Firm-level Climate Change Exposure

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Abstract

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Keywords: Climate change; climate risk; earnings conference calls; institutional investors

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

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Firm-level Climate Change Exposure*

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1. Introduction

Climate change has started to significantly affect a large number of firms. While some firms face direct costs from change in the physical climate, others are adversely affected by policies and regulations that are implemented to combat global warming. At the same time, climate change does provide opportunities for some firms, those, for example, operating in renewable energy, electric cars, or energy storage. With the consequences of climate change becoming more observable, the debate has intensified over whether capital markets are paying enough attention to the financial impacts of climate change.

It is a challenge for investors and regulators to properly quantify *firm-level* exposure to climate change, with respect to the associated risks, but also in terms of the opportunities that come with it. First, the effect of climate change on firms is highly uncertain because it remains unclear how the climate will eventually change and whether, how, and when policymakers will tighten regulation (Barnett, Brock, and Hansen, 2020). Second, the effects of climate change are heterogeneous across firms, even within the same industry. The reason for this is that many factors that plausibly affect a firm's ability to adapt to a greener economy exhibit large firm-level components (e.g., managerial skill, innovation, or financial constraints). Third, there is currently no common practice among academics or practitioners for how to reliably quantify firm-level climate change exposure. While firms' voluntary carbon emissions are gaining some traction as an exposure measure, the data exist only for a limited and selected sample (about half of all S&P 500 firms do not report their emissions). Furthermore, disclosed emissions reflect firms' historic (instead of future) business models, and do not distinguish between "good" and "bad" emissions.[1]

These challenges have the potential to impede the reallocation of resources from "brown" to "green" firms, which is one of the major tasks identified by policymakers for achieving global climate targets. Furthermore, the lack of a firm-level exposure measure may contribute to the potential mispricing of climate risks and opportunities in capital markets (Hong, Li, and Xu, 2019; Daniel, Litterman, and Wagner, 2017), and it complicates the development of financial instruments that allow market participants to hedge the effects of climate change (Engle et al., 2020). In a recent review of the literature, Giglio, Kelly, and Stroebel (2020) have therefore identified improvements in *measuring* firm-level climate change exposure, and especially its separation into physical and other components, as a key area where more research is needed.

[1] Some firms' emissions support the transition to a greener economy; these firms are called "climate enablers" (e.g., producers of building materials that make houses more energy efficient).

In this paper, we make progress in this direction by using transcripts of quarterly earnings conference calls of publicly-listed firms to construct time-varying measures of how market participants perceive these firms' exposures to climate change. Earnings calls are key corporate events on the investor relations agenda and allow financial analysts and other market participants to listen to management and to ask firm officials about material current and future developments (Hollander, Pronk, and Roelofsen, 2010). A benefit of using earnings calls is that they are less susceptible to "greenwashing" by management. Indeed, even if management tries to evade the topic of climate change or to window dress their achievements, analysts could act as a counterpoint by asking probing questions. This is different from other documents such as annual reports or press releases, which exclusively reflect the views of management. This argumentation is supported by the evidence in Bingler et al. (2021) that climate risk disclosure in annual reports is mostly cheap talk with firms cherry-picking the information they provide. To construct our measures, we build on recent work using these transcripts as a source for identifying firms' various risks and opportunities (Hassan et al., 2019, 2020a,b). These studies use the proportion of the conversation during a call that is centered on a particular topic as a measure of the firm's exposure to that topic.[2]

Importantly, we modify the approach of these prior papers along several dimensions. First, we address the fact that climate change has multifaceted effects, spanning the issues of physical threats, regulatory interventions, and technological opportunities. Our measures therefore encapsulate the perceived exposure to upside *and* downside shocks. Second, prior studies rely on pre-specified *signal* word combinations (or "bigrams") to identify the topic of interest. Hassan et al. (2019), who study political risk, determine these bigrams by comparing training libraries of political and nonpolitical texts. In Hassan et al. (2020a,b), who study Brexit and Covid-19, the words used to identify discussions about these shocks are self-evident and no training libraries are required. In our setting, there is no well-defined dictionary or single phrase like "Brexit" or "coronavirus" that can be used to identify climate discussions. Creating a new dictionary from scratch, on the other hand, has been shown to be challenging and susceptible to human error (Liu, Nowak, and Smith, 2019).[3]

[2]We follow these papers in defining "exposure" to a topic as the share of the conversation in a transcript devoted to that topic. While related, this definition of "exposure" is somewhat different from how risk exposure (e.g., a factor beta) is defined in the asset pricing literature. See Hassan et al. (2019) for a discussion of the relation between these two areas of literature.

[3]One way to reduce human error is having a transparent list of bigrams, as done by Loughran and McDonald (2011).

For this reason, we introduce a novel method that identifies word combinations signaling climate change conversation in earnings calls. The method builds on the finding that humans perform well when associating words to topics, but poorly when creating dictionaries from nothing (King, Lam, and Roberts, 2017). Our method adapts the machine learning keyword discovery algorithm proposed by King, Lam, and Roberts (2017) to produce four related sets of climate change bigrams; the first captures broadly-defined climate change aspects, while the remaining three cover specific climate "topics:" specifically, opportunity, physical (e.g., sea level rises, natural disasters), and regulatory shocks (e.g., carbon taxes, cap and trade markets). For each transcript, we employ these four sets of bigrams to construct an aggregate firm-level measure of exposure to climate change as well as three measures of exposure to the specialized "topics." The algorithm only requires human input to specify a short list of initial keywords associated with climate change. For validation purposes, we compare our exposure measure with an alternative that is constructed based on pre-specified keywords instead and show through a perturbation test that the measure is robust excluding one keyword at a time from our list of initial keywords.

The exposure measures count the frequency of certain climate change bigrams in a transcript, scaled by the total number of bigrams in that transcript. We interpret these measures as indicating the occurrence of climate change events or shocks at a firm as perceived by market participants. We construct measures of the first and second moment associated with these shocks, specifically, whether shocks represent (in expectation) good or bad news to the firm and whether shocks are uncertain. For the first moment, we construct "sentiment" measures, which count the relative frequency of climate change bigrams that occur in the vicinity of positive and negative tone words (Loughran and McDonald, 2011). For the second moment, or risk measures, we count the relative frequency of climate change bigrams mentioned in the same sentence as the words "risk," "uncertainty," or their synonyms. Following Hassan et al. (2019), we interpret these sentiment and risk measures as components of the exposure measures.[4]

As most of our other data varies at the year level, we create annual transcript-based measures for each firm by averaging measures from quarterly transcripts.[5] Our sample contains more than 80,000 annual observations originating from more than 10,000 unique

[4]Though they capture different theoretical constructs, we use the words "risk" and "uncertainty" interchangeable in this paper as participants in earnings calls may not be aware of the difference and use the terms as synonyms.

[5]Our publicly available data set provides climate change scores at a firm-quarter granularity, allowing researchers and policymakers to trace over-time variation in exposure at this higher frequency.

firms in 34 countries between 2002 and 2019.

To verify the validity of our measures, we conduct a human audit of the identified bigrams that signify discussion about the different dimensions of climate change. The top bigrams associated with exposure to climate change *opportunities* refer to new (green) technologies, such as electric vehicles. In a similar vein, top *regulatory* bigrams indicate regulatory and/or governmental interventions associated with climate change and the goal to reduce carbon emissions. Top bigrams linked to the exposure to *physical* shocks include word pairs related to hurricanes, desalination, or draughts. We also validate our approach by examining individual text fragments taken from the point in the transcripts identified by our algorithm as the moment when participants discuss climate change, and verifying that the call fragments are indeed centered on salient climate issues.

The time-series dynamics for the broadly-defined exposure measure reveals that the discussion of climate change issues increases over time until around 2011 (the increase starts by the mid-2000s already.) There is then a modest decline leading up to the largely unsuccessful 2012 Doha Climate Summit, but in subsequent years, we observe a renewed increase in climate change exposure (in particular following the Paris Agreement of 2015).

A similar exercise in which we aggregate our measures by taking sector averages shows that the sectors with the highest overall perceived exposure to climate change are Electric, Gas, & Sanitary Services (i.e., utilities), followed by Construction and Coal Mining. Utilities top the exposure ranking for both opportunity and regulatory shocks, which signifies that utilities face opportunities (e.g., renewable energy) and regulatory risks (e.g., carbon taxes) related to climate change. The observation that some firms with large regulatory risks also exhibit climate-related opportunities is consistent with Cohen et al. (2020), who document that some of the major carbon emitters are key innovators in green technologies.[6] Physical climate change exposure is highest for Paper & Allied Products, Heavy Construction, and Insurance. Importantly, for all measures, we find large within-industry variation, indicating that firms will benefit or suffer to various degrees from climate change. The large within-industry variation underscores the need for time-varying firm-level measures of climate change exposure.[7] Indeed, further analyses show that even the identity of firms exposed to climate change varies over time; climate change exposure

[6]This two-sided perspective is also consistent with how investment analysts view sectors with high regulatory risks (see "Morgan Stanley: 'Second wave of renewables' to drive 70 GW of coal retirements," *S&P Global Market Intelligence*, December 20, 2019.).

[7]Utilities are again an example, as they exhibit large within-industry heterogeneity in terms of renewable energy capacity or reliance on fossil fuels, leading to within-sector divergence in both risks and opportunities.

is not in all cases a persistent firm-level characteristic. Furthermore, exposure to climate change varies across countries, and we document reasonable associations between our exposure measures and country-year level proxies for the regulatory and physical impacts of climate change. In an analysis using country fixed effects, we find little evidence that our exposure measures are affected by the native language in a country and how distant this language is from English. Further, the exposure measure does not depend on individual bigrams included in the short list of initial keywords.

To validate that our measures quantify variation in the perceived exposure to climate change shocks *at the firm level*, we conduct an analysis of variance. Between 70 and 97% of variation in our exposure measures plays out at the firm level (rather than at the country or industry level or over-time). Only half of this firm-level variation is persistent, suggesting that firms within an industry are differentially exposed to climate change over time.[8] We compare the results of this analysis with a similar decomposition exercise for two important alternative measures of firm-level exposure to climate change: i) a firm's carbon intensity (emissions scaled by assets) and ii) a firm's carbon risk rating. The carbon risk rating is constructed by the proxy-advisory firm ISS, with the objective of providing investors with a comprehensive assessment of the carbon-related performance of firms.[9] The firm-level variation for carbon intensities and the ISS measures is substantially smaller (especially compared to our topics-based measures), amounting to only 56.6 and 73.0%, respectively. Two-thirds of the variation in the ISS ratings is persistent. Carbon intensities, which are increasingly used in climate finance literature are driven mostly by industry fixed effects.

Nevertheless, our measures overlap somewhat with carbon intensities and the ISS measure. This is expected, given that all three measures aim to capture dimensions of firms' climate change exposure. Carbon intensities appear to correlate most closely with our measures of opportunity and regulatory shocks. The ISS rating reflects our measure of opportunities more than our measures of regulatory or physical shocks. Together with the variance decomposition results, this suggests that the alternatives are more specialized than are our measures.

Our sample allows us to explore the role of important economic factors that prior

[8] At 97%, firm-level variation for exposure to physical shocks is by far the highest, which is reasonable since these shocks largely depend on firm-specifics (e.g., the location of a firm's production sites within a country, the supply chain specifics, or the insurance policies).

[9] ISS plans to include information from its ratings into its voting recommendations, with the objective to "*incorporate climate-related considerations systematically into their engagement and proxy voting strategies*" (see https://www.issgovernance.com/iss-launches-climate-voting-policy/).

work identifies as potentially related to climate change exposure. As our factors vary at the time, firm, and country levels, correlations between these factors and the exposure measures help us corroborate that we capture meaningful variation in climate change exposure. First, we explore the role of public attention to climate change, which has been shown to affect returns of carbon-intense stocks (Choi, Gao, and Jiang, 2020) and the cost of insurance against carbon tail risk (Ilhan, Sautner, and Vilkov, 2021). We proxy for attention by using the time-varying measure of climate change news developed in Engle et al. (2020). Higher attention to climate change is associated with a rise in firms' exposures to regulatory and physical climate shocks, but is not associated with opportunity shocks. A potential explanation for this asymmetry in the results is that the media pays more attention to environmental rules and physical threats than to the opportunities presented by climate change. Earnings call participants that follow the media may therefore be more likely to address the negative impacts of climate change.

Second, firm-level institutional ownership is negatively related to climate change exposure. This effect is particularly strong in recent years and stems primarily from a negative association between institutional ownership and the exposure to regulatory *and* opportunity shocks. The negative relation is consistent with institutional investors beginning to underweight (or to divest) firms with high climate change exposure, apparently without distinguishing much between firms with upside and downside exposures.

Third, the *voluntary* information exchanges between management and analysts during earnings calls do not appear to be driven by variation across countries in terms of mandatory ESG disclosure standards. This indicates that our measures of *voluntary* information exchange are unaffected by variation in *mandatory* disclosure across countries.

Next, we explore whether our exposure measures exhibit an association with firms' valuations. Firm exposure to regulatory shocks is negatively associated with valuation changes. Interestingly, we can only document this effect for the second half of the sample, that is, the years during which climate change exposure is relatively high (since 2011). At the same time, we do not detect any evidence that valuations reflect firm-level exposure to opportunity shocks; markets may therefore undervalue firms with high exposures to these shocks, bolstering the survey evidence in Krueger, Sautner, and Starks (2020).

Finally, we study the effects of the Covid-19 pandemic on our measures of climate change exposure. Covid-19 may decrease the perception of firms' climate change exposures in the short term by shifting the focus of the earnings calls away from climate topics and towards the effects of Covid-19 (Hassan et al., 2020a). The economic downturn associated with Covid-19 may also make climate-related regulation less likely, and it may reduce the financial resources available to support the transition to a greener economy. We find that climate change discussions in earnings calls declined with the pandemic, starting with Chinese firms in their 2020q1 calls, and then with U.S. and European firms in their 2020q2 calls. The differences in timing are consistent with the evolution of the pandemic across the world.

Over the last months, our exposure measures have been related to a series of important financial outcomes. This "out-of-sample evidence" indicates that the measures capture meaningful variation across firms and mitigates the concern that it reflects mostly noise. Specifically, the evidence in other papers shows that our measure of climate change exposure is associated with lower leverage after the Paris Climate Agreement (Ginglinger and Moreau, 2021), negatively predicts firm innovation (Li et al., 2021), positively relates to cash holdings (Heo, 2021), explains disclosure in Form 8-K filings (Gostlow, 2021), is priced in equity, options, and CDS markets (Sautner et al., 2021; Kölbel et al., 2021), and explains how strongly U.S. firms' emissions declined in response to the EPA's 2010 Greenhouse Gas Reporting Program (Tomar, 2021).

Most closely related to our paper is contemporaneous work by Li et al. (2020) who also use earnings calls to identify climate risks. We diverge from their work in terms of method, focus, and sample. First, Li et al. (2020) use a pre-specified training library to identify weather and climate risk words, which, we argue, is unlikely to uncover the exact language in earnings calls that is used to discuss climate change. Second, while Li et al. (2020) focus on physical climate risks related to extreme weather events among a sample of U.S. firms, we provide a more comprehensive analysis based on a global sample and, using the actual language in earnings calls, we extend our analysis to include the opportunities as well as the regulatory impacts of climate change. Rather than focusing on weather-related exposure, we take a broader perspective and include any manifestation of climate change.

More broadly, we contribute to papers that study climate risk disclosure. Solomon et al. (2011) show that institutional investors use private channels of discourse with portfolio firms to compensate for inadequacies in public climate reporting. Matsumura, Prakash, and Vera-Munoz (2014) find that markets discount firms that do not disclose emissions through the CDP, although Griffin, Lont, and Sun (2017) suggests that the differences may not arise from CDP disclosure. Matsumura, Prakash, and Vera-Munoz (2018) analyze voluntary 10-K climate risk disclosures and find that disclosing firms have lower costs of equity. Ilhan et al. (2021) study the preferences of institutional investors with respect to climate risk disclosures, while Flammer, Toffel, and Viswanathan (2021) find that activism by long-term institutional investors increases the voluntary disclosure of climate risks. Ramadorai and Zeni (2020) use data disclosed to the CDP to infer firms' beliefs about climate regulation and to document firms' plans for emission abatement. Krueger (2015) and Jouvenot and Krueger (2019) report beneficial valuation effects from the introduction of carbon emission disclosures in the U.K.

2. Data

2.1. Data on Earnings Conference Calls

We use transcripts of quarterly earnings conference calls held by publicly-listed firms to construct our time-varying measures of how market participants perceive firm-level exposure to climate change. On an earnings call, financial analysts and other market participants can listen to senior management present their views on the company's state of affairs and can ask questions about the firm's financial performance over the past quarter. Importantly, these earnings calls are also used to discuss current and future developments more broadly (Hollander, Pronk, and Roelofsen, 2010). Our measures of exposure to climate change are constructed using the entire conference call, including both the management presentation and the question-and-answer session with analysts.[10] As most of our other data varies at the year level, for each firm, we create annual transcript-based measures by averaging quarterly transcript-based measures. The transcripts are collected from the Refinitiv Eikon database; we use the complete set of English-language transcripts for the years 2002 to 2019. We restrict the analysis to firms in countries with at least 150 annual transcript observations. Our final sample includes 80,221 firm-year observations from 10,158 unique firms headquartered in 34 countries. Variable definitions are in Appendix A and summary statistics are in Table 1. IA Table 1 provides the distribution of firm-year observations across countries.

2.2. Data on Carbon Emissions

To benchmark and compare our measures, we use data on firms' Scope 1 carbon emissions from CDP. Scope 1 emissions are direct emissions, which come from the combustion of fossil fuels or from releases during manufacturing. We focus on Scope 1 emissions, rather than Scope 2 or Scope 3 emissions, as they are directly owned and controlled by firms. We scale these emissions by total assets in order to obtain a measure of $Carbon\,Intensity$.

[10] In Internet Appendix B and IA Table 23, we explore the point at which climate change discussions take place during earnings calls.

Our CDP sample includes 6,009 firm-year observations from 1,287 unique firms located in all 34 sample countries. The emissions come from between 2009 and 2017 (coverage has increased over the last years).

