	Insurance Agents, Brokers, & Service
15	Building Construction

Figure 1: Reports and Analysts Discussing Climate Topics in Most Exposed Industries

This figure presents the percentage of reports containing climate-related discussion and analysts producing at least one report discussing climate-related topics for the sub-sample of firms operating in any of the most exposed industries as identified by Sautner et al. (2023) in their Table . Panel A depicts the percentage of analyst reports containing more than five climate-related bigrams from Sautner et al. (2023)'s list of the Top 100 bigrams associated with their *CCExposure* measure. Panel B depicts the percentage of analysts producing at least one report discussing climate-related topics during the calendar year. The sample of analysts and reports consist of the 130,301 reports and 1,192 lead analysts covering firms in the most exposed industries as defined by Sautner et al. (2023) and matched to an outstanding IBES recommendation.

Panel A: Percentage of Reports Discussing Climate Topics



Panel B: Percentage of Analysts Discussing Climate Topics

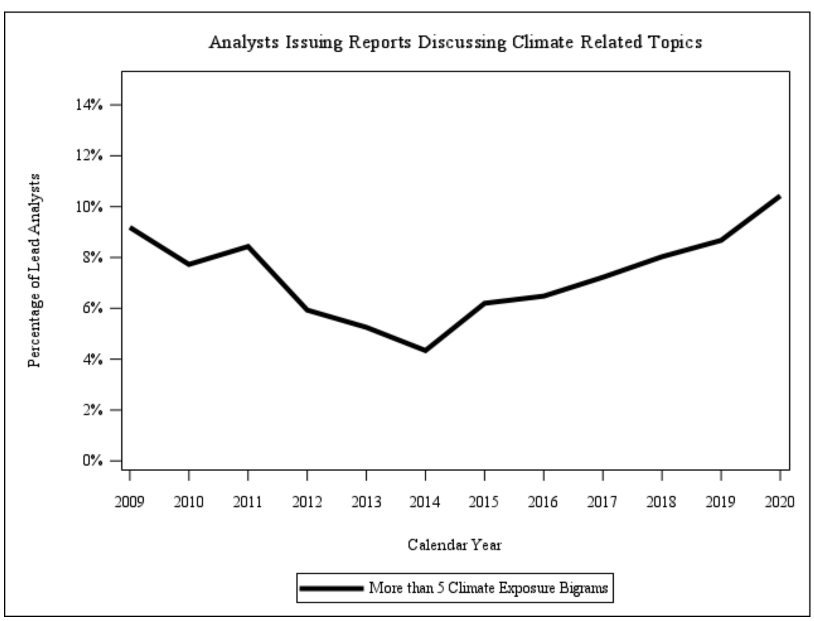
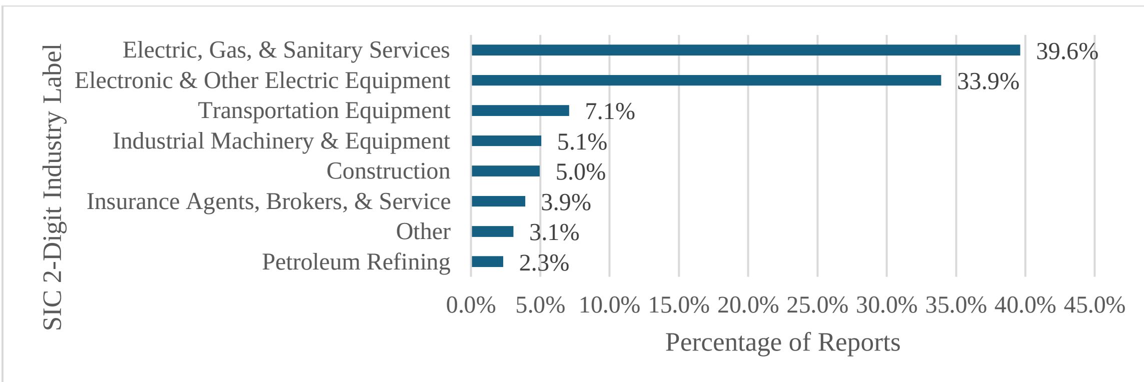


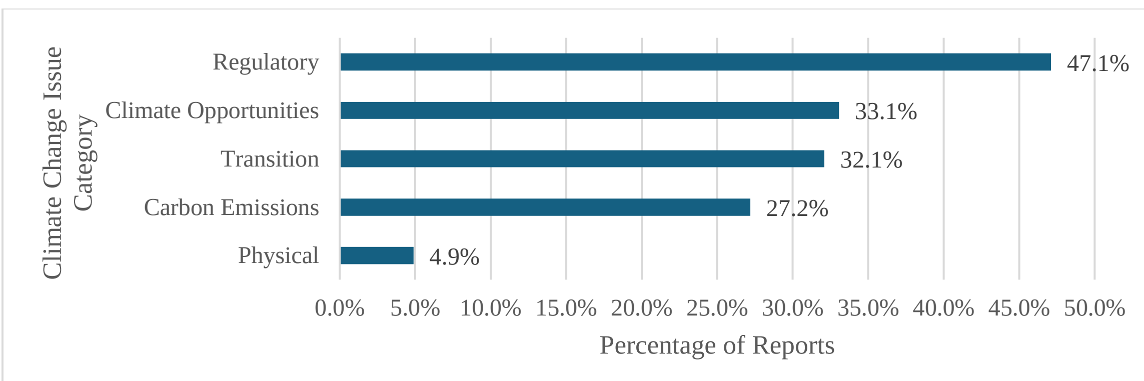
Figure 2: Industry composition and topical areas—most exposed industries

This figure presents the industry composition of analyst reports discussing climate change-related topics among firms in the most exposed industries (Panel A) and the climate change topical areas discussed in reports as identified using four LLMs to classify (Panel B) or reports containing one or more bigrams from classifying the Sautner et al. (2023) bigrams into sub-categories as identified in Table 4 (Panel C). I classify analyst reports as discussing climate-related topics if the report contains more than five climate-related bigrams from Sautner et al. (2023)'s list of the top 100 bigrams associated with *CCExposure*. The sample of analyst reports consists of the 946 analyst reports for firms in the most exposed industries as defined by Sautner et al. (2023) and classified as discussing climate-related topics. Appendix B details the list of industries Sautner et al. (2023) classified as most exposed to climate change.