2.3. Data on ISS Carbon Risk Ratings

As a second benchmark, we use data on firms' *ISS Carbon Risk Rating* from ISS ESG, which constructs these data to assess firms' carbon-related performance. ISS ESG, which claims to be the world's leading provider of ESG solutions for investors, is the responsible investment division of proxy voting advisor Institutional Shareholder Services (ISS). *ISS Carbon Risk Rating* is available at an annual frequency and is constructed based on several factors, including the carbon impact of a firm's products (e.g., the revenue shares of products associated with a positive or negative climate impact) and carbon emission reduction targets and action plans. Similarly to our approach, ISS aims to capture both the upside and downside exposure of firms to climate change. To reflect this spectrum, *ISS Carbon Risk Rating* ranges from 1 (poor performance) to 4 (excellent performance). The data are collected by ISS from publicly available sources (e.g., annual reports, ESG reports, or newspaper articles) and from interviews with firm management. Our ISS sample contains 9,995 firm-year observations from 3,306 firms in all 34 countries. The ratings are available from 2015 to 2019. Firm coverage has increased over the sample period, from 1,493 sample firms in 2015 to 3,032 firms in 2019.

2.4. Other Data

Climate Policy Regulation. To validate our measures, we use an index from Germanwatch that evaluates the climate policy regulations of a country. *Climate Policy Regulation* reflects a country's policies on renewable energies and emission reductions, the ambition level and "2 degree" compatibility of a country's Nationally Determined Contributions (NDCs), and the progress towards reaching these NDCs. The index varies at the country-year level and ranges between 0 and 20; higher numbers reflect better climate regulations. The data are available for 29 of our sample countries and from 2007 to 2019. Data from Germanwatch is used in Atanasova and Schwartz (2019) and Delis, de Greiff, and Ongena (2019).

Extreme Temperature. We further validate our measures by using information about the frequency of extreme temperature events from the Emergency Events Database (EM-DAT), which is compiled by the Centre for Research on the Epidemiology of Disasters at Université Catholique de Louvain. The measure varies at the country-year level and captures the frequency of extreme temperature episodes. *Extreme Temperature* ranges between 0 and 3 and is available for all countries from 2002 to 2019.

Public Attention to Climate Change. We borrow an index developed in Engle et al. (2020) to capture how public attention to climate change varies between 2002 and 2017. *Media Attention* is constructed by measuring positive and negative news about climate change in the *Wall Street Journal*. To quantify the intensity of climate news coverage in the *Wall Street Journal*, Engle et al. (2020) compare the news content to a corpus of authoritative texts on the subject of climate change.

Institutional Ownership. We measure the percentage ownership of institutional investors using Thomson Reuters data (available for North American firms from 2002 to 2019).

Country Mandatory ESG Disclosure. We use data from Krueger et al. (2021) to identify whether and when countries introduced mandatory ESG disclosure to enhance the disclosure of nonfinancial information to investors. Krueger et al. (2021) identify 25 countries that mandate firms to disclose ESG information from 2000 to 2017. Out of these 25 countries, 16 countries (Austria, Australia, Chile, China, France, Greece, Hong Kong, India, Italy, Netherlands, Norway, Singapore, South Africa, Spain, Switzerland, U.K.) are included in our sample.

Financial Statement Data. Data on firm financial variables such as total assets, debt, or cash holdings are from Compustat North America and Compustat Global.

3. Quantifying Firm-level Exposure to Climate Change

3.1. Objective of Climate Change Measures

To quantify a firm's exposure to climate change, we build on recent work that uses earnings call transcripts to identify firms' various risks and opportunities (Hassan et al., 2019, 2020a,b). These prior studies use the proportion of an earnings call that is centered on a particular topic as a measure of the firm's exposure to that issue. We face two challenges in applying this logic to the quantification of climate change exposure.

First, the effects of climate change are multifaceted, spanning from regulatory interventions to "physical threats" to a firm's plant, property, or equipment. Furthermore, new technologies and market opportunities provide some firms with a potential upside to climate change. Thus, an ideal measure encapsulates all of these facets to identify a firm's exposure to environmental changes. Ideally, the measure should also allow for the decomposition of a firm's (composite) exposure to contributing factors.

Second, prior studies identify the topics of interest in an earnings call by relying on pre-specified *signal* bigrams that are compiled in one of two ways. Hassan et al. (2019), who study political risk, determine signal bigrams by comparing training libraries of political texts (e.g., political textbooks and speeches by politicians) with nonpolitical libraries (e.g., accounting textbooks and novels). In Hassan et al. (2020a,b), which study Brexit and Covid-19, respectively, the words used to identify discussions about these shocks are self-evident and no training libraries are required. Neither of these two approaches yields satisfactory results in identifying climate change bigrams in our context. For example, using training libraries that consist of climate change reports issued by research institutions or professional investors fails to identify accurate climate change bigrams. This is because people tend to discuss climate change in conjunction with other topics, such as new technologies, government regulation, and tax credits. Thus, text documents in the training library reflect a mixture of genuine climate change discussions and conversations about extraneous topics. The same will hold true for the earnings call transcripts. Using a training library, the algorithm will then identify word combinations unrelated to climate change (e.g., signalling tax policies instead). Thus, Hassan et al. (2019)'s method yields word combinations which contain more "false positives" than valid climate change word combinations. Hassan et al. (2020a,b)'s method also falls short in our context, as there is no clear climate change equivalent to "Brexit" or "Corona." While researchers could, in principle, attempt to create a comprehensive word list (and we will also do this for comparison purposes), prior work suggests that humans tend to overlook important phrases when completing such tasks (King, Lam, and Roberts, 2017). For this reason, we introduce to the economics and finance literature a novel, purposeful method that can identify word combinations signalling climate change conversation in earnings calls.

3.2. Discovery of Climate Change Bigrams

We adapt the machine learning keyword discovery algorithm proposed by King, Lam, and Roberts (2017) to produce a set of climate change bigrams $\mathbb{C}$. This algorithm helps us overcome the challenges above in order to quantify climate change exposure. First, the algorithm does *not* need a comprehensive "climate change" training library; instead, it only requires a small set of "initial" bigrams (listed in IA Table 2). These initial bigrams are chosen because they unambiguously relate to climate change. The algorithm then uses these initial bigrams to search for new bigrams that also likely indicate conversation about climate change and it searches directly in the transcripts. Second, because each initial bigram is connected with a specific group of new bigrams discovered through the search algorithm, one can easily decompose the measure of climate change exposure (based on the presence of these bigrams) into its constituent parts.

The "initial" bigrams allows the algorithm to identify sentences of interests that clearly talk about climate change. Relying on supervised learning methods, the algorithm can then extract features, i.e., bigrams beyond the "initial" set, that predict climate change from the identified sentences of interests. Finally, the algorithm constructs a model predicting whether or not a sentence is related to climate change. We apply this prediction model to sentences that do *not* include any "initial" bigrams and then learn from whether or not the predicted sentences are climate-change-related. To discover new climate change bigrams, we reverse-engineer the machine learning process and trace back the bigrams that best discriminate climate-change-related from other sentences. The resultant set of climate change bigrams $\mathbb{C}$ includes the "initial" bigrams and the newly identified bigrams from the algorithm.[11]

The benefit of our approach is that the algorithm generates meaningful climate change bigrams that are based on the "initial" bigram set. This is helpful for several reasons. First, the algorithm extends the rather broadly specified initial bigrams into more specialized word combinations. For example, "rooftop solar" and "photovoltaic panel" come from the initial bigram "solar energy," while "nuclear power" or "event fukushima" come from "renewable energy," and "tesla battery" and "hybrid plug" correspond to the initial bigram "electric vehicle." Second, $\mathbb{C}$ includes the names of several power stations and wind farms (e.g., "kibby wind" or "coughlin power"), which are of interest to call participants that discuss the climate change exposure of the firms operating these facilities. These bigrams also illustrate the challenge of using training libraries or pre-specified word lists to identify climate change talk; few researchers would have the detailed institutional or field knowledge to recognize the relation of these words to climate change.

We adapt the bigram-searching algorithm to discover three unique sets of climate change bigrams, $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, from $\mathbb{C}$, which capture opportunity, regulatory, and physical shocks related to climate change, respectively. To this end, we feed a set of "initial" bigrams reflecting these three topics to the searching algorithm, and then allow the algorithm to discover bigrams that are related to the topic of interest.[12] For each topic, we customize the set of initial bigrams using the top-500 bigrams in $\mathbb{C}$ that occur

[11] Technical details, including how we define the set of initial bigrams, are in Internet Appendix A.

[12] See IA Table 6 for the list of initial bigrams used for the topic search.

in the earnings calls. We then re-perform the searching algorithm to find a broader set of bigrams for each topic. As the topics-based algorithm yields some general climate change bigrams, we drop bigrams appearing in more than one topic; this guarantees that we do not have overlapping topic measures. Last, we take the intersection between $\mathbb{C}$ and each set of topic bigrams to obtain the sets of opportunity, regulatory, and physical climate change bigrams (i.e., $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$), respectively.

3.3. Construction of Climate Change Exposure Measures

Using the four set of bigrams, we construct for each transcript measures of exposure, sentiment, and risk. To simplify exposition, we use the broad set of climate change bigrams $\mathbb{C}$ to illustrate how we construct these measures. The more narrow ("topic") measures are constructed analogously; we simply replace $\mathbb{C}$ with the set of bigrams that relate to the corresponding topic.

We construct a (broad) measure of climate change exposure ($CCExposure$) based on how frequently the specified bigrams appear in a given transcript. First, we take the set of climate bigrams $\mathbb{C}$ to the earnings call transcript of firm i in quarter t and count the frequency of these bigrams. We then scale the total count by the number of bigrams in the transcript to account for differences in the length of the calls:

$$CCExposure_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} (1[b \in \mathbb{C}]), \tag{1}$$

where $b = 0, 1, ..., B_{it}$ are the bigrams in the earnings call transcripts of firm i in quarter t and where $1[\cdot]$ is the indicator function.

Next, we create a measure of climate change sentiment ($CCSentiment$) by counting the number of climate change bigrams after conditioning on the presence of the positive and negative tone words in Loughran and McDonald (2011); we standardize again by the number of bigrams:

$$CCSentiment_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} (1[b \in \mathbb{C}]) \times \sum_{b}^{b \in S} \mathcal{T}(b), \tag{2}$$

where S represents the sentence containing bigrams $b = 0, 1, ..., B_{it}$ and where $\mathcal{T}(b)$ assigns sentiment to each bigram b:

$$\mathcal{T}(b) = \begin{cases} 1 & \text{if } b \text{ has a positive tone} \\ -1 & \text{if } b \text{ has a negative tone} \\ 0 & \text{if otherwise} \end{cases}$$

Finally, we construct a measure of climate change risk ($CCRisk$) by counting the relative frequency of climate change bigrams that are mentioned in the same sentence with the words "risk," "uncertainty," or their synonyms:

$$CCRisk_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} (1[b \in \mathbb{C}] \times 1[b, r \in S]), \tag{3}$$

where S represents a sentence containing bigrams ($b = 0, 1, \ldots, B_{it}$) and where r contains the words "risk," "uncertainty," or a synonym.

Since most of our other data vary at the year level, we create for each firm an annual transcript-based measure by averaging the quarterly measures. As explained above, we also produce measures of exposure, sentiment, and risk from $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, respectively, by scoring each transcript using the same method. We label the topics-based measures by adding the superscripts Opp, Reg, and Phy to a given measure (e.g., $CCExposure^{Opp}$).

4. Validation

4.1. Face Validity of Climate Change Bigrams

We validate our climate change measures using a multi-pronged approach.[13] First, we consider the face validity of the bigrams used to construct the exposure measures. Table 2 shows the 100 highest-frequency bigrams in $\mathbb{C}$. The top bigrams associated with $CCExposure$, our broad exposure measure, capture aspects of the opportunities and potential risks associated with climate change. The top-20 bigrams include opportunity-related word-pairs such as "carbon capture" or "rooftop solar," but also include risk-related terms such as "environmental concern" or "reduce emissions."[14] When considering individual bigrams, it is important to note that the exposure measures we construct are

[13]For brevity, in our discussion, we focus on the *exposure* measures. We also subject the corresponding *sentiment* and *risk* measures to the validation tests; a summary is reported in the Internet Appendix.

[14]"President Obama" may be mentioned because his administration proposed the Clean Power Plan, which would fight climate change by reducing carbon emissions from the generation of electric power.

composite measures, that is, they account for measurement error at the individual bigram level. IA Tables 3 and 4 show the top-100 and bottom-100 bigrams for $CCSentiment$, and IA Table 5 reports the top-100 bigrams for $CCRisk$ (recall that the bigrams for $CCSentiment$ and $CCRisk$ are subsets of $CCExposure$).

We next turn to the three topics-based measures. When we use initial bigrams such as "wind power," "solar energy," and "new energy," we find several new bigrams associated with $CCExposure^{Opp}$ that refer to new (green) technologies; these new bigrams include "nuclear renewable," "pv panel," and "carbon free." Several word combinations are linked to developments in "electric vehicles," including "charge infrastructure" and "battery electric" (see IA Table 7). In our measure of regulatory exposure, $CCExposure^{Reg}$, when we use initial bigrams such as "carbon tax," "air pollution," and "air quality," which are reminiscent of regulatory and/or governmental interventions associated with climate change, we find bigrams that explicitly include the word "regulation" or its synonyms, as "epa regulation," "control regulation," "energy regulatory," and "environmental standard" (see IA Table 8). Turning to the top bigrams for $CCExposure^{Phy}$, we use initial bigrams such as "natural hazard" or "sea level" to identify word pairs that are intuitively linked to the physical aspects of climate change, such as "island coastal," "hurricane ice," or "large desalination." (see IA Table 9).

For high scoring firms, Table 3 provides "snippets," that is, text fragments taken from the point in the respective transcript that the algorithm identifies as the moment when call participants are discussing climate change. The five highest scoring firms on $CCExposure$ are headquartered in the U.S. and China. Consider, for example, Ocean Power Technologies, a U.S. company which turns ocean wave power into electricity for offshore applications. In its 2008q4 earnings call, bigrams such as "energy requirement," "powerbuoy wave," "wave condition," and "wave power" were heavily featured. In the top snippet from the call, participants discuss the increased demand for the company's trademark technology (the PowerBuoy®) stemming from the heightened attention to renewable energy requirements. Similarly, the 2014q4 call of the China Ming Yang Wind Power Group uses bigrams that include "distribute renewable" and "wind power." Its top snippet discusses management's thoughts about the attainability of distributed renewable energy objectives. Not surprisingly, high scoring firms are involved in the production of energy or in the broader energy infrastructure. Indeed, when the call participants of ITC Holdings use climate change bigrams, they are discussing how their projects are central to delivering new sources of energy to customers. IA Tables 10 to 12 present more examples of snippets, focusing on the top-scoring firms for each topics-based measure.

This first validation exercise supports the idea that our algorithm identifies bigrams signifying a discussion of climate change. It is important to emphasize again, however, that our exposure measures are constructed at the *transcript* level and that each bigram only contributes a little to the final score of the exposure measures. For this reason, we shift our attention below to the properties of the final measures constructed using the full set of possible climate change bigrams.

4.2. Times-Series Variation of Measures

Accordingly, in our next step, we examine the *aggregate* properties of our broad exposure measure as well as the properties of the three topics-based measures. First, we compute the cross-sectional means of each measure and plot these over time in Figure 1, Panels A to D (the figures use quarterly transcript data to more precisely illustrate the time-series changes). The figures also highlight some key moments in the public awareness of climate change during the sample period, ranging from policy events to natural disasters. For purposes of exposition, in this and the remaining figures and tables, we multiply the exposure measures by 10^3.

In Panel A, the dynamics for (the cross-sectional average of) $CCExposure$ reveal that exposure to climate change increases over time, especially in the mid-2000s. The rise in the early years of the sample is somewhat surprising, as it indicates that earnings calls started to address climate change issues earlier than we might have expected. Reaching a plateau around the year 2011, we observe a small decline in the period leading up to the 2012 Doha Climate Summit, which was widely perceived as unsuccessful in addressing climate change, and a leveling off in the subsequent years (though this level remains high compared to the pre-2011 period). We note a renewed increase in climate change exposure since the 2015 Paris Agreement. At the end of the sample period climate change exposure reaches its peak, with the average earnings calls exhibiting about 1.7 climate change bigrams per 1,000 bigrams; this compares to about 0.1 political bigrams per 1,000 bigrams in Hassan et al. (2019).

The dynamics of the three topics vary in different ways over time. In Panel B, the time-series changes for $CCExposure^{Opp}$ resemble those of the aggregate measure; the changes clearly trend upward, especially in the beginning of the sample period. In Panel C, $CCExposure^{Reg}$ also trends upwards between 2002 and 2008, but varies around a markedly lower level between 2012 and 2017. Since 2017, and especially towards the end of the sample, the measure of regulatory aspects increases again substantially, as does the policy discussion on how to achieve the climate goals of the Paris Agreement. The similarity in the time-series patterns of $CCExposure^{Opp}$ and $CCExposure^{Reg}$ indicate that at times of higher (lower) regulatory shocks, opportunities for firms are also better (worse). This is consistent with priors, as, for example, regulation to limit emissions triggers business opportunities for firms in renewable energy or battery technology.

Differently from the previous patterns, $CCExposure^{Phy}$ in Panel D displays large swings over time around a mean of about 0.0125; there does not appear to be an upward or downward trend in this measure. IA Figure 1 provides additional figures, bifurcating climate change exposure into sentiment and risk scores. Perhaps the most noteworthy insight gleaned from these graphs is that the average *sentiment* related to regulatory climate shocks is negative and has decreased noticeably between 2002 and 2008.

4.3. Industry Variation of Measures

Next, we compute the average values of our four exposure measures by industry sector (at the two-digit SIC code level) and present a ranking of these means in Table 4.[15] In Panel A, using the broad exposure measure, the sectors with the highest overall exposure to climate change include Electric, Gas, & Sanitary Services, followed by Construction and Coal Mining. The mean of $CCExposure$ is highly skewed, even across the top-10 sectors, ranging between 6.6 and 1.4 (compared to a sample industry mean and median of 0.94 and 0.26, respectively).

Using our topics-based measures, utilities also top the list for $CCExposure^{Opp}$ (Panel B) and $CCExposure^{Reg}$ (Panel C). Coal Mining displays a high exposure to regulatory and physical climate shocks (Panels C and D). While the high regulatory exposure of coal mining is expected given the large carbon emissions from burning coal, the high physical exposure is more surprising. One explanation is that this high ranking position reflects mining firms' exposure to heavy precipitation, drought, and heat, which pose physical challenges to mining operations (Delevingne et al., 2020). A sector that also appears in the top 10 of $CCExposure^{Phy}$ (Panel D) is the insurance sector, which, unsurprisingly, is highly exposed to physical shocks such as storms, flooding, or droughts. The table also lists industries which appear *not* to have material (measured) exposure to climate change. These industries include educational services or hotels for $CCExposure^{Opp}$ and $CCExposure^{Reg}$, and communications for $CCExposure^{Phy}$.

[15]We report only those industries for which we have at least 30 firm-year observations. For comparison, we report the same ranking for *Carbon Intensity* and *ISS Carbon Risk Rating* in IA Table 13. IA Table 14 reports industry rankings for the sentiment and risk measures.

The large variation in climate change exposure *between* sectors masks the existing heterogeneity *within* each sector, which becomes apparent from the large within-sector standard deviations of the exposure measures. IA Figure 2, Panels A to D, provides some additional evidence to corroborate this observation for utilities. Using histograms, the panels display large within-industry variation for *each* of our measures. Again, the dispersion is unsurprising given the heterogeneity in business models in the sector.[16]

The within-industry variation underscores the need for a firm-level measure of climate change exposure. However, it also has implications for investors, as it illustrates differential firm-level exposure within a sector to climate opportunities *as well as* to regulatory and physical climate shocks. Thus, individual sectors likely have "winners" and "losers" regarding the effects of climate change. A consequence is that investors may be able to address climate risks and opportunities by keeping a broad industry diversification (rather than banning some industries entirely), and by then performing a negative (or exclusionary) screening of firms identified as climate change "losers." This observation echoes recent arguments by academics (Andersson, Bolton, and Samama, 2016) and by providers of low-carbon index solutions (e.g., the MSCI Low Carbon Index).

4.4. Country Variation of Measures

Exploiting the global nature of our sample, we report in Figure 2, Panel A to D, average values of climate change exposure by country. The panels document several noteworthy patterns. First, climate change exposure (Panel A) varies substantially across countries, with the highest average firm scores in Spain, Austria, and Chile, and the lowest in Israel. Second, in Panel B, Spain leads the ranking for $CCExposure^{Opp}$, outpacing New Zealand and Austria. The high ranking for Spanish firms likely stems from the country's high exposure to climate change opportunities; the country is ranked among the top 5 globally in terms of renewable energy use. Firms in Greece, Israel, and Ireland, on the other hand, have relatively modest $CCExposure^{Opp}$ according to our measure. Third, regulatory exposure (Panel C) is particularly strong for firms in New Zealand, Australia, South Africa, Singapore, and Hong Kong, but is also manifest in the EU and the U.K.[17]

[16] For example, at the U.S. utility AES, about 30% of the electricity capacity originates from renewable energy, compared to less than 10% at Duke Energy. Likewise, some power plants are much more exposed to physical climate shocks than others (e.g., those located near the sea versus those inland).

[17] The presence of South Africa in this list may be unexpected. However, as chair of the G77 and China group, South Africa played a key role in the adoption of the 2015 Paris Agreement. The country also cooperates closely with the EU on climate regulation. Among other things, it plans to fully decarbonise its electricity production by 2050.

Fourth, firms in countries that rely on or are constrained by natural resources vulnerable to climate change, such as Finland, Singapore, or Sweden, have high $CCExposure^{Phy}$.[18] Below we show that the country heterogeneity in climate change exposure likely does not originate from language differences (or how distant a language is from English).

More details on cross-country differences are provided in IA Figure 3, which decomposes the country-average exposure scores into climate change risk and sentiment. To single out just one observation from these figures, $CCSentiment^{Opp}$, while positive in almost all countries, is negative for firms in Korea, Russia, and South Africa. Unsurprisingly, sentiment about climate change regulation ($CCSentiment^{Reg}$) is negative in *all* countries (on average), consistent with the fact that firms generally perceive these regulations as bad news. Firms located in Chile, Finland, and Switzerland appear to be most negative about the physical aspects of climate change.

4.5. Climate Change Regulation and Extreme Temperature

Our next validity tests focus on associations between our measures and two proxies for the regulatory and physical impact of climate change. We use these proxies in the spirit of convergent validity tests since distinct measurements of the same underlying phenomenon should be correlated. However, these tests are by design noisy, as they do not provide variation at the firm level. Hence, we consider any documented correlation (or lack thereof) as suggestive evidence only.

In Table 5, Panel A, we consider firm-level regressions to explore the association between our exposure measures and the Germanwatch index that evaluates a country's climate change policies and regulations. As explained above, *Climate Policy Regulation* reflects issues such as subsidies for renewable energies or regulation to reduce carbon emissions. Column 1 reveals a positive association between the index and $CCExposure$, indicating that there are more climate change bigrams in the transcripts of firms located in countries with more climate-friendly policies and regulations. However, the explanatory power of *Climate Policy Regulation* is modest, as reflected in an adjusted R^2 of just 0.1%. When we look at the drivers of this overall effect by estimating regressions by exposure topic in Columns 2 to 4, we find that the aggregate effect stems mostly from firm-level exposure to opportunity and to regulatory shocks (not from physical shocks).

[18] For example, sea level rises impact firms in Singapore, and changes in precipitation and temperature affect firms producing forest products in Finland or Sweden, whose economies are very dependent on such products (it remains highly uncertain among scientists whether climate change positively or negatively affects forest growth (CCSP, 2008); this uncertainty is also reflected in the high scores of $CCRisk$ for these two countries in IA Figure 3).

The economic magnitudes are reasonable. For example, a one-standard-deviation shock to $Climate\,Policy\,Regulation$ is associated with an increase in $CCExposure^{Reg}$ of 0.041, or 10% of the variable's mean.[19]

Table 5, Panel B, examines the association between our exposure measures and a country-level proxy for the physical impact of climate change (more specifically, the frequency of extreme temperature events in the prior year).[20] The estimates provide some weak evidence supporting the validity of our measures. Most notably, $CCExposure^{Reg}$ in Column 3 shows no statistical or economic association with $Extreme\,Temperatures$, while there is a positive association in Column 4 for $CCExposure^{Phy}$ (the effect is marginally insignificant with a t-stat of 1.65, though it becomes statistically significant when we condition on sentiment in IA Table 15). The weak explanatory power of the temperature variable, which varies at the level of a firm's headquarters' country, may also arise because firm operations are spread across countries; this would be reflected in $CCExposure^{Phy}$ but not in $Extreme\,Temperatures$, leading to noise in the estimation.

4.6. Comparison with Pre-Specified Climate Change Keywords

As another validity check, we construct from a list of *pre-specified* climate change keywords alternative exposure, sentiment, and risk measures in order to compare these measures with those produced by our keyword discovery algorithm. To obtain a list of pre-specified keywords, we use the set of unique stemmed unigrams and bigrams $\mathbb{C}^{Pre}$ used by Engle et al. (2020) to build their time-varying, news-based measure of climate change attention. These keywords originate from 74 authoritative texts on climate change (e.g., from the IPCC and the EPA) and they are listed in Engle et al. (2020)'s Figure 1.

To create an alternative exposure measures, $CCExposure^{Pre}$, we replace our set of bigrams $\mathbb{C}$ with $\mathbb{C}^{Pre}$ and recompute the relative frequency with which the alternative terms appear in quarterly earnings calls. Also for this measure, we construct an annual version by averaging values across the quarterly measures. We apply the same procedure to create alternative measures of sentiment ($CCSentiment^{Pre}$) and risk ($CCRisk^{Pre}$).

IA Table 16 shows that the unigrams and bigrams in $\mathbb{C}^{Pre}$ appear more frequently

[19] The difference in effects across the four measures is plausible; new climate policies or regulations should trigger call participants in firms with high exposure to climate change to discuss the impact of these changes on business opportunities (e.g., the promotion of renewable energy) and on costs (e.g., carbon pricing). At the same time, these changes should not directly lead to discussions about a firm's exposure to extreme weather events or droughts. The difference in patterns also imply that the measures of climate change exposure capture distinct dimensions along which firms are exposed to climate change.

[20] To account for systematic differences across countries that are caused by geographic location or topography, we absorb average country effects.

in earnings calls than the bigrams in $\mathbb{C}$, probably because $\mathbb{C}^{Pre}$ includes more unigrams and more general terms (e.g., the top-3 bigrams are "market," "increase," and "time"). Furthermore, the table demonstrates that several of the unigrams in $\mathbb{C}^{Pre}$ are part of the top-100 bigrams in $\mathbb{C}$ (e.g., "carbon," "energy," or "water").

IA Table 17 provides summary statistics for $CCExposure^{Pre}$, $CCSentiment^{Pre}$, and $CCRisk^{Pre}$, and correlations with $CCExposure$, $CCSentiment$, and $CCRisk$. As would be expected from IA Table 16, the mean values of the alternative measures are much larger, implying that larger parts of the earnings calls are classified as discussing climate topics if we use $\mathbb{C}^{Pre}$ instead of $\mathbb{C}$ (at the extensive margin, only about 400 transcripts are classified as having zero climate change exposure). At the same time, the correlations indicate that measures based on the pre-specified keywords correlate positively, albeit only weakly, with those based on our keyword discovery mechanism. While the correlation between $CCExposure$ and $CCExposure^{Pre}$ is 36%, the corresponding figures for the sentiment and risk measures are only 23% and 15%. Panel C shows that when we classify firm-year observations into quartiles for $CCExposure$ and $CCExposure^{Pre}$, 36% of the observations are classified into the same exposure quartiles for both measures. In more than half of the cases (13% relative to 25%), both measures agree in identifying the firms with the highest overall climate change exposure (top quartile).

4.7. Perturbation Tests for Individual Initial Bigrams

Finally, we evaluate how strongly our measure of climate change exposure depends on the individual bigrams included in the initial list of bigrams displayed in IA Table 2. For this perturbation test, we successively exclude one initial bigram at a time, and then each time recompute the modified set of bigrams $\mathbb{C}^{Pert}$ as well as the modified transcript-based measure $CCExposure^{Pert}$. As our initial short list contains a total of 50 bigrams, we in turn construct 50 new versions of $CCExposure^{Pert}$. When we calculate the correlation of each of these 48 exposure measures with $CCExposure$, we find that the correlations vary between 96% and 97%. These numbers show that our measure of climate change exposure does not depend on individual bigrams used in the keyword discovery algorithm.

4.8. Summary of the Validation Exercise

The evidence in this section supports the validity of our approach. Our algorithm identifies word combinations that accurately describe different facets of climate change, and by counting the occurrence of climate change bigrams in transcripts, we construct various measures of climate change exposure. Moreover, our topics-based measures exhibit cross-sectional and time-series variations that align with reasonable priors. However, the aggregation of the scores on our measures over time, by industry, or by country, may potentially mask large heterogeneity or measurement error at the firm level. To examine this possibility, we explore below which individual firms score high or low on our measures, and how these scores correlate with two widely-used alternative measures of firm-level exposure to climate change (*Carbon Intensity* and *ISS Carbon Risk Rating*). Before we turn to this analysis, we try to better understand the drivers of the variations in our and the alternative measures.

5. Variance Decomposition

We conduct a variance analysis in order to examine the extent to which *CCExposure* and its topics-based components quantify firm-level variation in climate change exposure. We then compare this analysis with a similar decomposition for *Carbon Intensity* and *ISS Carbon Risk Rating*. Table 6, Panel A, reports the incremental explanatory power from conditioning our exposure measures fixed effects that plausibly drive the variation. Time fixed effects, i.e., economy-wide changes in aggregate climate change exposure, explain little of the variation, yielding an incremental R^2 below 1% for each exposure measure. For industry fixed effects, the same observation holds true *only* with respect to the variation in $CCExposure^{Phy}$. To the contrary, exposures to opportunity or to regulatory shocks both have a sizeable industry component (19% and 10%, respectively), which might stem from regulation that targets specific industries or from technological developments affecting entire sectors. The interaction of industry and time fixed effects accounts for, at most, an additional 2% of variation (in the case of $CCExposure^{Opp}$). We find little additional explanatory power when we include country fixed effects; this also mitigates the concern that our exposure measures strongly affected by the native language in a country and how distant this language is from English. Importantly, depending on the specific measure, between 70 and 97% of variation is *unexplained* by these sets of fixed effects, which means that variation plays out at the firm level rather than at the level of the country, industry, or over-time.[21] The high unexplained variation for $CCExposure^{Phy}$ is unsurprising given that exposure to physical shocks is highly dependent on firm-specifics, including the location of a firm's production sites or its specific insurance policies. Adding firm fixed effects, we find that permanent differences across firms in an industry and

[21] As in Hassan et al. (2019), we refer to the within-country and industry-time variation as "firm level."

country account for 52, 56, 41, and 48% of variation of $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively. The remaining 48, 44, 59, and 52% come from variation over time in the identity of firms in industries and countries most affected by the respective climate change variables.

Table 6, Panel B, provides the same analysis for *Carbon Intensity* and *ISS Carbon Risk Rating*. Carbon intensities seem to reflect substantially more industry-level variation than do our measures. Regressing carbon intensities onto industry fixed effects yields an incremental R^2 of 38%. Including a full set of fixed effects reduces the variation at the "firm level" to 57%, about half of which reflects permanent differences across firms. *ISS Carbon Risk Rating* has higher firm-level variation remaining after accounting for the full set of fixed effects, but at 73%, this measure also considerably distant from our topics-based measures. Furthermore, about two-thirds of the variation in the ISS ratings is persistent, which is much higher than the persistence in our measures. In other words, *ISS Carbon Risk Rating* largely reflects persistent differences across firms and in the industry assessments of climate change risk exposure, despite ISS's attempt to account for the fact that "*some sectors exhibit a very heterogeneous exposure to climate change risks*" (ISS, 2020).[22,23]

6. Climate Change Exposure and Firm Characteristics

Having documented meaningful variation at the firm level for our exposure measures, we next examine their correlations with a series of fundamental firm characteristics. We perform this analysis because within-industry heterogeneity in climate change exposure could arise from firms having different technology vintages, capital structures, or growth opportunities. Our specification isolates the "firm-level" variation in climate change exposure by including a full set of fixed effects (i.e., industry-by-time and country),

$$CCExposure^T_{it} = \gamma X_{it} + \delta_c + \delta_j \times \delta_t + \epsilon_{it} \tag{4}$$

[22] ISS also provides two subscores of the $ISS Carbon Risk Rating$: $ISS Carbon Performance Score$ and $ISS Carbon Risk Classification$. By ISS construction, the latter of the two subscores is an industry-based measure of climate change exposure, while the former focuses more on firm-level variation. Nevertheless, even for $ISS\ Carbon\ Performance\ Score$, firm-level variation is only 69%.

[23] Our finding that "firm-level" variation in $CCExposure$ is economically meaningful, could be helpful for future explorations of causal relations. In particular, Gabaix and Koijen (2020) argue that idiosyncratic shocks at the firm-level (e.g., to climate change exposure) can be used to create "granular instrumental variables" for aggregate shocks.

where $CCExposure^T$ is $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, or $CCExposure^{Phy}$, and where the vector X_{it} contains a set of firm characteristics that includes $SalesGrowth$, $Log(Assets)$, $Debt/Assets$, $Cash/Assets$, $PPE/Assets$, $EBIT/Assets$, $Capex/Assets$, and $R\&D/Assets$. δ_c, δ_j, and δ_t are country, industry, and time fixed effects, respectively.

Table 7 presents OLS estimates of Equation 4; t-statistics based on standard errors clustered at the industry-year level are reported in brackets. We find that larger firms tend to have fewer climate change opportunities as well as a lower exposure to physical climate change events. At the same time, and consistent with the political economy literature (Peltzman, 1976; Stigler, 1971), these firms are more exposed to climate change regulation. We find a significant negative association between profitability ($Ebit/Assets$) and both $CCExposure^{Opp}$ (t-stat of 4.65) and $CCExposure^{Reg}$ (t-stat of 4.41). A one-standard-deviation increase in $EBIT/Assets$ is associated with a 0.055 lower value for $CCExposure^{Reg}$ (21% of the variable's standard deviation). Cash holdings are positively associated with $CCExposure^{Opp}$ (at the 5% level or higher) and with $CCExposure^{Reg}$, but are negatively (albeit marginally) associated with $CCExposure^{Phy}$. While these results are broadly consistent with earlier studies examining the characteristics of firms most exposed to climate change (Shive and Forster, 2020), there is a puzzling negative association between R&D and climate opportunities. However, we do not over-interpret this relation as overall R&D expenditure may be too noisy to capture innovation in climate-related technologies. Consistent with evidence that greater climate risk leads to lower firm leverage (Ginglinger and Moreau, 2021), firms with higher regulatory exposure have lower leverage ($Debt/Assets$). The opposite relation holds for climate opportunities, and there is no relation between leverage and physical exposure. IA Table 18 documents correlations between firm characteristics as well as climate change *sentiment* and *risk*.

7. Climate Change Exposure and Alternative Firm-Level Measures

We next explore how well our measures of climate change exposure correlate with *Carbon Intensity* and $ISSCarbonRiskRating$, the two alternative exposure measures available at the firm level. Carbon intensities, emissions relative to a firm's asset base, play an important role as a measure for firm-level exposure to climate change (especially to regulatory shocks), and this measure is used in several papers (Bolton and Kacperczyk, 2021, 2020; Ilhan, Sautner, and Vilkov, 2021; Shive and Forster, 2020; De Haas and Popov, 2020). The analysis of a firm's carbon footprint is also the most frequently used climate risk management tool of institutional investors, according to the survey evidence in Krueger, Sautner, and Starks (2020). A benefit of using carbon intensities is that they are easy to understand and compute, readily available for subscribers to the CDP database (or databases that use CDP data as an input), and genuinely related to changes in the global climate. Drawbacks of the measure include its lack of forward-looking scope.[24] Furthermore, in many countries disclosure on carbon emissions is not mandatory, which hinders the ability of these emissions to act as a measure for a broad international sample.

The ISS ratings have mostly been employed by investment professionals. A strength of the ratings is that they consider factors beyond a firm's carbon footprint, such as carbon reduction targets and actions, or an assessment of the management's perspective on climate change. That said, the index also faces selection issues as ISS decides on firm coverage using factors such as investor interest or index membership. Moreover, it is only available for a limited number of firms.[25]

We first explore the relation of our exposure measures with carbon intensities. Higher carbon intensities should be related to at least some of our exposure measures. Notably, high carbon intensities might attract the scrutiny of regulators seeking to reduce emissions because of international agreements to limit global warming. This regulatory attention to firms is likely to emerge as a topic of conversation in earnings calls, though high carbon intensities may also spur technological innovation that provides firms with new opportunities in the market place. Utilities, for example, which have a large carbon footprint (see IA Table 13) may have strong incentives to develop low-carbon alternatives (e.g., wind or solar farms), which provide future opportunities. On the other hand, a firm's carbon emissions should be unrelated to its exposure to physical shocks, such as floods, storms, or ice.