Panel A: Industry composition of analyst reports discussing climate change



Panel B: Topical areas of climate change-related discussion in analyst reports (LLM coders)



Panel C: Sub-categories of Sautner et al. (2023) keywords

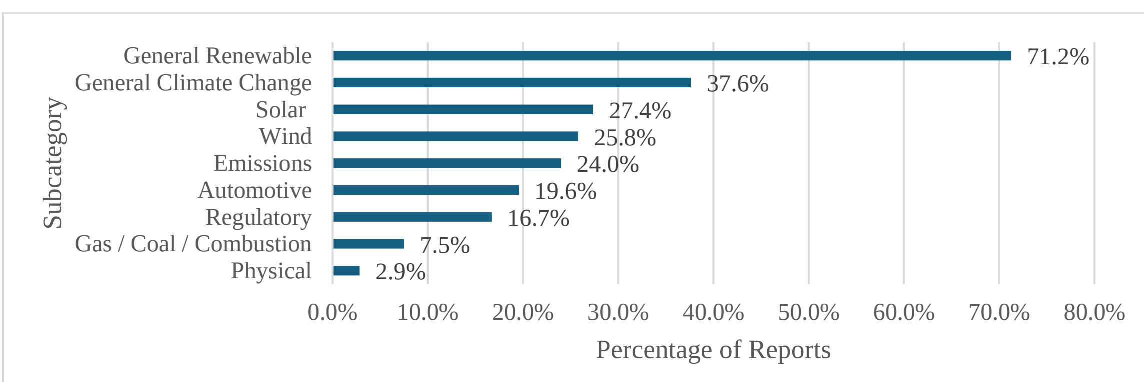


Table 1: Sample Selection

This table presents details about the sample selection process used throughout the paper for the report-level tests. Panel A details the sample selection process used for the descriptive analyses in Tables 2 and 3. Panel B, C, and D detail the sample selection process for the earnings forecasts, long-term growth, and target price tests respectively. Appendix A defines all variables.

Panel A: Sample selection for descriptive analyses

	Analyst Reports	Firms	Analysts	Brokers
Analyst reports located in ThomsonOne for members of the S&P 500 from 1/1/2009-10/1/2020	1,026,478			
Analyst reports matched to an IBES broker ID (ESTIMID) and an analyst ID (AMASKCD)	701,562	915	2,858	112
Analyst reports matched to an outstanding IBES recommendation	526,740	876	2,627	109
with non-missing report-level characteristics	510,847	868	2,122	102
with non-missing analyst-level characteristics	451,755	793	2,085	101
with non-missing firm-level characteristics	449,252	792	2,085	101
with non-missing firm-level environmental related characteristics	415,531	651	2,062	97
Sample across all industries for descriptive analyses	**415,531**	**651**	**2,062**	**97**
Sample selection for most exposed industries sub-sample				
Analyst reports matched to an outstanding IBES recommendation for firms operating in the most exposed industries (see Appendix B for list of most exposed industries)	130,301	251	1,192	98
with non-missing report-level characteristics	126,357	249	1,036	87
with non-missing analyst-level characteristics	115,153	231	1,015	86
with non-missing firm-level characteristics	114,814	231	1,015	86
with non-missing firm-level environmental related characteristics	107,578	191	995	85
Sample for most exposed industries for descriptive analyses	**107,578**	**191**	**995**	**85**

Panel B: Sample selection for earnings forecasts tests

	Analyst Reports	Firms	Analysts	Brokers
Analyst reports matched to an outstanding IBES recommendation for firms operating in the most exposed industries (see Appendix B for list of most exposed industries)	130,301	251	1,192	98
with non-missing report- and analyst-level characteristics	117,968	232	1,020	86
with non-missing earnings forecast and share price data for year *t* and issued within 90 days of report issuance	110,399	231	1,014	86
Sample for earnings forecast error tests	**110,399**	**231**	**1,014**	**86**
non-initiating analyst reports with non-missing earnings forecast revisions	78,744	223	984	84
Sample for earnings forecast revision tests	**78,744**	**223**	**984**	**84**

Panel C: Sample selection for long-term growth

	Analyst Reports	Firms	Analysts	Brokers
Analyst reports matched to an outstanding IBES recommendation for firms operating in the most exposed industries with non-missing report- and analyst-level characteristics	117,968	232	1,020	86
with non-missing long-term growth forecasts issued within 90 days of report issuance	16,914	200	404	52
Sample for long-term growth levels tests	**16,914**	**200**	**404**	**52**
non-initiating analyst reports with non-missing long-term growth forecast revisions	14,685	190	318	47
Sample for long-term growth revisions tests	**14,685**	**190**	**318**	**47**

Panel D: Sample selection for target price analyses

	Analyst Reports	Firms	Analysts	Brokers
Analyst reports matched to an outstanding IBES recommendation for firms operating in the most exposed industries with non-missing report- and analyst-level characteristics	117,968	232	1,020	86
with non-missing target price forecasts issued within 90 days of report issuance	86,443	222	919	82
Sample for target price analyses	86,443	222	919	82

Table 2: Summary Statistics

This table presents summary statistics for variables used in empirical tests at the report level for tests of individual analyst discussion of climate-related topics, separately for the full sample, firms in the most exposed industries, and firms operating outside the most exposed industries. I winsorize all continuous variables at the 1 and 99 percentiles. Appendix A details all variable definitions.

	Full Sample N=415,531		**Most Exposed Industries N=107,578**		**Not Most Exposed Industries N=307,953**		
	Mean	Median	Mean	Median	Mean	Median	Difference in Means (Exposed minus Non-Exposed)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Report Characteristics							
CLIMATE-RELATED	0.002	0.000	0.007	0.000	0.000	0.000	0.007
LN_REPORT LENGTH	8.118	8.221	8.107	8.236	8.122	8.215	-0.015
INITIATING	0.006	0.000	0.006	0.000	0.006	0.000	-0.001
REPORTS ISSUED SAME DAY	1.829	1.000	1.733	1.000	1.862	1.000	-0.129
WITHIN 3 DAYS OF AN EA	0.494	0.000	0.492	0.000	0.494	0.000	-0.002
WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM	0.376	0.000	0.379	0.000	0.375	0.000	0.004
Analyst Characteristics							
GENERAL EXPERIENCE	9.484	9.000	9.514	10.000	9.474	9.000	0.039
FIRM-SPECIFIC EXPERIENCE	5.813	5.000	6.004	5.000	5.746	5.000	0.258
NUMBER OF COVERED FIRMS	18.990	19.000	19.124	19.000	18.943	19.000	0.181
NUMBER OF COVERED INDUSTRIES	6.028	6.000	5.997	6.000	6.038	6.000	-0.041
NUMBER OF ANNUAL FORECASTS	13.097	12.000	12.312	11.000	13.371	12.000	-1.059
BROKER SIZE	80.468	70.000	82.733	76.000	79.677	70.000	3.056
FEMALE	0.102	0.000	0.088	0.000	0.107	0.000	-0.019
PRIMARILY COVERS EXPOSED INDUSTRIES	0.265	0.000	0.817	1.000	0.073	0.000	0.744
POLITICAL SPECTRUM	-0.014	0.000	0.011	0.000	-0.023	0.000	0.033
NUMBER OF REPORTS ISSUED DURING THE YEAR	85.865	77.000	82.033	74.000	87.203	77.000	-5.170
NUMBER OF PORTFOLIO FIRMS IN CDP	5.055	5.000	5.470	5.000	4.911	4.000	0.559
Firm Characteristics							
FIRM SIZE	9.892	9.750	9.899	9.726	9.890	9.755	0.009
FIRM AGE	34.809	29.000	44.804	42.000	31.317	26.000	13.486
FOLLOWING	24.847	24.000	25.153	22.000	24.741	24.000	0.413
LEVERAGE	0.614	0.608	0.602	0.621	0.618	0.604	-0.015
BOOK-TO-MARKET	0.406	0.322	0.414	0.358	0.403	0.311	0.011
ROA	0.066	0.061	0.065	0.060	0.066	0.062	-0.001
INSTITUTIONAL OWNERSHIP %	0.737	0.799	0.742	0.784	0.735	0.805	0.007
Firm Environmental Related Characteristics							
FIRM COMPLETES CDP	0.519	1.000	0.536	1.000	0.513	1.000	0.023
FIRM PARTICIPATES IN EPA GHG REPORTING PROGRAM	0.026	0.000	0.096	0.000	0.001	0.000	0.095
FIRM RECEIVED ENVIRONMENTAL PENALTY LAST YEAR	0.215	0.000	0.341	0.000	0.171	0.000	0.171
RESOURCE USE SCORE	0.528	0.587	0.585	0.645	0.509	0.571	0.076
EMISSIONS SCORE	0.498	0.538	0.564	0.601	0.475	0.510	0.088
ENVIRONMENTAL INNOVATION SCORE	0.302	0.203	0.439	0.400	0.253	0.000	0.186

Table 3: Frequency of Climate Change Bigrams Across Reports

This table presents Sautner et al. (2023)'s list of the top 100 bigrams associated with climate change exposure, as presented in their Table 2. I rank the bigrams based on the frequency of appearance in the sample of analyst reports used for this study. I also reproduce the Sautner et al. (2023) frequency rank order of each bigram in their sample of conference call data for comparison purposes.