We examine these possibilities by augmenting the dependent variables in Equation 4 with $Carbon\ Intensity$, and by basing the estimation on the intersection of the CDP sample and our sample for $CCExposure^{T}$. Our findings in Table 8, Panel A, are in line with our predictions. In Column 1, we find a strong positive association between $Carbon\ Intensity$ and the aggregate exposure measure; this association originates from the positive correlations between $Carbon\ Intensity$ and $CCExposure^{Opp}$ in Column 2, and $Carbon\ Intensity$ and $CCExposure^{Reg}$ in Column 3 (t-stat of 3.87 and 5.69, re-

[24] An exception of work that uses forward-looking data on emissions is Ramadorai and Zeni (2020), who use CDP information about firms' plans for future carbon emissions abatement. However, these data are available only for a subset of firms.

[25] IA Table 19 shows that in about 70% (66%) of the observations, our measure indicates positive (nonzero) exposure, while carbon intensities (ISS ratings) are missing. In only 1% (2%) of cases, our measures suggests zero exposure when a firm's carbon intensity is nonzero (an ISS rating exists).

spectively). A one-standard-deviation increase in a firm's carbon intensity increases its exposure to regulatory shocks by 0.10, which is about 37% of its standard deviation. As expected, in Column 4, we find no association between carbon intensities and exposure to physical shocks. In IA Table 20, higher carbon emissions are associated with lower sentiment and with a higher risk of regulatory exposure to climate change.

In Table 8, Panel B, we explore the relation between our exposure measures and the ISS ratings (the intersection of the ISS and $CCExposure^{T}$ data sets yields again a smaller number of observations). In Column 1, a high value of *ISS Carbon Risk Rating* (indicating a lower assessed risk) is associated with a higher overall exposure to climate change. This increased exposure to climate change stems primarily from a higher exposure to climate opportunities, as shown in Column 2. This indicates a concordance between our and ISS's assessment about which firms are most (or least) exposed to climate change opportunities. We find little evidence of an association between *ISS Carbon Risk Rating* and either $CCExposure^{Reg}$ (Column 3) or $CCExposure^{Phy}$ (Column 4). The nonexisting association with physical exposure is unsurprising, given that ISS does not aim to capture such risk. The lack of a relation with $CCExposure^{Reg}$ suggests that our measures capture different aspects when it comes to a firm's exposure to regulatory shocks.[26]

From this examination, we conclude that our exposure measures reflect some variation in carbon intensities and ISS carbon risk ratings. However, the overlap is partial at best, especially for the ISS rating, and appears to be mostly limited to climate change *opportunities* (and to regulatory impacts for carbon intensities). The measurement disagreement we document is consistent with our variance decomposition analysis, which reveals that carbon intensities and the ISS carbon risk rating have large common industry components. Our climate change exposure measures, on the other hand, capture more firm-level heterogeneity and vary less with industry-level shocks. This type of disagreement is not unique to our climate setting, as it resembles evidence from ESG ratings. For example, Berg, Koelbel, and Rigobon (2020) document only modest correlations between the ESG ratings from six prominent rating agencies. As in our setting, disagreement is particularly high among firms with high risk (low ratings), not among firms with high opportunities (high ratings). Gibson, Krueger, and Schmidt (2020) provide similar evidence on ESG rating disagreement, especially for environmental ratings, where the disagreements are generally higher than for governance or social aspects.

[26] In IA Table 20, *ISS Carbon Risk Rating* is negatively associated with $CCSentiment^{Reg}$ and is positively associated with $CCRisk^{Reg}$; this suggests that firms with high (good) ISS ratings are more negatively exposed to the regulatory impacts of climate change that are also less risky.

8. Economic Correlates of Climate Change Exposure

Guided by prior theoretical and empirical evidence, we next explore the role of important economic variations at the time, firm, and country levels that are plausibly related to climate change exposure. This analysis helps us establish that our measures capture meaningful economic variation. The goal of this analysis is to explore important associations in the data rather than to establish causality.

First, we examine the role of time-series variation in public attention to climate change. This attention, which tends to increase after natural disasters or climate summits, has been shown to affect financial market participants. Choi, Gao, and Jiang (2020) show that retail investors sell carbon-intensive firms when climate change attention spikes, leading to the underperformance of carbon-intense stocks. Choi, Gao, and Jiang (2020) also demonstrate a much weaker positive performance effect of "clean" stocks when attention to climate change is low. This indicates that climate attention has an asymmetric effect on firms; firms with exposure to regulatory shocks suffer, while firms with opportunities do not benefit to the same degree. Ilhan, Sautner, and Vilkov (2021) document that high public attention to climate change increases the cost of option protection against carbon tail risk. Based on this evidence, we predict that earnings call discussions react to the salience of climate change topics in the public arena. We expect that times of high climate attention are associated with an increase in firm-level climate change exposure, especially when it comes to regulatory and physical shocks. To proxy for public climate attention, we use the time-varying measure of climate change news developed in Engle et al. (2020). To test our prediction, we augment Equation 4 by adding $Media\,Attention$.

The results in Table 9, Panel A, are in line with our prediction. In Columns 3 and 4, we find a positive association between media attention to climate change and the firm-level exposures to regulatory and physical shocks. A one-standard-deviation increase in $Media\ Attention$ is associated with an increase in $CCExposure^{Opp}$ of 0.004 or 9% of the variable's mean. There is no significant correlation between $Media\ Attention$ and $CCExposure^{Opp}$, indicating that exposure to climate opportunities is unrelated to media reporting, a finding that is consistent with the asymmetry documented in Choi, Gao, and Jiang (2020). In our context, an explanation of the asymmetry may be that the media is paying more attention to environmental rules and physical threats than to the opportunities from climate change. Earnings call participants who follow the business media may therefore be more inclined to address "downside" topics.

Second, we explore the relation between firm-level institutional ownership and climate change exposure. As documented in Krueger, Sautner, and Starks (2020), institutional investors are increasingly concerned about the effects of climate change on portfolio firms, causing more and more investors to divest (or underweight) holdings in firms with high climate exposure. In fact, some institutions have even started to impose ex-ante investment restrictions towards firms with particularly high risks. One example of this phenomenon is Norges Bank Investment Management (NBIM), which has excluded firms that produce coal or coal-based energy from its investment universe.[27] This process of exclusionary screening has accelerated over recent years and is likely to increase even further. Based on these developments, we predict a negative association between climate change exposure and institutional ownership, especially during recent years.

To test this prediction, we augment Equation 4 by adding $Institutional\ Ownership$. Table 9, Panel B, documents in Column 1 that institutional ownership is negatively associated with $CCExposure$. This overall effect stems from a negative correlation with $CCExposure^{Opp}$ (Column 2) and with $CCExposure^{Reg}$ (Column 3). While the negative correlation with regulatory exposure is unsurprising, the negative effect for opportunities is indicative that institutions fail to differentiate between the sources of climate change exposure. Furthermore, in unreported regressions, these associations are particularly strong in more recent years. These findings indicate that institutional investors are increasingly avoiding firms with high climate change exposure, apparently without distinguishing much between upside and downside exposures. However, as we are unable to establish any causation, it may also be that low institutional ownership leads to an increase in climate change exposure.

Third, we investigate whether climate change exposure is higher in country-years when firms are legally required to disclose more environmental information. This information could increase climate change exposure, encouraging analysts to ask additional questions. To explore the role of mandatory ESG disclosure, we augment Equation 4 by adding *Mandatory ESG Disclosure*. In Table 9, Panel C, we find no evidence of a positive association between mandatory ESG disclosure and perceived climate change exposure. These estimates suggest that our exposure measures, which are based on *voluntary* information exchanges between management and financial analysts during earnings calls, are not affected by variation in disclosure standards across countries.

[27] These firms are strongly exposed to stranded asset risk and to regulation that limits carbon emissions. On average, NBIM owns about 1.5% of every publicly-listed firm in the world, and the actions of NBIM are often echoed by other investors. See "Norway's oil fund sells out of Glencore, Anglo American and RWE," *Financial Times*, May 13, 2020.

9. Climate Change Exposure and Firm Valuations

We next test whether the exposure to opportunity, regulatory, and physical climate shocks are reflected in firm valuations. Our tests exploit the fact that the cross-sectional average of climate change exposure has two distinct phases: a phase of steady increase until 2011 and a phase holding at a relatively high level since 2011 (see Figure 1). We therefore allow the effects of climate change exposure to vary across these two phases by estimating the following regression model for the years before *and* after 2011:

$$\begin{aligned} \Delta Tobin's\,Q_{it} = \beta_1 CCExposure_{it}^{Opp} + \beta_2 CCExposure_{it}^{Reg} + \beta_3 CCExposure_{it}^{Phy} + \\ \gamma X_{it} + \delta_c + \delta_j \times \delta_t + \epsilon_{it} \end{aligned} \tag{5}$$

where $\Delta Tobin's\,Q$ is the year-on-year change in Tobin's Q, and where $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the measures of climate change exposure that we include individually and jointly. X_{it} contains our standard set of firm-level control variables. δ_c, δ_j, and δ_t represent country, industry, and time fixed effects, respectively.

Results are reported in Table 10. For the years after 2011, reported in Columns 1 to 4, changes in firm valuation do not statistically significantly reflect climate change opportunities. However, exposure to regulatory events does negatively correlates with valuation changes (t-stat of 1.98). A one-standard-deviation shock in $CCExposure^{Reg}$ is associated with a 0.076 change in $\Delta Tobin's\,Q$, which is roughly equal to the variable's mean. Exposure to physical shocks is also negatively associated with valuation changes, but the effect is statistically insignificant. For the period prior to 2011, shown in Columns 5 to 8, neither of the exposure measures is related to firm valuation changes. Our evidence is consistent with Delis, de Greiff, and Ongena (2019), who document that banks have only started to price regulatory climate risks in the recent past.

IA Table 22 provides the results for the sentiment and risk measures. When conditioning on sentiment, the post-2011 valuations reflect climate change opportunities, though the effect is only significant at the 10% level. When combined with positive sentiment words, there is also a positive effect of a firm's exposure to physical shocks (some firms benefit from physical changes in the climate, e.g., producers of certain agricultural products or genetically modified seeds). For our risk measures, we find a strong negative relation between regulatory climate risk and firm valuation changes in the post-2011 sample. Interestingly, for physical climate risk, there also appears to be a negative effect in the pre-2011 sample.

10. Climate Change Exposure and Covid-19

A concern raised by climate scientists, pro-climate politicians, and institutional investors is that the global focus on Covid-19 has distracted from the fight against climate change. Thus, Covid-19 may decrease market participants' perceptions of firms' climate change exposure in the short term without having a corresponding positive effect on the environment.[28] Furthermore, apart from directly affecting firms' risks and opportunities, the economic downturn associated with Covid-19 may make climate-related regulation less likely (arguably so as not to overburden firms), and it may reduce the financial resources available to firms to support the transition to a greener economy. We therefore expect that our climate change exposure measures will also react to the Covid-19 shock.

Figure 3 reports firms' average climate change exposures between 2018q1 and 2020q2 at the quarterly level.[29] Panel A shows *CCExposure* across all firms and countries, while Panels B to D report *CCExposure* separately for China, the U.S., and Europe, respectively. Panel A shows that *CCExposure* reaches a peak in 2020q1, and then sharply declines from 1.43 in 2020q1 to 0.92 in 2020q2, a drop of 36%. Interesting heterogeneity exists across world regions within this aggregate trend. For firms in China, there is a decrease of climate change exposure in 2020q1 (Panel B). These changes are not yet visible for firms in the U.S. and Europe (Panels C and D), where climate change exposure reaches the highest level in 2020q1. U.S. and European firms see a sharp decline in climate-related discussions in their earnings calls covering 2020q2, while Chinese firms have already rebounded. The different patterns are consistent with the evolution of the pandemic across different regions of the world. While China was hit by the pandemic in January 2020, Europe and the U.S. witnessed an acceleration in Corona cases only in March 2020. The divergence in the timing is consistent with Hassan et al. (2020a), who document that the earnings calls of Chinese firms started to discuss the effects of Covid-19 about one quarter earlier than did U.S. and European firms.

11. Conclusion

A challenge for investors and regulators is the difficulty in quantifying firm-level exposure to climate change, both in terms of associated risks and in terms of opportunities (Giglio,

[28]See "How Coronavirus Could Set Back the Fight Against Climate Change," *Time*, March 10, 2020. The pandemic and the associated lock-downs reduced contemporaneous carbon emissions (due to reduced air and automobile travel), but these lower emissions have no effect on the climate (Forster et al., 2020).

[29]We do not use the 2020 data in earlier tests as our other data is not yet available for that year.

Kelly, and Stroebel, 2020). We introduce a new method that identifies firm-level climate change exposure from word combinations signaling climate change conversation in earnings conference calls. As these calls reflect the demand (analysts) and the supply side (management) of a "market for information," our measures reflect the combined views of key stakeholders about a firm's climate change exposure. Furthermore, earnings calls are largely forward-looking; while analysts review past results, they also spend much of their time probing management about future plans (Huang et al., 2018).

Our measures builds on recent work that has identified earnings calls as a source for identifying the various risks and opportunities that firms face over time (Hassan et al., 2019, 2020a,b). We adjust the approach of this prior work along several important dimensions, allowing us to capture aspects of the opportunities as well as the (physical and regulatory) risks associated with climate change. For this purpose, we adapt the machine learning keyword discovery algorithm proposed by King, Lam, and Roberts (2017) to produce several sets of climate change bigrams. Rather than choosing a training library, we start with a short list of initial bigrams that most experts would agree are related to climate change. Our exposure measures capture the proportion of the earnings call that is centered on climate change topics, and they are available for a global sample of more than 10,000 firms covering the years 2002 to 2019.

The measures exhibit cross-sectional and time-series variation that align with reasonable priors, and they are better at capturing firm-level variation in climate change exposure than are other alternatives, specifically, carbon intensities or ISS carbon risk ratings. While our measures of climate change exposure reflect some variation in carbon intensities and ISS carbon risk ratings, the overlap is partial at best, especially for the ISS rating. It appears that measurement agreement is mostly limited to climate change *opportunities* (and to regulatory shocks for carbon intensities). Firm-level variation in our exposure measures are related to economic factors that the literature identifies as important correlates of climate change exposure (e.g., public climate attention and institutional ownership). Furthermore, firm exposure to regulatory shocks is negatively associated with changes in firm valuations, but only for the years after 2011. Climate change discussions in earnings calls sharply declined during the Covid-19 pandemic, first in China, and then in Europe and the U.S.

Appendix A: Variable Definitions

Variable	Years	Definition
$CCExposure$	2002-2019	Relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCExposure^{Opp}$	2002-2019	Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCExposure^{Reg}$	2002-2019	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCExposure^{Phy}$	2002-2019	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCSentiment^{Opp}$	2002-2019	Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the positive and negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCSentiment^{Reg}$	2002-2019	Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the positive and negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCSentiment^{Phy}$	2002-2019	Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the positive and negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCRisk^{Opp}$	2002-2019	Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.

Variable	Years	Definition
$CCRisk^{Reg}$	2002-2019	Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
$CCRisk^{Phy}$	2002-2019	Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. We average values of the four analyst earnings conference calls during the year. Source: Self-constructed.
Carbon Intensity	2009-2017	Annual Scope 1 carbon emissions (metric tons of CO2) divided total assets (in $ millions) (Compustat data item AT) at the end of the year. Winsorized at the 1% level. Source: CDP and Compustat NA/Global.
ISS Carbon Risk Rating	2015-2019	Measure constructed by ISS to provide a comprehensive assessment of the carbon-related performance of companies. The rating is based on a combination of quantitative indicators (e.g. current intensity and trend of greenhouse gas emissions, carbon impact of the product portfolio including revenue shares of products or services associated with positive as well as negative climate impact), forward-looking qualitative indicators (e.g. corporate policies, ongoing shift in product and services portfolio, emission reduction targets and action plans, etc.), and a classification of the company's absolute climate risk exposure due to its business activities. The rating takes values between 1 (poor performance) and 4 (excellent performance). Source: ISS.
Sales Growth	2002-2019	Total sales at the end of the year (Compustat item SALE) divided by total sales at the end of the previous year, minus one. Winsorized at the 1% level. Source: Compustat NA/Global.
Assets	2002-2019	Total assets (in $ millions) at the end of the year (Compustat item AT). Source: Compustat NA/Global
Debt/Assets	2002-2019	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
Cash/Assets	2002-2019	Cash and short-term investments (Compustat data item CHE) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
PPE/Assets	2002-2019	Property, plant, and equipment (Compustat data item PPENT) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
EBIT/Assets	2002-2019	Earnings before interest and taxes (Compustat data item EBIT) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global
Capex/Assets	2002-2019	Capital expenditures at the end of the year (Compustat data item CAPX) divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.

Variable	Years	Definition
$R\&D/Assets$	2002-2019	R&D expenditures at the end of the year (Compustat data item XRD) divided by total assets at the end of the year (Compustat data item AT). Missing values set to zero. Winsorized at the 1% level. Source: Compustat NA/Global.
$\Delta Tobin's\,Q$	2002-2019	Year-on-year change in the market value of a firm divided by total assets (Compustat data item AT). For Compustat NA firms, the market value of a firm is defined as the market value of equity (Compustat data item MKVALT) plus the book value of debt (data item DLTT + DLC). For Compustat Global firms, the market value of a firm is defined as the market value of equity (Data item CSHOC x PRCCD), minus the book value of equity (CEQ), plus total assets (AT). Winsorized at the 1% level. Source: Compustat NA/Global.
Climate Policy Regulation	2007-2017	Index constructed by Germanwatch that evaluates climate policies of a country. It covers a country's policies and regulations on the promotion of renewable energies, the increase of efficiency and other measures to reduce CO2 emissions, the ambition level and 2° compatibility of countries' Nationally Determined Contributions (NDCs) as well as their progress towards reaching these goals, and the performance at UNFCCC conferences and in other international conferences and multilateral agreements. Higher numbers of the index reflect stronger/stricter climate policies in a country. Source: Germanwatch.
$Extreme\,Temperatures$	2002-2019	Frequency with which extreme temperature episodes occurred in a country-year. Source: EM-DAT.
$Media\,Attention$	2002-2017	Index developed in Engle et al. (2020) that captures climate change news in the $Wall\,Street\,Journal$. To quantify the intensity of climate news coverage in the $Wall\,Street\,Journal$, Engle et al. (2020) compare the news content to a corpus of authoritative texts on the subject of climate change. Source: Engle et al. (2020).
Institutional Ownership	2002-2018	Percentage ownership by institutional investors (Thomson Reuters data item INSTOWN_PERC) at the end of the year. Winsorized at the 1% level. Source: Thomson Reuters.
Mandatory ESG Disclosure	2002-2019	Dummy variable constructed in Krueger et al. (2021) that takes the value one if a country has mandatory ESG disclosure; and zero otherwise. Source: Krueger et al. (2021).