Rank	Bigram	Frequency	Sautner et al. (2023) Rank	Rank	Bigram	Frequency	Sautner et al. (2023) Rank	Rank	Bigram	Frequency	Sautner et al. (2023) Rank
1	renewable energy	2572	1	35	energy reform	46	78	68	world population	4	28
2	clean energy	1170	3	36	renewable natural	45	89	69	supply energy	4	74
3	solar pv	832	41	37	environmental standard	42	72	70	deliver energy	4	93
4	solar energy	517	10	38	carbon price	39	27	71	cell power	3	63
5	electric vehicle	460	2	39	extreme weather	39	15	72	plant power	1	79
6	wind power	327	6	40	water resource	38	17	73	coastal area	1	44
7	solar farm	269	29	41	driver assistance	35	85	74	laser diode	1	92
8	autonomous vehicle	264	18	42	vehicle manufacturer	33	52	75	help state	1	71
9	onshore wind	235	35	43	gas vehicle	33	81	76	electric hybrid	1	75
10	scale solar	229	42	44	carbon tax	32	33	77	design use	1	47
11	greenhouse gas	219	9	45	future energy	31	53	78	source power	1	76
12	climate change	211	5	46	environmental concern	30	67	79	compare conventional	0	80
13	wind resource	191	20	47	electric energy	28	98	80	protect environment	0	94
14	wind energy	155	7	48	obama administration	25	31	81	promote use	0	90
15	new energy	152	4	49	efficient solution	23	38	82	combine heat	0	55
16	gas emission	138	14	50	energy star	22	45	83	energy environment	0	19
17	carbon emission	135	13	51	farm project	21	91	84	pass house	0	83
18	cycle gas	122	65	52	carbon intensity	17	68	85	need clean	0	43
19	solar installation	111	87	53	carbon free	16	84	86	manage energy	0	96
20	clean power	107	26	54	environmental benefit	15	58	87	major design	0	51
21	clean air	93	12	55	coal gasification	13	66	88	area energy	0	48
22	electric motor	89	36	56	sustainable energy	13	95	89	invest energy	0	97
23	energy regulatory	83	30	57	energy team	12	64	90	integrate resource	0	25
24	energy efficient	82	8	58	electrical energy	12	86	91	capacity energy	0	100
25	power agreement	71	73	59	energy application	11	69	92	charge station	0	49
26	carbon dioxide	66	16	60	carbon neutral	11	61	93	heat power	0	32
27	battery electric	65	24	61	forest land	10	99	94	effort energy	0	82
28	air quality	65	11	62	provide energy	9	37	95	eco friendly	0	59
29	clean water	61	50	63	produce electricity	8	70	96	distribute power	0	57
30	motor control	59	54	64	environmental footprint	8	46	97	unite nation	0	34
31	power generator	57	40	65	battery power	6	22	98	sustainability goal	0	77
32	air pollution	54	23	66	electrical vehicle	5	60	99	snow ice	0	88
33	global warm	54	39	67	fast charge	5	62	100	government india	0	21
34	electric bus	52	56								

Table 4: Grouping the Sautner et al. (2023) bigrams into sub-categories

This table presents Sautner et al. (2023)'s list of the top 100 bigrams associated with climate change exposure, as presented in their Table 2, but grouped into sub-topical areas for subsequent analyses. I rank the bigrams within each sub-topical area based on the frequency of appearance in the sample of analyst reports used for this study and reproduce the Sautner et al. (2023) frequency rank order of each bigram in their sample of conference call data for comparison purposes.

Bigram	Frequency	Rank	Sautner et al. (2023) Rank
solar related bigrams			
solar pv	832	3	41
solar energy	517	4	10
solar farm	269	7	29
scale solar	229	10	42
solar installation	111	19	87
farm project	21	51	91
wind related bigrams			
wind power	327	6	6
onshore wind	235	9	35
wind resource	191	13	20
wind energy	155	14	7
emissions related bigrams			
greenhouse gas	219	11	9
gas emission	138	16	14
carbon emission	135	17	13
carbon dioxide	66	26	16
carbon price	39	38	27
carbon tax	32	44	33
carbon intensity	17	52	68
carbon free	16	53	84
carbon neutral	11	60	61
automotive related bigrams			
electric vehicle	460	5	2
autonomous vehicle	264	8	18
electric motor	89	22	36
battery electric	65	27	24
motor control	59	30	54
electric bus	52	34	56
driver assistance	35	41	85
vehicle manufacturer	33	42	52
battery power	6	65	22
electrical vehicle	5	66	60
fast charge	5	67	62
electric hybrid	1	76	75
charge station	0	92	49
regulatory related bigrams			
energy regulatory	83	23	30
power agreement	71	25	73
energy reform	46	35	78
environmental standard	42	37	72
obama administration	25	48	31
energy star	22	50	45
pass house	0	84	83
sustainability goal	0	98	77
government india	0	100	21
general renewable related bigrams			
renewable energy	2572	1	1
clean energy	1170	2	3
new energy	152	15	4
clean power	107	20	26
physical related bigrams			
extreme weather	39	39	15
coastal area	1	73	44
snow ice	0	99	88
gas / coal / combustion related bigrams			
cycle gas	122	18	65
gas vehicle	33	43	81
coal gasification	13	55	66
general climate change-related bigrams			
climate change	211	12	5
clean air	93	21	12
energy efficient	82	24	8
air quality	65	28	11
clean water	61	29	50
power generator	57	31	40
air pollution	54	32	23
global warm	54	33	39
renewable natural	45	36	89
water resource	38	40	17
future energy	31	45	53
environmental concern	30	46	67
electric energy	28	47	98
efficient solution	23	49	38
environmental benefit	15	54	58
general climate change-related bigrams (continued)			
sustainable energy	13	56	95
energy team	12	57	64
electrical energy	12	58	86
energy application	11	59	69
forest land	10	61	99
provide energy	9	62	37
produce electricity	8	63	70
environmental footprint	8	64	46
world population	4	68	28
supply energy	4	69	74
deliver energy	4	70	93
cell power	3	71	63
plant power	1	72	79
laser diode	1	74	92
help state	1	75	71
design use	1	77	47
source power	1	78	76
compare conventional	0	79	80
protect environment	0	80	94
promote use	0	81	90
combine heat	0	82	55
energy environment	0	83	19
need clean	0	85	43
manage energy	0	86	96
major design	0	87	51
area energy	0	88	48
invest energy	0	89	97
integrate resource	0	90	25
capacity energy	0	91	100
heat power	0	93	32
effort energy	0	94	82
eco friendly	0	95	59
distribute power	0	96	57
unite nation	0	97	34