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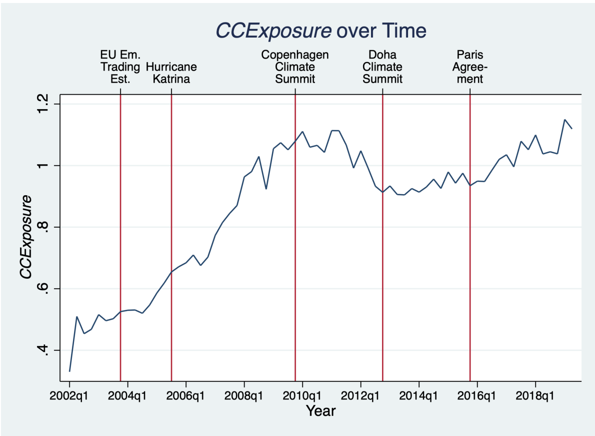
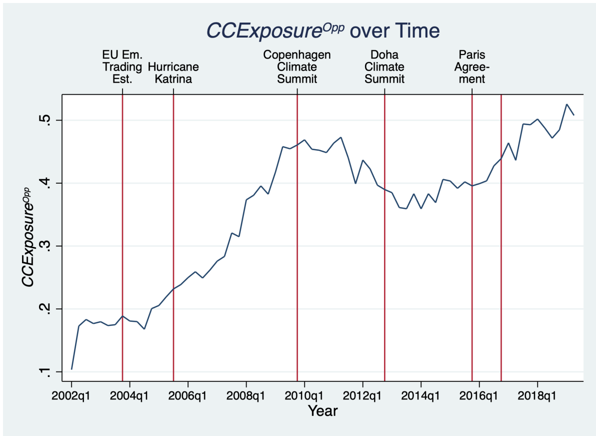
Figure 1: Climate Change Exposure over Time



(a)



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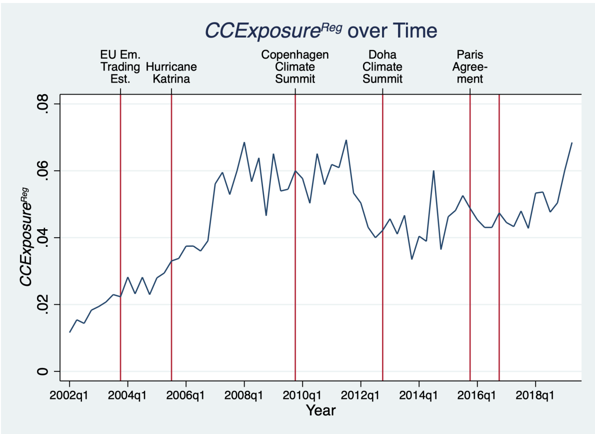

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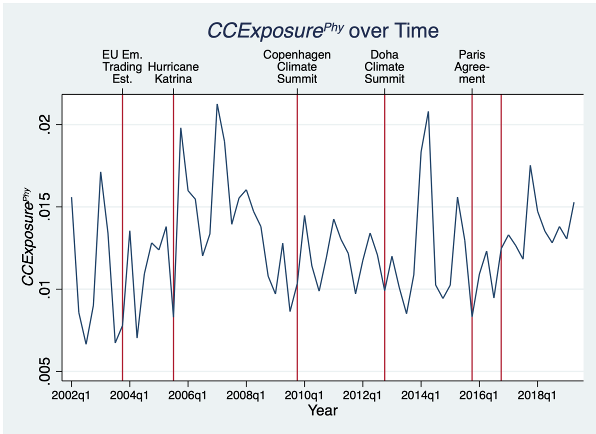
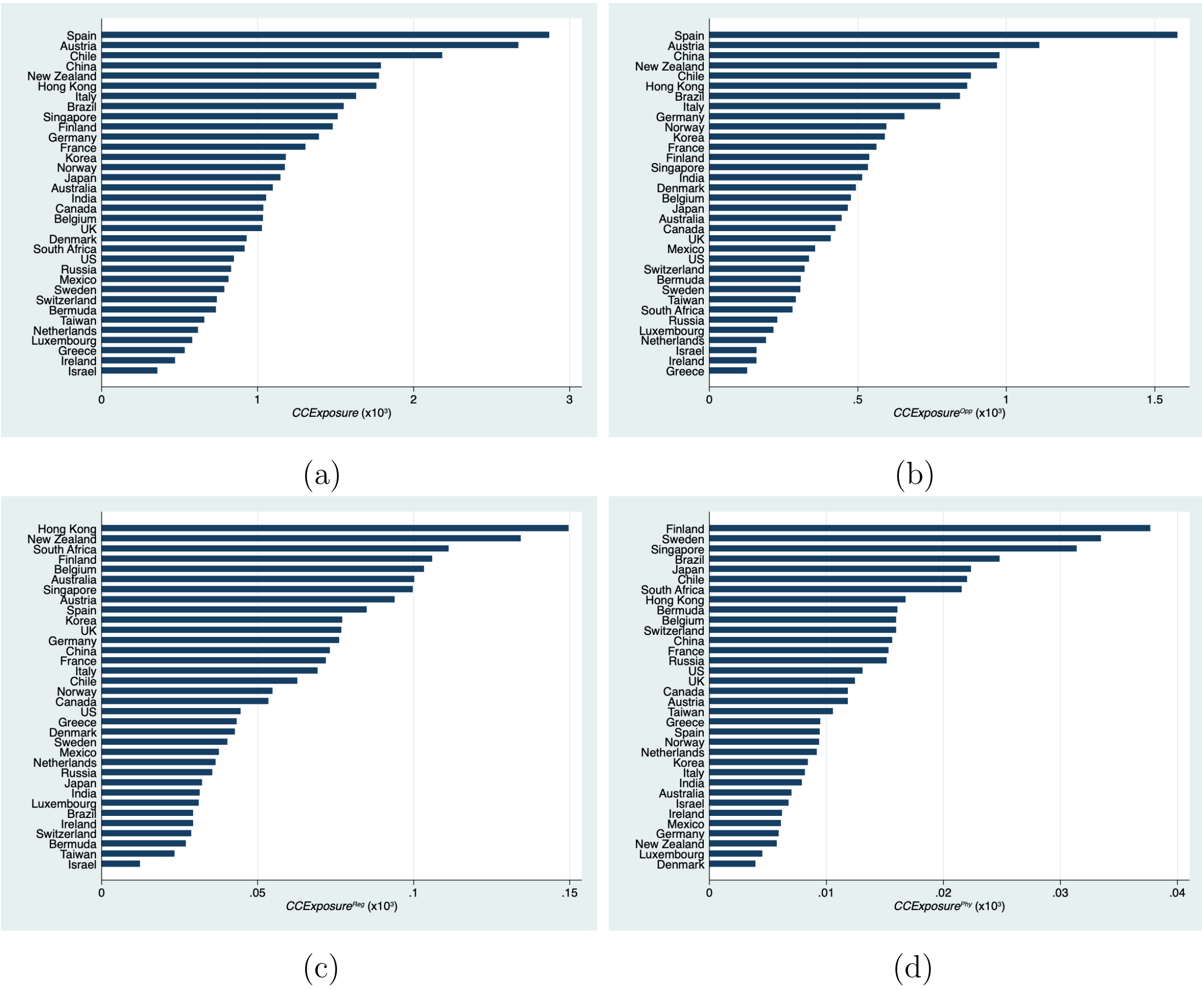


(d)

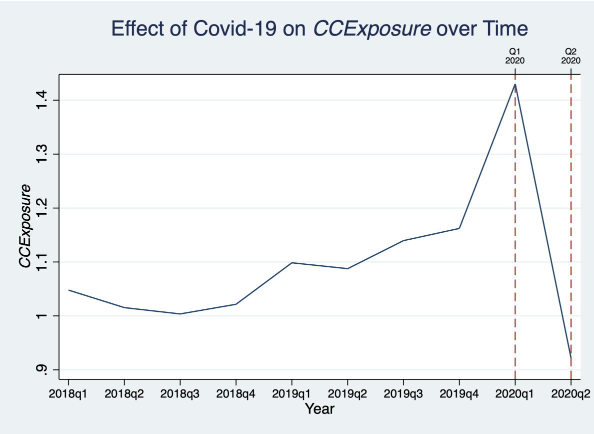
Notes: These figures report firms' average climate change exposures over time. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. The vertical (red) lines show when the quarters of i) the Introduction of the EU Emission Trading System; ii) Hurricane Katrina; iii) the Copenhagen Climate Summit; iv) the Doha Climate Summit; and v) the Paris Agreement. Appendix A defines all variables in detail.

Figure 2: Climate Change Exposure across Countries



Notes: These figures report firms' average climate change exposures across countries. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. Appendix A defines all variables in detail.

Figure 3: Climate Change Exposure and Covid-19



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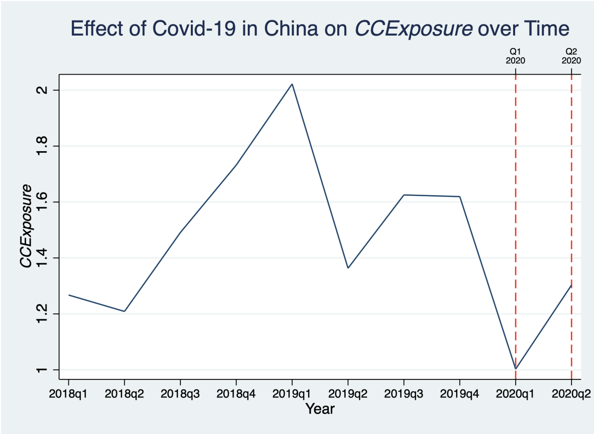

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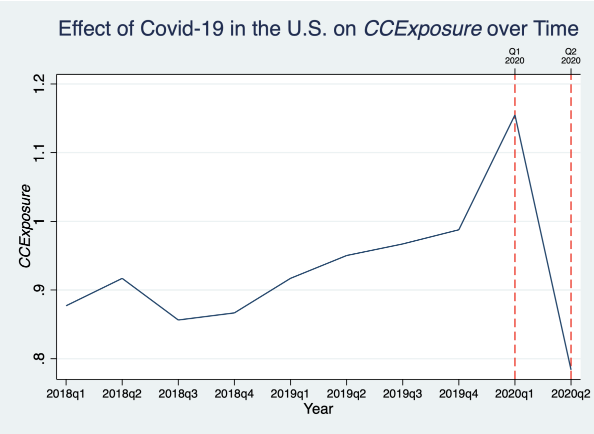

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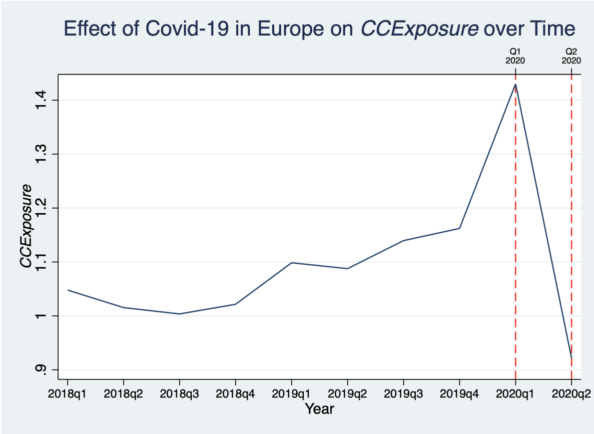


(d)

Notes: These figures report firms' average climate change exposures between 2018q1 and 2020q2. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. Panel A reports results across all sample firms, Panel B for firms in China, Panel C for firms in the U.S., and Panel D for firms in Europe. Appendix A defines all variables in detail.

Table 1: Summary Statistics

	Mean	STD	25%	Median	75%	Obs.
$CCExposure$ ($\times 10^3$)	0.943	2.443	0.072	0.264	0.709	80221
$CCExposure^{Opp}$ ($\times 10^3$)	0.391	1.344	0.000	0.000	0.239	80221
$CCExposure^{Reg}$ ($\times 10^3$)	0.049	0.264	0.000	0.000	0.000	80221
$CCExposure^{Phy}$ ($\times 10^3$)	0.013	0.103	0.000	0.000	0.000	80221
$CCSentiment$ ($\times 10^3$)	0.007	0.660	-0.063	0.000	0.067	80221
$CCSentiment^{Opp}$ ($\times 10^3$)	0.033	0.416	0.000	0.000	0.000	80221
$CCSentiment^{Reg}$ ($\times 10^3$)	-0.016	0.135	0.000	0.000	0.000	80221
$CCSentiment^{Phy}$ ($\times 10^3$)	-0.001	0.040	0.000	0.000	0.000	80221
$CCRisk$ ($\times 10^3$)	0.036	0.173	0.000	0.000	0.000	80221
$CCRisk^{Opp}$ ($\times 10^3$)	0.015	0.106	0.000	0.000	0.000	80221
$CCRisk^{Reg}$ ($\times 10^3$)	0.002	0.030	0.000	0.000	0.000	80221
$CCRisk^{Phy}$ ($\times 10^3$)	0.001	0.012	0.000	0.000	0.000	80221
Carbon Intensity	151.14	399.90	1.95	11.02	84.62	6009
ISS Carbon Risk Rating	1.817	0.513	1.435	1.706	2.111	9995
Sales Growth	0.624	3.735	-0.050	0.061	0.194	79224
Log(Assets)	7.314	2.102	5.884	7.340	8.712	79590
Debt/Assets	0.685	2.806	0.061	0.223	0.408	79301
Cash/Assets	0.430	1.627	0.035	0.102	0.279	79586
PPE/Assets	0.830	3.588	0.051	0.160	0.430	77051
EBIT/Assets	0.200	1.065	0.017	0.060	0.113	79506
Capex/Assets	0.138	0.581	0.011	0.029	0.063	79031
R&D/Assets	0.064	0.197	0.000	0.000	0.041	80017
$\Delta Tobin's\ Q$	-0.072	5.765	-0.213	0.000	0.202	63773
Climate Policy Regulation	7.635	5.131	3.060	7.260	12.100	61639
Extreme Temperatures	0.525	0.618	0.000	0.000	1.000	80221
Media Attention	0.007	0.001	0.006	0.006	0.008	68925
Institutional Ownership	0.609	0.310	0.378	0.675	0.860	54318
Mandatory ESG Disclosure	0.099	0.299	0.000	0.000	0.000	80221

Notes: Summary statistics are reported at the firm-year level. The sample includes 10,158 unique firms from 34 countries over the period 2002 to 2019. Appendix A defines all variables in detail.

Table 2: Top-100 Bigrams Captured by Climate Change Exposure ($CCExposure$)

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
renewable energy	12406	coastal area	738	snow ice	481
electric vehicle	6732	energy star	737	electrical energy	480
clean energy	4815	scale solar	708	electric hybrid	476
new energy	3751	major design	696	solar installation	474
wind power	3673	transmission grid	692	connect grid	474
wind energy	3611	energy plant	678	driver assistance	473
energy efficient	3588	global warm	671	reach gigawatt	471
climate change	2709	motor control	661	provide clean	466
greenhouse gas	2341	battery electric	659	reinvestment act	460
solar energy	2153	clean water	648	invest energy	454
clean air	2019	combine heat	645	green build	453
air quality	1959	need energy	602	sector energy	452
reduce emission	1567	future energy	581	california department	449
water resource	1336	use water	564	plant use	447
energy need	1291	environmental concern	560	friendly product	447
carbon emission	1273	include megawatt	557	energy initiative	444
carbon dioxide	1247	build owner	557	issue rfp	443
carbon footprint	1180	electric grid	551	transmission capacity	442
gas emission	1166	energy team	544	close megawatt	441
energy environment	1145	world energy	544	market solar	437
wind resource	1065	energy application	544	business air	437
air pollution	1063	wind capacity	541	construction megawatt	435
reduce carbon	1004	transmission infrastructure	540	rooftop solar	434
president obama	980	population center	532	application power	431
battery power	969	energy reform	523	forest land	426
clean power	955	charge station	523	grid power	421
energy regulatory	921	wind park	522	advance driver	419
plug hybrid	890	produce power	521	northern pass	418
obama administration	886	environmental footprint	519	nox emission	418
build power	849	source power	512	wind facility	418
world population	838	pass house	512	energy component	417
heat power	835	gas vehicle	511	vehicle application	415
light bulb	808	plant power	500	emission trade	412
carbon capture	804				

Notes: This table reports the top-100 bigrams associated with $CCExposure$, which measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. Appendix A defines all variables in detail.

Table 3: Snippets of Top Climate Change Exposure Firms

Firm	HQ	SIC	Time	Assets ($ millions)	Bigrams	Top Snippet
China Ming Yang Wind Power Group Ltd	China	3511	2014Q4	2,040	development distribute; distribute renewable; energy goal; renewable energy; wind power	therefore we believe that with large wind power base, large power transmission channels, large off-shore wind power projects and the development of distributed renewable energies, the goal of 200 gigawatts by 2020 will be achieved, no regardless of any tariff adjustments.
ECOtality Inc	U.S.	3621	2008Q2	8	consumption energy; efficiency power; energy conversion; power factor	for example the new fc system, which we actually introduced in early 2009, is specifically designed for heavy duty material handling applications, and reduces a facilities' electrical consumption as it has a 97% energy conversion efficiency, which allows it to have the highest efficiencies and power factors among chargers in its class.
Xinjiang Goldwind Science & Technology Co Ltd	China	3511	2018Q4	11,873	connect capacity; gigawatt represent; grid connect	through january to september this year, domestic newly grid-connected capacity was 12.6 gigawatts, representing 29.9% increase year-on-year.
ITC Holdings Corp	U.S.	4911	2008Q2	3,467	coal technology; efficiency demand; expansion nuclear; mouth coal; new energy; response clean; technology wind	transmission is the common denominator that enables all new energy technologies such as wind, solar, biofuel, energy efficiency, demand response, clean coal technology, mine-mouth coal and the expansion of the nuclear fleets to come online.
Ocean Power Technologies Inc	U.S.	3511	2008Q4	97	energy requirement; increase renewable; population center; powerbuoy wave; renewable energy; wave condition; wave power	these areas represent strong potential markets for our powerbuoy wave power stations because they combine favorable wave conditions, political and economic stability, large population centers, high levels of industrialization, and significant and increasing renewable energy requirements.

Table 4: Industry Distribution of Climate Change Exposure

Panel A. $CCExposure$ (x10ˆ3)					Panel B. $CCExposure^{Opp}$ (x10ˆ3)				
Industry (SIC2)	Mean	STD	Median	Obs.	Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries					Top-10 Industries				
49 Electric, Gas, & Sanitary Services	6.565	5.985	4.996	2675	49 Electric, Gas, & Sanitary Services	2.944	3.517	1.805	2675
16 Heavy Construction, Except Building	3.149	4.619	1.432	450	16 Heavy Construction, Except Building	1.379	2.703	0.398	450
17 Construction	1.930	2.982	0.863	167	36 Electronic & Other Electric Equipment	0.954	2.351	0.171	5896
12 Coal Mining	1.826	1.396	1.441	285	37 Transportation Equipment	0.930	1.743	0.349	1401
36 Electronic & Other Electric Equipment	1.787	3.676	0.480	5896	35 Industrial Machinery & Equipment	0.831	2.572	0.164	2305
35 Industrial Machinery & Equipment	1.776	4.036	0.615	2305	17 Construction	0.752	1.666	0.229	167
37 Transportation Equipment	1.678	2.504	0.886	1401	75 Auto Repair, Services, & Parking	0.648	0.798	0.413	121
29 Petroleum Refining	1.558	2.072	0.926	685	55 Automotive Dealers & Service Stations	0.636	0.889	0.413	283
34 Fabricated Metal Products	1.492	2.561	0.613	925	34 Fabricated Metal Products	0.609	1.483	0.178	925
87 Engineering & Management Services	1.431	2.451	0.454	1216	87 Engineering & Management Services	0.539	1.206	0.109	1216
Bottom-10 Industries					Bottom-10 Industries				
58 Eating & Drinking Places	0.231	0.296	0.136	196	70 Hotels	0.076	0.164	0.000	542
60 Depository Institutions	0.223	0.440	0.118	3585	31 Leather & Leather Products	0.075	0.151	0.000	112
82 Educational Services	0.221	0.284	0.145	415	59 Miscellaneous Retail	0.070	0.172	0.000	342
27 Printing & Publishing	0.221	0.326	0.127	1309	82 Educational Services	0.065	0.187	0.000	415
57 Home Furniture	0.180	0.246	0.105	136	58 Eating & Drinking Places	0.061	0.138	0.000	196
31 Leather & Leather Products	0.179	0.265	0.105	112	83 Social Services	0.061	0.106	0.000	96
78 Motion Pictures	0.179	0.446	0.104	417	78 Motion Pictures	0.059	0.116	0.000	417
59 Miscellaneous	0.168	0.233	0.089	342	80 Health Services	0.058	0.126	0.000	1265
21 Tobacco Products	0.138	0.168	0.090	85	56 Social Services	0.047	0.103	0.000	347
56 Apparel & Accessory Stores	0.135	0.171	0.090	347	21 Tobacco	0.038	0.085	0.000	85

Table 4 continued

Panel C. $CCExposure^{Reg}$ (x10ˆ3)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
49 Electric, Gas, & Sanitary Services	0.405	0.727	0.122	2675
12 Coal Mining	0.162	0.270	0.000	285
29 Petroleum Refining	0.128	0.286	0.000	685
32 Stone, Clay, & Glass Products	0.105	0.332	0.000	577
10 Metal Mining	0.088	0.313	0.000	1245
33 Primary Metal	0.085	0.271	0.000	748
34 Fabricated Metal Products	0.080	0.337	0.000	925
37 Transportation Equipment	0.076	0.209	0.000	1401
87 Engineering & Management Services	0.075	0.257	0.000	1216
16 Heavy Construction, Except Building	0.070	0.236	0.000	450
Bottom-10 Industries				
70 Hotels	0.007	0.048	0.000	542
78 Motion Pictures	0.006	0.040	0.000	417
82 Educational Services	0.006	0.032	0.000	415
23 Apparel & Other Textile Products	0.006	0.027	0.000	194
60 Depository Institutions	0.005	0.040	0.000	3585
57 Home Furniture	0.005	0.042	0.000	136
56 Apparel & Accessory Stores	0.005	0.043	0.000	347
21 Tobacco Products	0.002	0.019	0.000	85
59 Miscellaneous Retail	0.002	0.014	0.000	342
83 Social Services	0.002	0.011	0.000	96

Panel D. $CCExposure^{Phy}$ (x10ˆ3)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
26 Paper & Allied Products	0.097	0.329	0.000	705
16 Heavy Construction, Except Building	0.059	0.261	0.000	450
64 Insurance Agents, Brokers, & Service	0.047	0.184	0.000	204
14 Nonmetallic Minerals, Except Fuels	0.047	0.133	0.000	182
49 Electric, Gas, & Sanitary Services	0.040	0.151	0.000	2675
12 Coal Mining	0.039	0.209	0.000	285
35 Industrial Machinery & Equipment	0.034	0.301	0.000	2305
10 Metal Mining	0.029	0.125	0.000	1245
15 General Building Contractors	0.029	0.104	0.000	690
24 Lumber & Wood	0.029	0.136	0.000	708
Bottom-10 Industries				
61 Non-Depository Institutions	0.003	0.030	0.000	667
48 Communication	0.003	0.024	0.000	2274
83 Social Services	0.003	0.019	0.000	96
82 Educational Services	0.003	0.022	0.000	415
21 Tobacco	0.002	0.023	0.000	85
57 Home Furniture	0.002	0.020	0.000	136
62 Security & Commodity Brokers	0.002	0.035	0.000	1280
78 Motion Pictures	0.002	0.015	0.000	417
67 Holding & Other Investment Offices	0.002	0.021	0.000	101
59 Miscellaneous Retail	0.002	0.024	0.000	342

Notes: This table reports firms' climate change exposure measures for the top-10 and bottom-10 industries. Statistics are reported at the firm-year level across different SIC2 industries. We rank sectors by the average values of the climate change exposure measures. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. We report only those industries for which we have at least 30 firm-year observations. Appendix A defines all variables in detail.

Table 5: Climate Change Regulation, Extreme Temperature, and Climate Change Exposure Measures

Panel A. Climate Policy Regulation

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Climate Policy Regulation	0.012***	0.008***	0.001*	0.000
	(3.22)	(3.51)	(1.96)	(0.11)
Obs.	61635	61635	61635	61635
adj. R-sq.	0.001	0.001	0.000	-0.000

Panel B. Extreme Temperatures

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Extreme Temperatures	-0.028	-0.024	0.000	0.001
	(-0.87)	(-1.43)	(0.13)	(1.62)
Obs.	70058	70058	70058	70058
adj. R-sq.	0.014	0.016	0.004	0.001

Notes: Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. *Climate Policy Regulation* is an index that evaluates climate policies and regulations in a country-year. *Extreme Temperatures* is the frequency with which extreme temperature episodes occur in a country-year. In Panel B, we include country fixed effects to absorb average country effects with respect to local or topography. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Table 6: Variance Decomposition of Firm-Level Measures

Panel A. Variance Decomposition of Climate Change Exposure Measures

Variable	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	Incremental R-sq.	Incremental R-sq.	Incremental R-sq.	Incremental R-sq.
Time Fixed Effects	0.6%	0.6%	0.2%	0.0%
Sector Fixed Effects	26.3%	18.6%	10.3%	1.6%
Sector x Time Fixed Effects	1.9%	2.4%	2.0%	1.4%
Country Fixed Effects	0.8%	0.9%	0.7%	0.2%
“Firm Level”	70.4%	77.4%	86.8%	96.8%
Sum	100.0%	100.0%	100.0%	100.0%
	Fraction of variation	Fraction of variation	Fraction of variation	Fraction of variation
Permanent differences across firms within sector and countries (Firm Fixed Effects)	51.8%	56.3%	41.1%	48.3%
Variation over time in the identity of firms within sectors and countries most affected by climate change variable (Residual)	48.3%	43.8%	58.9%	51.7%
Sum	100.0%	100.0%	100.0%	100.0%

Table 6 continued

Panel B. Variance Decomposition of Carbon Intensities and ISS Carbon Risk Measures		
Variable	*Carbon Intensity*	*ISS Carbon Risk Rating*
	Incremental R-sq.	Incremental R-sq.
Year Fixed Effects	0.3%	1.0%
Sector Fixed Effects	38.4%	17.3%
Sector x Year Fixed Effects	1.2%	1.7%
Country Fixed Effects	3.5%	7.1%
"Firm Level"	56.6%	73.0%
Sum	100.0%	100.0%
	Fraction of variation	Fraction of variation
Permanent differences across firms within sectors and countries (Firm Fixed Effects)	53.2%	66.9%
Variation over time in the identity of firms within sectors and countries most affected by climate change variable (Residual)	46.8%	33.2%
Sum	100.0%	100.0%

Notes: This table provides a variance decomposition of the climate change exposure measures and alternative measures for climate change exposure. Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. *Carbon Intensity* measures Scope 1 carbon emissions divided by total assets. *ISS Carbon Risk Rating* is constructed by ISS and provides an assessment of the carbon-related performance of companies. Appendix A defines all variables in detail.

Table 7: Climate Change Exposure Measures and Firm Characteristics

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
$Sales\,Growth$	-0.001	-0.001	0.000	-0.000
	(-0.62)	(-1.22)	(0.03)	(-0.88)
$Log(Assets)$	-0.011	-0.009*	0.002**	-0.001**
	(-1.29)	(-1.89)	(2.52)	(-2.25)
$Debt/Assets$	0.018***	0.008***	-0.001***	0.000
	(3.22)	(2.73)	(-2.83)	(0.55)
$Cash/Assets$	0.027***	0.013**	0.002***	-0.001*
	(2.89)	(2.43)	(2.68)	(-1.74)
$PPE/Assets$	0.009	0.002	0.000	0.001
	(1.22)	(0.37)	(0.33)	(1.50)
$EBIT/Assets$	-0.118***	-0.052***	-0.006***	-0.001
	(-6.55)	(-4.65)	(-4.41)	(-1.53)
$Capex/Assets$	0.092**	0.037	0.003	0.001
	(1.97)	(1.33)	(0.85)	(0.58)
$R\&D/Assets$	-0.444***	-0.220***	-0.003	-0.004
	(-5.63)	(-5.01)	(-0.25)	(-0.97)
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	65932	65932	65932	65932
adj. R-sq.	0.284	0.211	0.114	0.014

Notes: Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Table 8: Firm-level Carbon Intensity, ISS Carbon Risk Ratings, and Climate Change Exposure Measures

Panel A. Carbon Intensity				
	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Carbon Intensity (×100)	0.133***	0.027***	0.026***	-0.001
	(7.47)	(3.87)	(5.69)	(-1.03)
Sales Growth	-0.021	-0.006	-0.002**	-0.002***
	(-1.54)	(-0.89)	(-2.34)	(-3.48)
Log(Assets)	0.041	0.027	0.008*	-0.002
	(1.37)	(1.48)	(1.92)	(-1.61)
Debt/Assets	0.063***	0.017*	-0.002	0.001
	(2.85)	(1.88)	(-1.13)	(0.78)
Cash/Assets	0.049	0.030*	-0.002	-0.004
	(0.91)	(1.77)	(-0.71)	(-1.23)
PPE/Assets	-0.086**	-0.024	-0.009	-0.003
	(-2.09)	(-1.27)	(-1.57)	(-1.04)
EBIT/Assets	-0.084	-0.009	0.009**	0.005*
	(-1.04)	(-0.30)	(2.00)	(1.73)
Capex/Assets	0.373*	0.000	0.019	0.039*
	(1.68)	(0.00)	(0.62)	(1.65)
R&D/Assets	-0.107	-0.091	0.058***	-0.030*
	(-0.30)	(-0.66)	(3.10)	(-1.67)
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	5404	5404	5404	5404
adj. R-sq.	0.505	0.369	0.254	0.026

Table 8 continued

Panel B. ISS Carbon Risk Rating				
	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
ISS Carbon Risk Rating	1.142***	0.740***	0.020	0.005
	(5.87)	(5.55)	(1.46)	(1.49)
Sales Growth	-0.014	-0.009*	0.001	-0.000
	(-1.58)	(-1.76)	(0.66)	(-1.49)
Log(Assets)	-0.165***	-0.090**	0.006	-0.004**
	(-2.72)	(-2.33)	(1.07)	(-2.11)
Debt/Assets	0.064***	0.035***	-0.001	-0.001
	(4.81)	(4.70)	(-0.68)	(-1.09)
Cash/Assets	0.009	0.019	0.000	-0.000
	(0.34)	(1.27)	(0.00)	(-0.50)
PPE/Assets	-0.041*	-0.019	-0.002	0.002*
	(-1.73)	(-1.45)	(-0.72)	(1.85)
EBIT/Assets	-0.132***	-0.054*	-0.006	-0.001
	(-2.81)	(-1.79)	(-1.63)	(-0.46)
Capex/Assets	0.359***	0.093	0.013	-0.004
	(2.64)	(1.22)	(1.23)	(-0.99)
R&D/Assets	-0.537***	-0.345***	-0.040***	-0.019***
	(-2.95)	(-3.60)	(-2.80)	(-2.88)
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	8747	8747	8747	8747
adj. R-sq.	0.414	0.337	0.155	0.001

Notes: Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. *Carbon Intensity* measures Scope 1 carbon emissions divided by total assets. *ISS Carbon Risk Rating* is constructed by ISS and provides an assessment of the carbon-related performance of companies. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Table 9: Economic Correlates of Climate Change Exposure

Panel A. Effects of Media Attention to Climate Change

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Media Attention	17.311	-1.839	4.441**	1.422*
	(0.72)	(-0.12)	(2.01)	(1.77)
Controls	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	56445	56445	56445	56445
adj. R-sq.	0.281	0.204	0.116	0.015

Panel B. Effects of Institutional Ownership

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Institutional Ownership	-0.282***	-0.176***	-0.022***	-0.000
	(-6.44)	(-7.18)	(-5.86)	(-0.23)
Controls	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	43100	43100	43100	43100
adj. R-sq.	0.265	0.185	0.150	0.021

Panel C. Effects of Mandatory ESG Disclosure

	$CCExposure$	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
	(1)	(2)	(3)	(4)
Mandatory ESG Disclosure	0.006	0.021	0.000	0.000
	(0.12)	(0.68)	(0.06)	(0.13)
Controls	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	65932	65932	65932	65932
adj. R-sq.	0.284	0.211	0.114	0.014

Table 9 continued

Notes: Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. $Median\ Attention$ is an index developed in Engle et al. (2020) that captures climate change news in the *Wall Street Journal*. $Institutional\ Ownership$ is the percentage ownership by institutional investors. $Mandatory\ ESG\ Disclosure$ is a dummy variable constructed in Krueger et al. (2021) that takes the value one if a country has mandatory ESG disclosure; and zero otherwise. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Table 10: Climate Change Exposure Measures and Firm Valuations

	Δ *Tobin's Q* After 2011 (1)	Δ *Tobin's Q* After 2011 (2)	Δ *Tobin's Q* After 2011 (3)	Δ *Tobin's Q* After 2011 (4)	Δ *Tobin's Q* Before 2011 (5)	Δ *Tobin's Q* Before 2011 (6)	Δ *Tobin's Q* Before 2011 (7)	Δ *Tobin's Q* Before 2011 (8)
$CCExposure^{Opp}$	0.007			0.020	-0.012			-0.014
	(0.32)			(0.83)	(-0.44)			(-0.50)
$CCExposure^{Reg}$		-0.302**		-0.323**		0.004		0.020
		(-1.98)		(-2.00)		(0.03)		(0.15)
$CCExposure^{Phy}$			-0.132	-0.098			0.104	0.114
			(-0.60)	(-0.45)			(0.35)	(0.40)
Sales Growth	-0.018	-0.018	-0.018	-0.018	-0.025***	-0.025***	-0.025***	-0.025***
	(-0.83)	(-0.82)	(-0.83)	(-0.82)	(-2.71)	(-2.71)	(-2.71)	(-2.71)
Log(Assets)	0.090***	0.091***	0.090***	0.091***	0.032	0.032	0.032	0.032
	(2.71)	(2.73)	(2.71)	(2.73)	(0.93)	(0.93)	(0.93)	(0.93)
Debt/Assets	-0.117	-0.117	-0.117	-0.117	0.255*	0.255*	0.255*	0.255*
	(-1.28)	(-1.28)	(-1.28)	(-1.29)	(1.71)	(1.71)	(1.71)	(1.71)
Cash/Assets	0.226	0.226	0.226	0.226	0.469	0.468	0.468	0.469
	(1.30)	(1.30)	(1.30)	(1.30)	(1.32)	(1.32)	(1.32)	(1.32)
PPE/Assets	0.190	0.190	0.190	0.190	0.206	0.206	0.206	0.206
	(1.25)	(1.24)	(1.25)	(1.24)	(0.88)	(0.88)	(0.88)	(0.88)
EBIT/Assets	-0.773**	-0.775**	-0.773**	-0.775**	-1.240*	-1.239*	-1.238*	-1.240*
	(-2.55)	(-2.56)	(-2.55)	(-2.56)	(-1.69)	(-1.70)	(-1.69)	(-1.69)
Capex/Assets	-0.961*	-0.960*	-0.961*	-0.960*	-0.836	-0.838	-0.837	-0.836
	(-1.66)	(-1.66)	(-1.66)	(-1.66)	(-0.66)	(-0.66)	(-0.66)	(-0.66)
R&D/Assets	1.468	1.471	1.467	1.475	-2.604*	-2.599*	-2.597*	-2.602*
	(1.11)	(1.12)	(1.11)	(1.12)	(-1.95)	(-1.96)	(-1.95)	(-1.95)
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25107	25107	25107	25107	28694	28694	28694	28694
Adj. R-sq	0.039	0.039	0.039	0.039	0.058	0.058	0.058	

Table 10 continued

Notes: Regressions are estimated at the firm-year level. $\Delta Tobin's\, Q$ is the year-on-year change in Tobin's Q. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For all measure, we average values of the four analyst earnings conference calls during the year. We separate the sample into the years before (and including) 2011 and the years after 2011. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Internet Appendix

to

"Firm-level Climate Change Exposure"

A. Climate Change Bigrams Searching Algorithm

We create $\mathbb{C}$ from the union of two separate sets of bigrams: i) a set containing 50 very general and ex-ante specified climate change bigrams, and ii) a set created with machine learning algorithms that construct bigrams directly from analyst conference call transcripts.