Table 5: Determinants of Climate Change Discussion in Analyst Reports

This table presents results from OLS regressions of an indicator equal to 1 if an analyst report is classified as discussing climate-related topics (CLIMATE-RELATED=1) on report (Column 1), analyst, (Column 2), firm (Column 3), firm environmental related (Column 4), both sets of firm characteristics (Column 5), or all four sets of characteristics (Column 6). For readability purposes, I multiply the indicator by 100 to create CLIMATE-RELATED (SCALED), which takes on a value of 100 for reports classified as discussing climate-related topics and 0 otherwise. Appendix A defines all variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. Parentheses denote standard errors clustered by firm, broker, and analyst.

	Report	Analyst	Firm	Firm Environmental Related	Firm and Firm Environmental Related	Report, Analyst, and Firm
DV = CLIMATE-RELATED (SCALED)	(1)	(2)	(3)	(4)	(5)	(6)
LN_REPORT LENGTH	0.916***					1.109***
	(0.225)					(0.302)
INITIATING	5.885***					5.690***
	(1.718)					(1.686)
REPORTS ISSUED SAME DAY	-0.002					0.004
	(0.053)					(0.046)
WITHIN 3 DAYS OF AN EA	-0.495***					-0.459***
	(0.103)					(0.105)
WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM	-0.019					-0.110
	(0.084)					(0.121)
LN_GENERAL EXPERIENCE		-0.593**				-0.352
		(0.291)				(0.215)
LN_FIRM SPECIFIC EXPERIENCE		0.284				0.150
		(0.206)				(0.145)
LN_NUMBER OF COVERED FIRMS		0.447				0.263
		(0.431)				(0.408)
LN_NUMBER OF COVERED INDUSTRIES		0.023				0.328
		(0.516)				(0.477)
LN_NUMBER OF ANNUAL FORECASTS		-0.329**				-0.164
		(0.127)				(0.132)
LN_BROKER SIZE		0.025				-0.296
		(0.096)				(0.200)
FEMALE		-0.138				-0.072
		(0.144)				(0.159)
PRIMARILY COVERS EXPOSED INDUSTRIES		0.170				-0.082
		(0.187)				(0.155)
POLITICAL SPECTRUM		0.354				0.351
		(0.346)				(0.326)
NUMBER OF REPORTS ISSUED DURING THE YEAR		-0.003				-0.001
		(0.002)				(0.002)
NUMBER OF PORTFOLIO FIRMS IN CDP		0.073**				-0.010
		(0.034)				(0.029)
FIRM SIZE			0.289		0.302	0.233
			(0.245)		(0.253)	(0.251)
LN_FIRM AGE			0.012		-0.132	-0.109
			(0.166)		(0.160)	(0.143)
LN_FOLLOWING			-0.874		-0.615	-0.532
			(0.544)		(0.508)	(0.545)
LEVERAGE			0.133		-0.152	-0.198
			(0.563)		(0.504)	(0.585)
BOOK-TO-MARKET			0.765		0.326	0.351
			(0.473)		(0.366)	(0.377)
ROA			-2.308		-3.164	-3.030
			(3.347)		(3.562)	(3.516)
INSTITUTIONAL OWNERSHIP %			-0.950		-0.769	-0.834
			(0.581)		(0.625)	(0.624)
FIRM COMPLETES CDP				0.218	0.174	0.144
				(0.282)	(0.266)	(0.268)
FIRM PARTICIPATES IN EPA GHG REPORTING PROGRAM				1.988***	1.784**	2.053**
				(0.728)	(0.791)	(0.831)
FIRM RECEIVED ENVIRONMENTAL PENALTY LAST YEAR				0.072	-0.191	-0.179
				(0.332)	(0.237)	(0.233)
RESOURCE USE SCORE				-0.397	-0.450	-0.441
				(0.622)	(0.630)	(0.638)
EMISSIONS SCORE				-0.500	-0.773	-0.582
				(0.674)	(0.795)	(0.747)
ENVIRONMENTAL INNOVATION SCORE				1.607**	1.492**	1.489***
				(0.650)	(0.568)	(0.535)
Observations	107,578	107,578	107,578	107,578	107,578	107,578
Adjusted R-squared	0.011	0.004	0.005	0.009	0.010	0.022
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Climate-related discussion in analyst reports and earnings forecasts

This table presents results from OLS regressions of signed EPS forecast revisions (Columns 1-3), EPS forecast optimism (signed forecast errors; Columns 4-6), and EPS forecast accuracy (absolute forecast errors; Columns 7-9) on an indicator equal to 1 for climate-related reports. I match each analyst report with the closest in time earnings forecast issued within 90 days of the report date for the firm by the analyst. I multiply all dependent variables by 100 to enhance readability. Appendix A defines all variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. Parentheses denote standard errors clustered by broker and analyst.