Defining the search set. To enable an algorithm to self-discover climate change bigrams from conference call transcripts, we start by compiling a set of conference call transcripts that potentially discuss climate change topics. As a "rough" climate-change training library $\mathbb{C}^R$, we use climate change bigrams in a comprehensive set (288 MB) of research reports issued by the Intergovernmental Panel on Climate Change (IPCC). We lemmatize and stem the textual IPCC data, removing digits, punctuation, and stop words, and drop bigrams with a text frequency that is lower than ten.

We also construct a non-climate-change training library $\mathbb{N}$, which consists of English-language novels taken from Project Gutenberg; news articles on technology, business, and politics from BBC and Thomas Reuters; IMF research reports; and textbooks of accounting and econometrics. We then apply the method in Hassan et al. (2019) and compute a "rough" climate change exposure score for each transcript as following:

$$RoughCCExposure_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left(1[b \in \mathbb{C}^{\mathbb{R}} \setminus \mathbb{N}] \right), \tag{6}$$

Although the non-climate-change training library $\mathbb{N}$ includes extensive sources of textual data, we find that the set of bigrams $\mathbb{C}^R \setminus \mathbb{N}$ is still contaminated by a considerable number of non-climate change bigrams. The reason is that many climate change bigrams often inherently relate to a broad domain of other topics that conference call participants are likely to discuss in contexts unrelated to climate change, such as economic growth, commercial feasibility and technology development. Moreover, conference call participants tend to view climate change from different perspectives compared to the scientists that write the IPCC reports.

To address these problems, we construct a new set $\mathbb{M}$, which consists of sentences in transcripts with positive "rough" climate change bigrams (i.e., those reports in which bigrams $\mathbb{C}^R \setminus \mathbb{N}$ occurred). The goal of constructing this new set is to find the sentences that actually discuss climate change topics and to then extract climate change bigrams from these sentences.

Defining the reference set. In a next step, we partition $\mathbb{M}$ into a reference and search set. To do so, we define a set of 50 very general climate change bigrams, $\mathbb{C}^0$, which includes terms such as "climate change", "global warming", or "carbon emission". We then partition $\mathbb{M}$ based on these initial bigrams into the reference set $\mathbb{R}$ (6.8 MB), which contains about 60,000 sentences containing bigrams in $\mathbb{C}^0$, and the search set $\mathbb{S}$ (3.56 GB), which contains about 70 million sentences not containing any bigrams in $\mathbb{C}^0$. The key difference between the two sets is that the reference set contains sentences almost certainly related to discussions of climate change. To the contrary, the search set may mention climate change topics not captured by the bigrams specified in $\mathbb{C}^0$, but it may also contain pure noise.

Partitioning the search set. To partition the search set, we construct a training set consisting of the reference set $\mathbb{R}$ and a random sample of the search set $\mathbb{S}$ (100,000 sentences). Next, we fit three machine learning classifiers, Multinomial Naive Bayes, Support Vector Classification, and Random Forest, to the training set. These classifiers use the content of each sentence to predict whether or not a sentence belongs to $\mathbb{R}$. For each classifiers, we use grid-search cross validation to select hyper-parameters that optimizes their performance. We then use the optimized parameters from each classifiers to fit the search set and estimate for each sentence in $\mathbb{S}$ the predicted probability of belonging to $\mathbb{R}$. Once we have these predicted probabilities, we group sentences into a target set $\mathbb{T}$ if any of the three classifiers we use predicts a probability of $\mathbb{R}$ membership that is higher than 0.8 for that sentence. The resulting target set contains about 700,000 sentences that do not contain any "obvious" climate change bigrams but are likely to mention climate change contents not captured by $\mathbb{C}^0$.

Finding climate change bigrams. In a last step, we identify bigrams that best discriminate the target set $\mathbb{T}$ from the nontarget set $\mathbb{S} \setminus \mathbb{T}$. We first mine all bigrams $\mathbb{T}$ and $\mathbb{S} \setminus \mathbb{T}$. We find that about 3,800 bigrams appears only in $\mathbb{T}$ but not $\mathbb{S} \setminus \mathbb{T}$. We call this set of bigrams $\mathbb{C}^S$.

For the bigrams that appear in both $\mathbb{T}$ and $\mathbb{S} \setminus \mathbb{T}$, we calculate the document frequencies of each bigram in each of the two sets and keep those bigrams that appear more frequently in the target set than in the nontarget set. For example, if a bigram appears in 2 out of 10 $\mathbb{T}$ sentences and in 10 out of 100 $\mathbb{S} \setminus \mathbb{T}$ sentences, this bigram appear more frequent in $\mathbb{T}$ (frequency of 0.2 versus 0.1). We then rank the bigrams that we kept based on how well they discriminate the two sets. Specifically, we compute a modified version of the likelihood metric suggested in King, Lam, and Roberts (2017) for each bigrams and then add the bigrams with a top 5% likelihood into set $\mathbb{C}^S$ (about 5,000 bigrams).We use a log-gamma function instead of a gamma function because the size of search set is so large that the gamma function cannot return a numeric value. The 5 percent threshold significantly reduces false positives.

Creating a final climate change bigrams library. We define the final climate change bigrams library $\mathbb{C}$ as $\mathbb{C} = \mathbb{C}^0 \cup \mathbb{C}^S$. The benefit of our approach is that the algorithms generate various meaningful climate change bigrams based on the initial bigram set $\mathbb{C}^0$.

B. Origins of climate change discussion in conference calls

Our climate change exposure measures are constructed using the entire conference call. A natural question that may arise is whether discussions about climate change originate in the management presentation part of the call or in the (subsequent) question-and-answer session with market participants. In our main analysis, we choose to use the entire call based on the insight that management is likely to present those issues that they anticipate to be on the mind of their audience. Thus, when expecting probing questions from analysts later on, management is bound to preempt the same in their presentation.

In OA Table 23, Panel A, we document that climate change bigrams are located both in the presentation part and in the Q&A part of the call.[30] At the same time, comparing the means of the exposure, sentiment, and risk measures computed from the presentation and Q&A parts, we find that bigrams from the former, not the latter, contribute most to the various measures. As a final takeaway from this panel, we note that the mean sentiment in the presentation is much more positive than in the Q&A, implying that management discusses climate change in more optimistic terms, whereas the follow-up discussion between management and analysts is more skeptical.

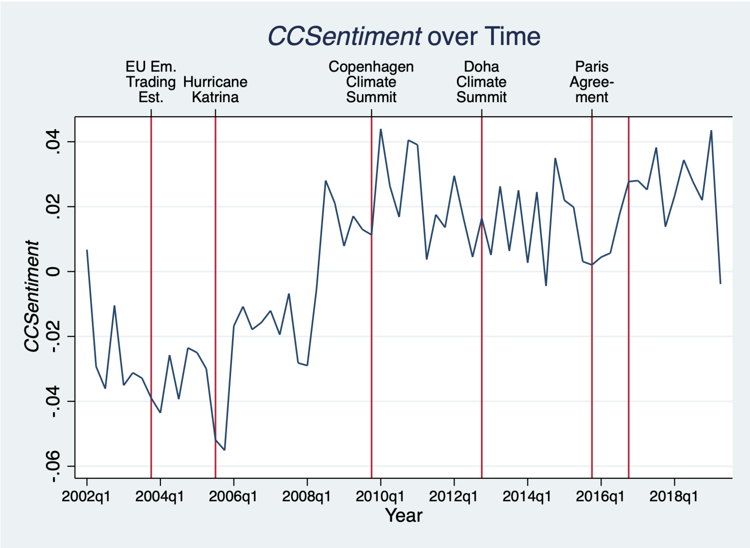
Panel B of the table reports correlations between the climate changes measures (computed from the presentation and Q&A, respectively). We find positive correlations between all measures, but the correlations are stronger between measures corresponding to the presentation. Comparing alike measures across presentation and Q&A, we note that the correlation between the opportunity exposure measures is much higher (0.35) than that between either the regulatory or physical exposure measures (0.05 and 0.03). This implies that the Q&A about opportunities overlaps to some extent with the views presented by management in the opening statement of the call, but that regulatory and physical exposure are discussed in terms unique to the segment of the call in which they appear.

Finally, in Panel C, we document the number of firm-year observations in which climate change exposure is positive in the Q&A session, but zero in the presentation. This condition describes cases in which climate change topics are raised during the interaction with analysts only. Such happens quite frequently for regulatory and physical exposure, but not for opportunities. Together with the evidence from the correlations in Panel B, the picture that emerges is consistent with management using the presentation to highlight the opportunities of climate change, whereas the Q&A with analysts raises issues corresponding to regulatory and physical exposure.

[30] Note that the number of observations differs from Table 1 as not all conference calls feature Q&A sessions, in which case they will be recorded as missing in the current table.

C. Additional Tables and Figures

IA Figure 1: Climate Change Sentiment/Risk over Time



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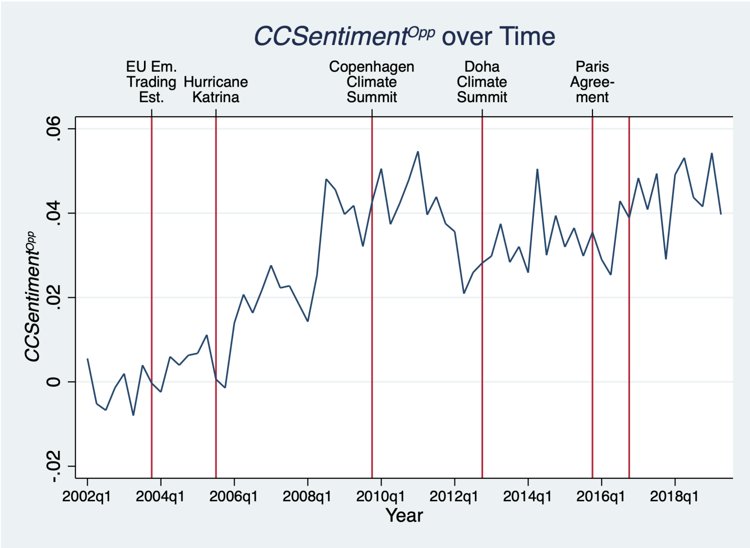

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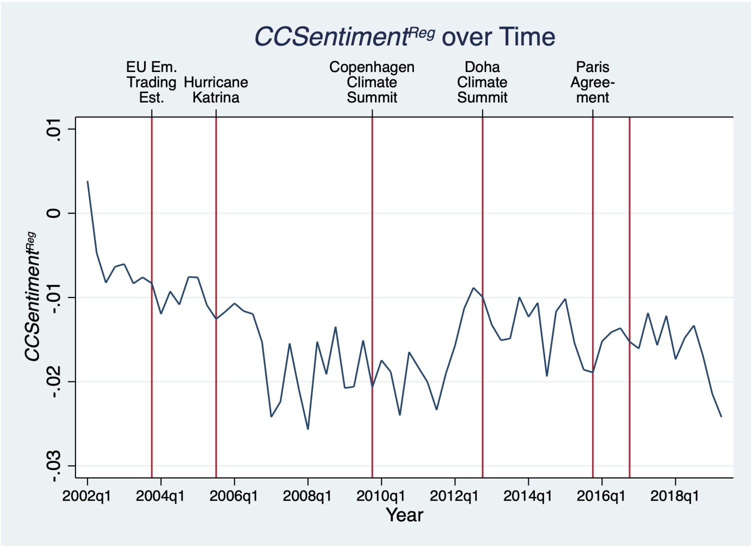

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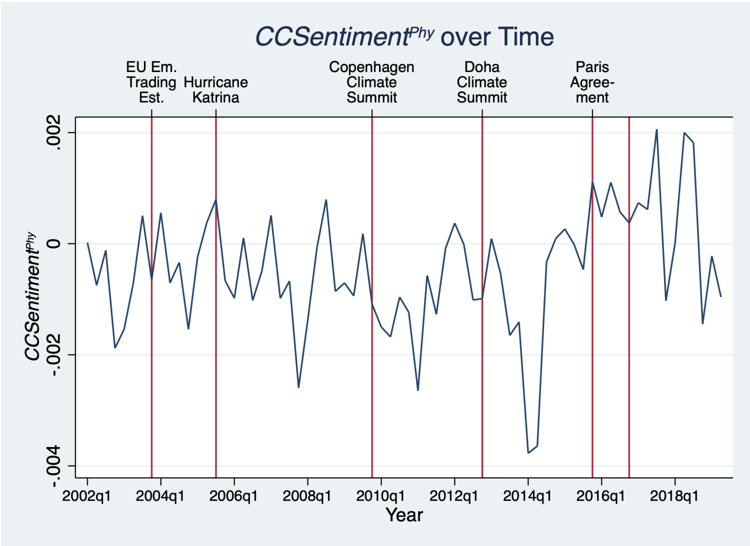
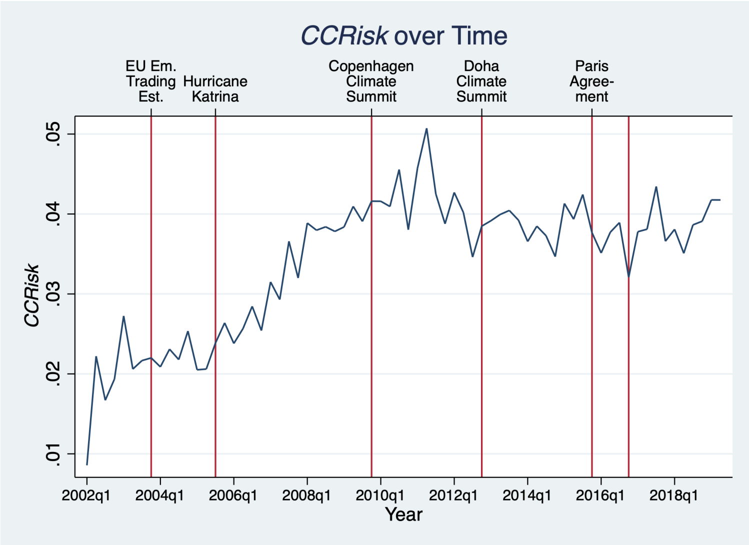


(d)

IA Figure 1 continued



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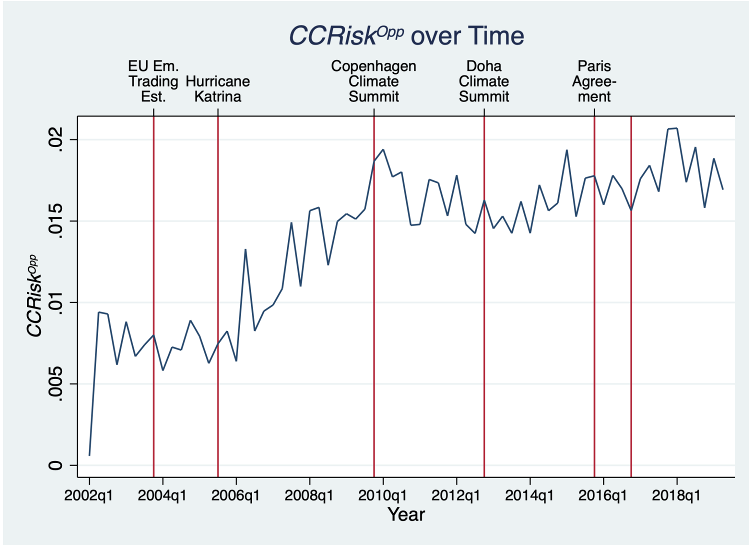

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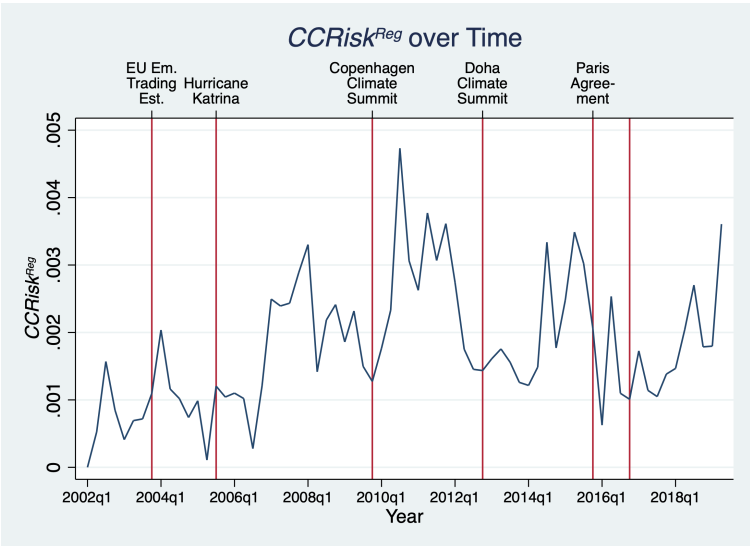