	DV = REVISION			DV = SCALED_FE			DV = SCALED_AFE		
	Fiscal year *t*	Fiscal year *t+1*	Fiscal year *t+2*	Fiscal year *t*	Fiscal year *t+1*	Fiscal year *t+2*	Fiscal year *t*	Fiscal year *t+1*	Fiscal year *t+2*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CLIMATE-RELATED	-0.017	-0.001	-0.010	-0.089	-0.055	-0.140	-0.012	0.069	0.137
	(0.022)	(0.048)	(0.050)	(0.066)	(0.103)	(0.144)	(0.050)	(0.146)	(0.144)
LN_REPORT LENGTH	0.008	0.010	-0.006	-0.011	-0.024	-0.019	-0.008	-0.008	0.029
	(0.006)	(0.008)	(0.013)	(0.014)	(0.019)	(0.036)	(0.005)	(0.023)	(0.033)
INITIATING				0.066	0.013	-0.036	0.056	0.030	0.087
				(0.070)	(0.099)	(0.129)	(0.058)	(0.099)	(0.119)
REPORTS ISSUED SAME DAY	0.006***	-0.007*	-0.021***	-0.009*	-0.002	0.014	0.011**	-0.001	-0.007
	(0.002)	(0.003)	(0.006)	(0.005)	(0.008)	(0.014)	(0.005)	(0.009)	(0.013)
WITHIN 3 DAYS OF AN EA	0.053***	0.023*	0.009	0.002	-0.018	-0.024	-0.018*	0.038***	0.026
	(0.008)	(0.013)	(0.015)	(0.009)	(0.020)	(0.024)	(0.009)	(0.014)	(0.026)
WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM	0.033***	0.015	0.022**	-0.019*	0.019	0.114***	-0.010	-0.037**	-0.089***
	(0.011)	(0.010)	(0.009)	(0.011)	(0.023)	(0.028)	(0.011)	(0.017)	(0.031)
LN_GENERAL EXPERIENCE	0.002	0.065	0.176**	-0.019	-0.189	0.216	-0.037	0.239*	-0.152
	(0.036)	(0.051)	(0.076)	(0.071)	(0.163)	(0.264)	(0.064)	(0.139)	(0.202)
LN_FIRM SPECIFIC EXPERIENCE	-0.000	-0.005	-0.066*	0.003	0.038	-0.010	0.016	-0.003	0.061
	(0.010)	(0.013)	(0.034)	(0.015)	(0.059)	(0.096)	(0.019)	(0.044)	(0.107)
LN_NUMBER OF COVERED FIRMS	-0.041*	-0.040	-0.046	0.060	0.050	0.003	0.081**	0.081	0.041
	(0.025)	(0.033)	(0.053)	(0.042)	(0.096)	(0.176)	(0.038)	(0.080)	(0.117)
LN_NUMBER OF COVERED INDUSTRIES	0.068**	0.061*	0.001	-0.022	0.165	-0.304	-0.082**	-0.351***	0.122
	(0.030)	(0.036)	(0.087)	(0.059)	(0.120)	(0.222)	(0.041)	(0.094)	(0.198)
LN_NUMBER OF ANNUAL FORECASTS	0.001	0.005	0.010	0.012	0.001	0.013	-0.014	0.011	0.025
	(0.007)	(0.009)	(0.027)	(0.010)	(0.030)	(0.042)	(0.016)	(0.026)	(0.062)
LN_BROKER SIZE	0.013	-0.005	0.188***	0.054	-0.018	-0.010	-0.042	-0.005	-0.092
	(0.016)	(0.023)	(0.060)	(0.034)	(0.051)	(0.122)	(0.034)	(0.057)	(0.112)
PRIMARILY COVERS EXPOSED INDUSTRIES	-0.043	-0.034	-0.020	-0.027	-0.133*	-0.332*	-0.017	0.115**	0.150
	(0.027)	(0.039)	(0.070)	(0.045)	(0.070)	(0.171)	(0.041)	(0.050)	(0.139)
NUMBER OF REPORTS ISSUED DURING THE YEAR	-0.000	-0.000	0.001**	-0.001*	-0.001**	-0.001	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
NUMBER OF PORTFOLIO FIRMS IN CDP	0.005*	0.004	-0.004	0.002	0.002	0.015	-0.004	-0.008	-0.007
	(0.002)	(0.004)	(0.008)	(0.005)	(0.009)	(0.019)	(0.005)	(0.008)	(0.016)
HORIZON	-0.000	0.001***	0.000***	-0.001***	-0.002***	-0.003***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	78,299	74,218	32,215	109,928	101,526	52,840	109,928	101,526	52,840
Adjusted R-squared	0.288	0.239	0.295	0.550	0.818	0.831	0.703	0.843	0.839
Lead Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Climate-related discussion and long-term growth and target price forecasts

This table presents results from OLS regressions of long-term growth and target price forecast properties on an indicator equal to 1 if I classify an analyst report as a climate-related report. I match each analyst report with the closest in time long-term growth or target price forecast issued for the firm by the analyst within 90 days of report issuance. Columns 1 and 2 measure outstanding long-term growth forecast levels (column 1) and revisions scaled by the previous long-term growth forecast (column 2) while columns 3 and 4 measure target price as a percentage of the stock price three days prior to target price issuance (column 3) and the natural log of 1 plus the number of days the target price is met over the 252 trading days following target price issuance (column 4). In Columns 5-8, I split the sample of reports based on whether the report is matched with a long-term growth forecast (columns 5 and 7) or not matched with a long-term growth forecast (columns 6 and 8) to explore whether target price optimism concentrates in either subsample. Appendix A defines all variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. Parentheses denote standard errors clustered by broker and analyst.

	DV= LONG-TERM GROWTH	DV = LONG-TERM GROWTH FCST REVISIONS	DV = TARGET PRICE AS % OF SHARE PRICE	DV = LN(TARGET PRICE MET NUMBER OF DAYS)	DV = TARGET PRICE AS % OF SHARE PRICE		DV = LN(TARGET PRICE MET NUMBER OF DAYS)	
					Matched to a Long-term growth forecast	Not Matched to a Long-term growth forecast	Matched to a Long-term growth forecast	Not Matched to a Long-term growth forecast
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CLIMATE-RELATED	-0.318	-0.108**	0.016*	-0.270***	0.002	0.019**	-0.114	-0.304***
	(0.195)	(0.044)	(0.008)	(0.088)	(0.005)	(0.009)	(0.144)	(0.074)
LN_REPORT LENGTH	-0.128**	-0.037***	0.001	-0.033*	-0.002	0.001	-0.034*	-0.037*
	(0.052)	(0.013)	(0.002)	(0.019)	(0.003)	(0.002)	(0.018)	(0.020)
INITIATING	0.366		0.000	-0.208***	0.007	-0.000	-0.075	-0.218***
	(0.399)		(0.006)	(0.065)	(0.008)	(0.007)	(0.125)	(0.082)
REPORTS ISSUED SAME DAY	0.059*	0.006	0.000	-0.002	0.000	0.000	0.029**	-0.006
	(0.035)	(0.007)	(0.000)	(0.005)	(0.001)	(0.000)	(0.014)	(0.005)
WITHIN 3 DAYS OF AN EA	0.045	0.003	-0.008***	0.166***	-0.003*	-0.008***	0.118***	0.162***
	(0.076)	(0.012)	(0.001)	(0.020)	(0.002)	(0.001)	(0.037)	(0.021)
WITHIN 3 DAYS OF AN EA FOR ANOTHER FIRM	0.029	-0.002	-0.001	0.025*	-0.002*	-0.001	0.005	0.030*
	(0.089)	(0.016)	(0.001)	(0.013)	(0.001)	(0.001)	(0.036)	(0.016)
LN_GENERAL EXPERIENCE	-0.648	0.125	-0.006	0.131	-0.062**	-0.013	0.129	0.179
	(1.201)	(0.231)	(0.012)	(0.105)	(0.027)	(0.014)	(0.257)	(0.138)
LN_FIRM SPECIFIC EXPERIENCE	-0.386	0.031	0.009**	-0.027	0.009	0.011**	-0.113**	-0.024
	(0.436)	(0.044)	(0.004)	(0.033)	(0.007)	(0.005)	(0.055)	(0.033)
LN_NUMBER OF COVERED FIRMS	1.245	-0.075	-0.006	-0.082	0.021	-0.003	-0.536***	-0.110
	(0.746)	(0.226)	(0.007)	(0.085)	(0.015)	(0.008)	(0.127)	(0.103)
LN_NUMBER OF COVERED INDUSTRIES	0.509	0.121	0.011	0.069	0.002	0.011	0.509***	0.069
	(1.290)	(0.198)	(0.012)	(0.080)	(0.018)	(0.013)	(0.182)	(0.082)
LN_NUMBER OF ANNUAL FORECASTS	0.331	-0.003	-0.004**	0.052**	0.002	-0.006***	0.115*	0.056**
	(0.503)	(0.024)	(0.002)	(0.021)	(0.004)	(0.002)	(0.059)	(0.024)
LN_BROKER SIZE	0.056	0.002	0.001	-0.010	-0.031**	-0.001	0.243	-0.018
	(0.753)	(0.114)	(0.006)	(0.042)	(0.013)	(0.006)	(0.176)	(0.044)
PRIMARILY COVERS EXPOSED INDUSTRIES	-0.811	-0.546***	0.003	-0.031	-0.009	0.004	-0.220	-0.016
	(1.409)	(0.188)	(0.005)	(0.076)	(0.025)	(0.006)	(0.199)	(0.087)
NUMBER OF REPORTS ISSUED DURING THE YEAR	-0.004	-0.000	0.000	-0.001	0.000	0.000	-0.003***	-0.000
	(0.004)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
NUMBER OF PORTFOLIO FIRMS IN CDP	0.002	-0.016	0.000	0.008	0.000	-0.000	0.040	0.008
	(0.076)	(0.017)	(0.001)	(0.008)	(0.002)	(0.001)	(0.025)	(0.009)
Observations	16,742	14,533	86,060	86,060	12,831	73,128	12,831	73,128
Adjusted R-squared	0.758	0.241	0.753	0.470	0.851	0.754	0.595	0.469
Lead Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Sub-topical decompositions of climate-related discussion

This table presents results from OLS regressions of long-term growth forecast revisions (columns 1-2) and target price forecast properties (columns 3-6) on decompositions of the measure indicating climate-related discussion in analyst reports based on the Sautner et al. (2023) top 100 keywords associated with climate change exposure. I use two approaches to decompose this measure. First, I use an LLM-based approach in columns 1, 3, and 5 to prompt four different LLMs to read each report and answer yes or no to a series of prompts asking whether the report contains discussion about carbon emissions, climate opportunities, climate-related physical risks, climate-related regulatory risks, and climate-related transition risks and classify a report as discussing each of these topics only if all four LLMs answer in the affirmative. Second, I group each of the Sautner et al. (2023) keywords into the sub-areas detailed in Table 8 and create indicators for whether each report includes keywords in these sub-topical areas. In columns 3-6, I study only the subsample of reports matched with a target price forecast but not matched with a long-term growth forecast given the findings in Table 6. Appendix A defines all variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. Parentheses denote standard errors clustered by broker and analyst.