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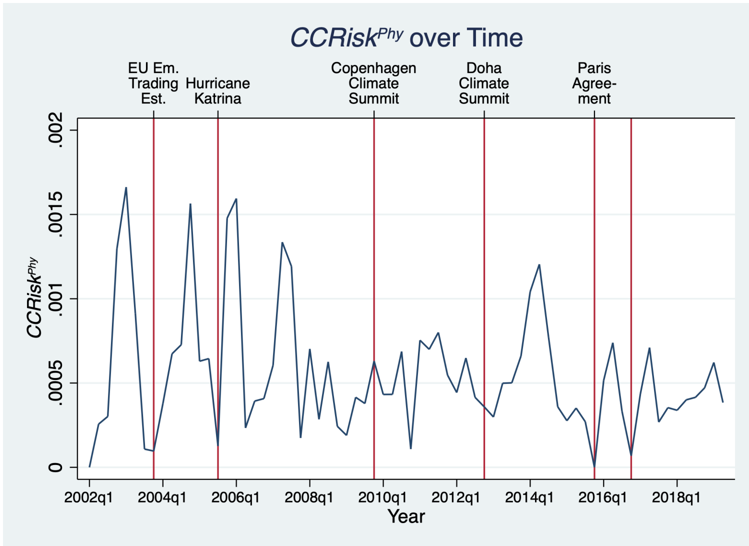
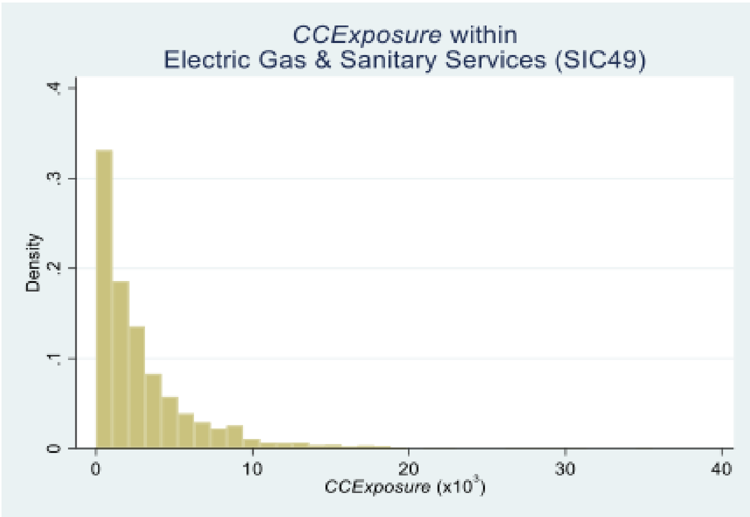


(h)

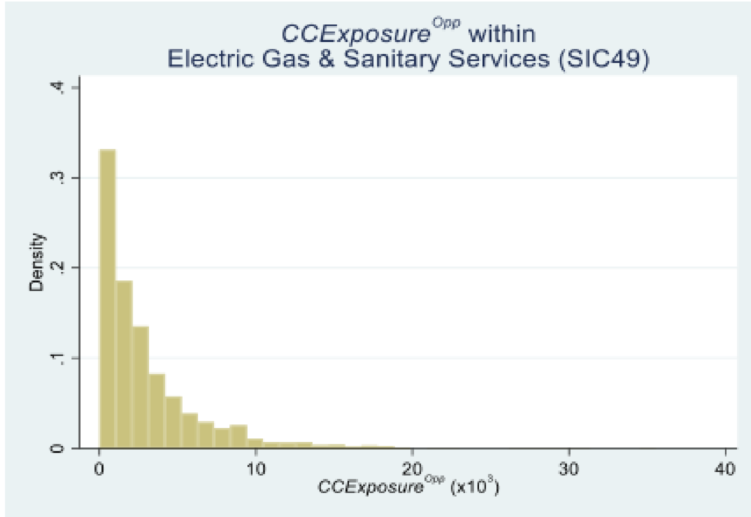
IA Figure 1 continued

Notes: These figures report firms' average climate change sentiments and risks over time. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). The vertical (red) lines show when the quarters of i) the Introduction of the EU Emission Trading System; ii) Hurricane Katrina; iii) the Copenhagen Climate Summit; iv) the Doha Climate Summit; and v) the Paris Agreement. Appendix A defines all variables in detail.

IA Figure 2: Climate Change Measures within the Electric, Gas, & Sanitary Services Sector (Utilities)



(a)



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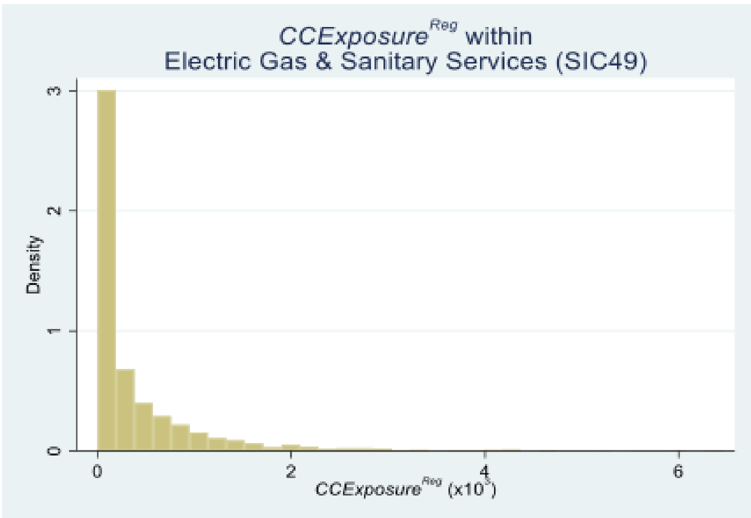

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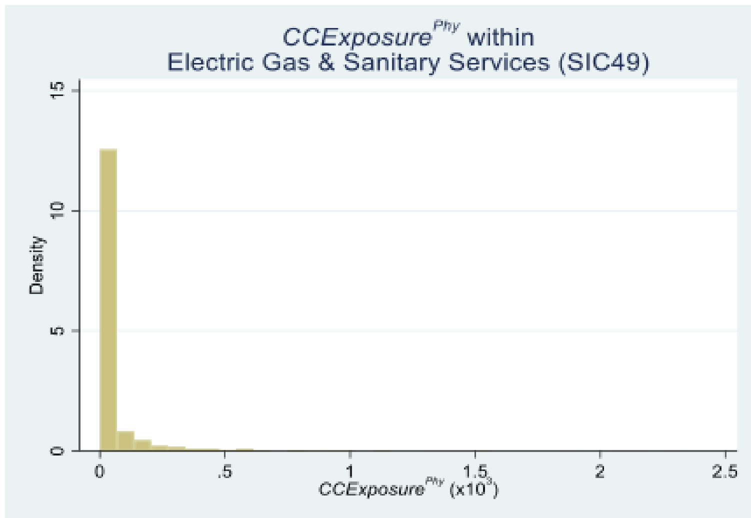
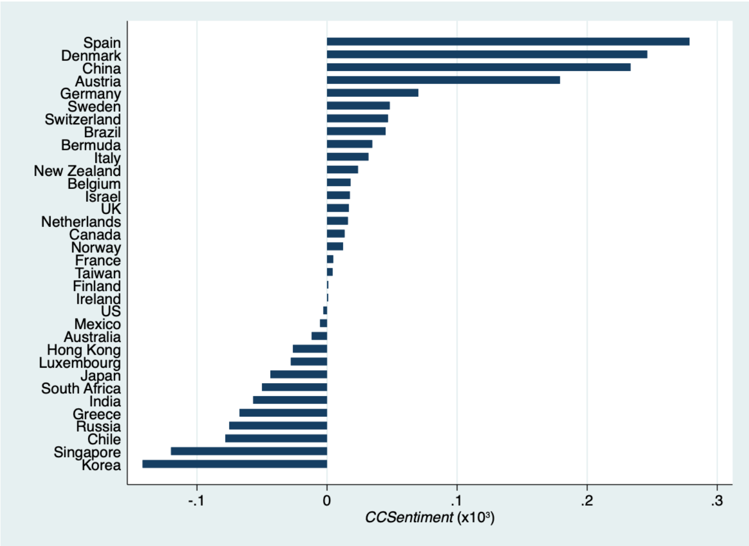


(d)

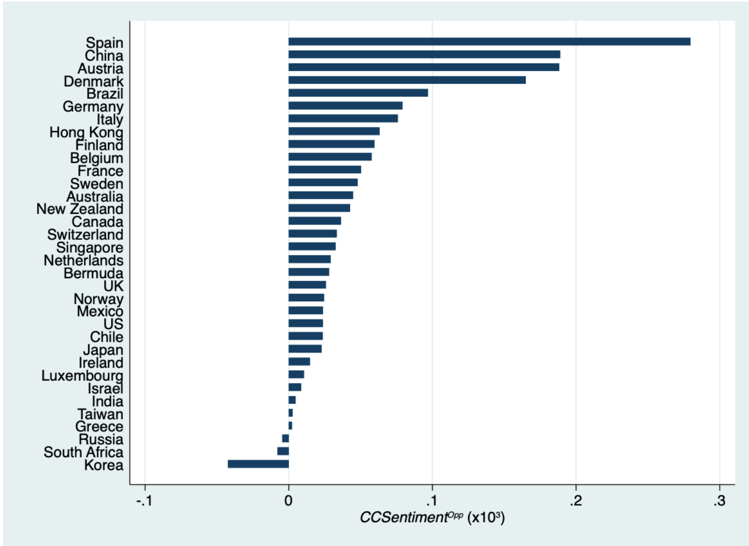
IA Figure 2 continued

Notes: These figures report the distribution of firms' climate change exposure measures within the utilities sector (Electric, Gas, & Sanitary Services, SIC2 49). $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. Appendix A defines all variables in detail.

IA Figure 3: Climate Change Sentiment/Risk across Countries



(a)



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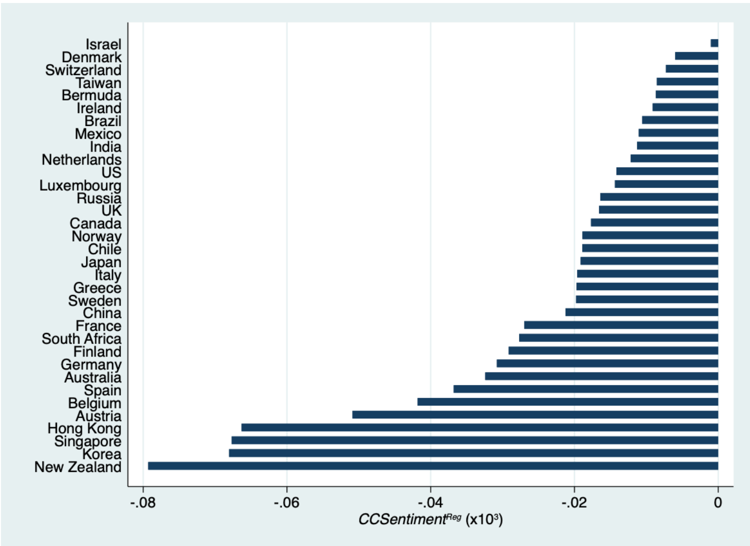

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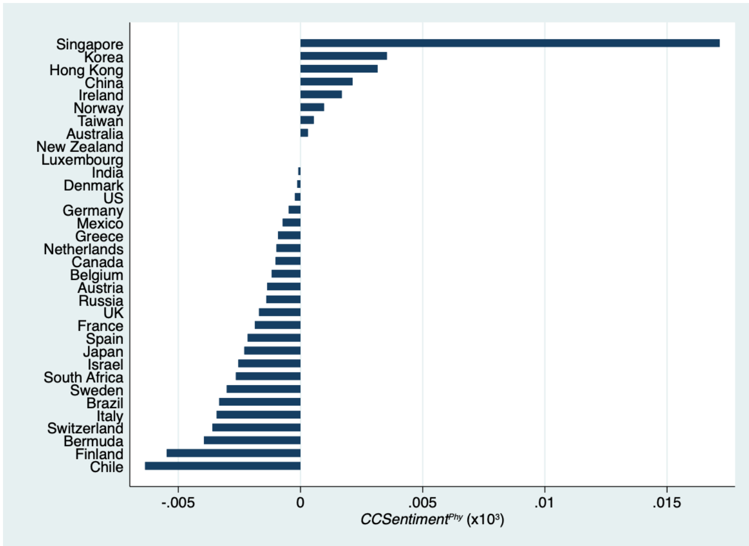
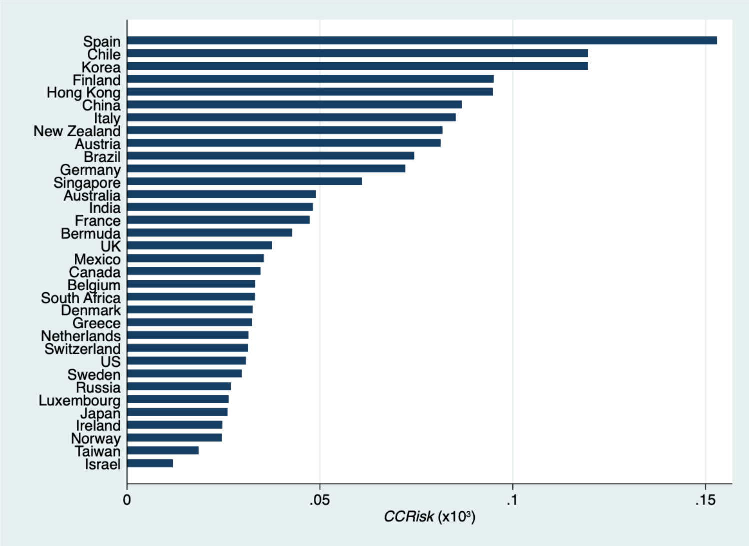
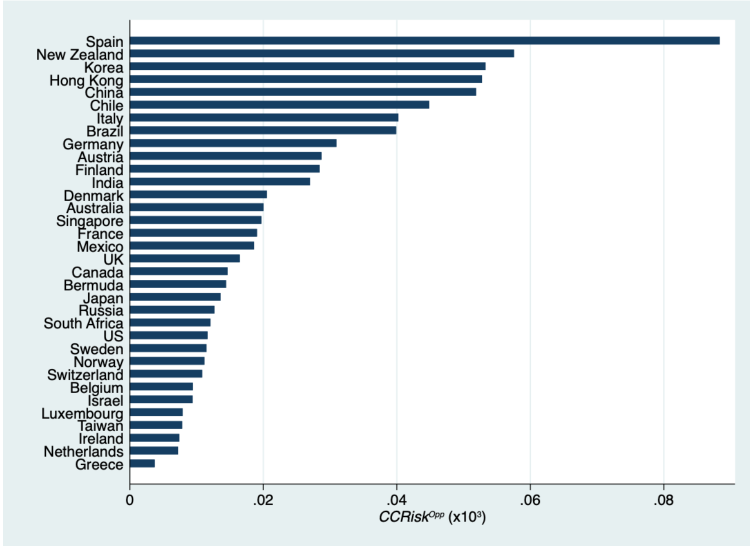


(d)

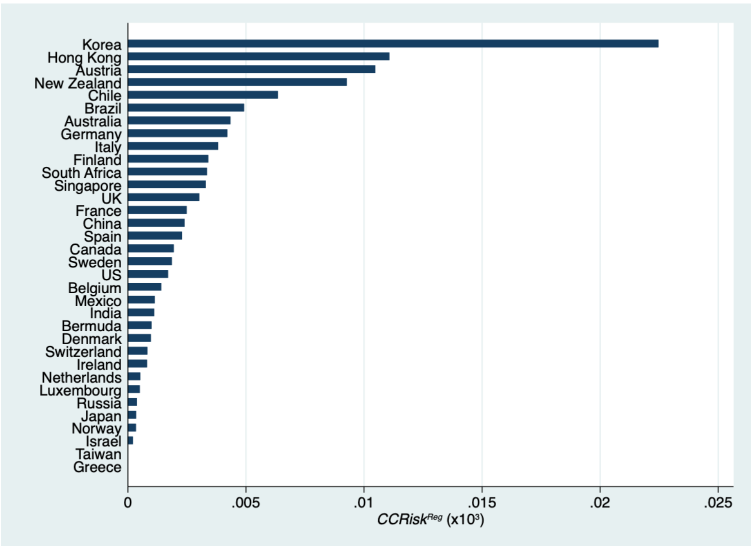
IA Figure 3 continued



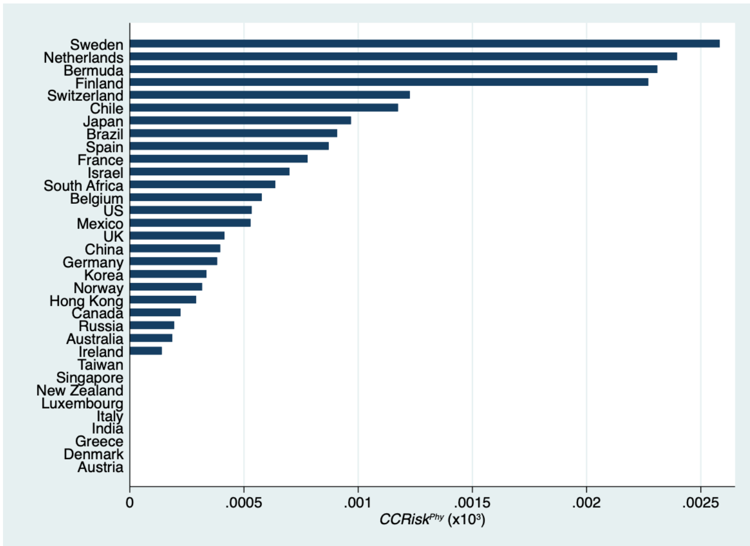
(e)



(g)



(g)



(h)

IA Figure 3 continued

Notes: These figures report firms' average climate change sentiments and risks across countries. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). Appendix A defines all variables in detail.

IA Table 1: Number of Observations Across Countries

Country	Obs.	Percent
Australia	1213	1.5%
Austria	172	0.2%
Belgium	248	0.3%
Bermuda	682	0.9%
Brazil	958	1.2%
Canada	5502	6.9%
Chile	211	0.3%
China	1289	1.6%
Denmark	401	0.5%
Finland	438	0.5%
France	1275	1.6%
Germany	1230	1.5%
Greece	217	0.3%
Hong Kong	426	0.5%
India	984	1.2%
Ireland	609	0.8%
Israel	680	0.8%
Italy	536	0.7%
Japan	1293	1.6%
Korea	278	0.3%
Luxembourg	234	0.3%
Mexico	501	0.6%
Netherlands	763	1.0%
New Zealand	158	0.2%
Norway	388	0.5%
Russia	317	0.4%
Singapore	229	0.3%
South Africa	432	0.5%
Spain	461	0.6%
Sweden	878	1.1%
Switzerland	903	1.1%
Taiwan	327	0.4%
UK	3075	3.8%
US	52913	66.0%
Total	80221	100%

Note: This table reports the distribution of firm-year observations across countries.

IA Table 2: Initial Bigrams for Searching Climate Change Bigrams

air pollution	electric vehicle	new energy
air quality	energy climate	ozone layer
air temperature	energy conversion	renewable energy
biomass energy	energy efficient	sea level
carbon dioxide	energy environment	sea water
carbon emission	environmental sustainability	snow ice
carbon energy	exterme weather	solar energy
carbon neutral	flue gas	solar thermal
carbon price	forest land	sustainable energy
carbon sink	gas emission	water resource
carbon tax	ghg emission	water resources
clean air	global decarbonization	wave energy
clean energy	global warm	weather climate
clean water	greenhouse gas	wind energy
climate change	heat power	wind power
coastal area