	DV = LONG-TERM GROWTH FORECAST REVISIONS		DV = TARGET PRICE AS % OF SHARE PRICE		DV = LN(TARGET PRICE MET NUMBER OF DAYS)	
	(1)	(2)	(3)	(4)	(5)	(6)
DISCUSSES EMISSIONS (LLM)	0.227		0.010		-0.092	
	(0.387)		(0.013)		(0.220)	
DISCUSSES OPPORTUNITIES (LLM)	0.585		0.018*		-0.075	
	(0.438)		(0.009)		(0.189)	
DISCUSSES PHYSICAL (LLM)	0.076		-0.033**		-0.182	
	(0.311)		(0.016)		(0.245)	
DISCUSSES REGULATORY (LLM)	-0.426		-0.002		0.033	
	(0.506)		(0.009)		(0.132)	
DISCUSSES TRANSITION (LLM)	-0.256*		0.004		-0.588***	
	(0.143)		(0.009)		(0.171)	
SOLAR		0.233*		0.046***		-0.087
		(0.121)		(0.014)		(0.167)
WIND		-0.164		0.015		-0.044
		(0.258)		(0.011)		(0.173)
EMISSIONS		-0.270**		0.027**		-0.421*
		(0.125)		(0.011)		(0.212)
AUTOS		0.301**		0.023**		-0.218
		(0.140)		(0.011)		(0.149)
GAS / COAL / COMBUSTION		-0.509**		0.008		0.086
		(0.190)		(0.017)		(0.337)
GENERAL RENEWABLES		-0.209		-0.014		-0.141
		(0.242)		(0.009)		(0.112)
PHYSICAL		-0.022		-0.008		0.088
		(0.158)		(0.026)		(0.396)
REGULATORY		0.358***		0.006		0.284
		(0.090)		(0.015)		(0.231)
GENERAL CLIMATE-RELATED		0.125		0.002		-0.123
		(0.159)		(0.012)		(0.146)
Observations	14,529	14,533	73,119	73,128	73,119	73,128
Adjusted R-squared	0.241	0.241	0.754	0.754	0.469	0.469
Controls	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst
Lead Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Climate-related discussion in analyst reports and market outcomes

This table presents results from OLS regressions of cumulative abnormal returns (columns 1-6) or average turnover (columns 7-12) on an indicator equal to 1 if I classify a report as discussing climate-related topics and decompositions of this measure using an LLM-based approach (columns 2, 5, 8, and 11) or sub-groupings of specific keywords from Sautner et al. (2023) (columns 3, 6, 9, and 12). I measure these outcome measures over the [0,1] window beginning with report issuance and only retain observations with non-missing values over the entire window. Given the findings from Table 6, I separately examine reports matched with a long-term growth forecast (columns 1-3 and 7-9) and reports not matched with a long-term growth forecast (columns 4-6 and 10-12). Appendix A defines all variables. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels respectively. Parentheses denote standard errors clustered by broker and analyst.

	DV = CAR[0,1]						DV = Turnover[0,1]					
Sub-sample =	Non-Missing LONG-TERM GROWTH			Missing LONG-TERM GROWTH			Non-Missing LONG-TERM GROWTH			Missing LONG-TERM GROWTH		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CLIMATE-RELATED	-0.005*			0.001			-0.018			0.001		
	(0.002)			(0.001)			(0.042)			(0.018)		
DISCUSSES EMISSIONS (LLM)		-0.001			0.001			0.063			-0.068	
		(0.004)			(0.003)			(0.051)			(0.051)	
DISCUSSES OPPORTUNITIES (LLM)		-0.006			0.001			-0.043			-0.025	
		(0.005)			(0.003)			(0.112)			(0.030)	
DISCUSSES PHYSICAL (LLM)		0.005			0.004			-0.129**			0.028	
		(0.004)			(0.008)			(0.051)			(0.077)	
DISCUSSES REGULATORY (LLM)		0.003			0.000			0.026			0.030	
		(0.004)			(0.003)			(0.066)			(0.036)	
DISCUSSES TRANSITION (LLM)		-0.006			0.000			-0.128*			0.066	
		(0.006)			(0.002)			(0.068)			(0.043)	
SOLAR			-0.003			0.004			-0.051			-0.006
			(0.006)			(0.002)			(0.097)			(0.051)
WIND			-0.003			-0.002			-0.094			0.011
			(0.004)			(0.001)			(0.082)			(0.038)
EMISSIONS			-0.004			-0.000			0.038			-0.021
			(0.004)			(0.003)			(0.055)			(0.036)
AUTOS			-0.004			0.000			-0.070			-0.059*
			(0.005)			(0.003)			(0.055)			(0.030)
GAS / COAL / COMBUSTION			0.004			0.003			0.075			0.009
			(0.004)			(0.004)			(0.080)			(0.057)
GENERAL RENEWABLES			-0.003			0.001			0.080			0.025
			(0.004)			(0.001)			(0.069)			(0.025)
PHYSICAL			0.000			0.016			0.586***			0.074
			(0.008)			(0.010)			(0.198)			(0.079)
REGULATORY			0.007			-0.002			-0.065			0.004
			(0.005)			(0.002)			(0.073)			(0.032)
GENERAL CLIMATE-RELATED			-0.001			0.001			-0.089*			0.002
			(0.004)			(0.001)			(0.047)			(0.038)
Observations	16,354	16,350	16,354	98,445	98,428	98,445	16,354	16,350	16,354	98,445	98,428	98,445
Adjusted R-squared	0.095	0.095	0.094	0.096	0.096	0.096	0.697	0.698	0.698	0.737	0.737	0.737
Controls	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst	Report, Analyst
Lead Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes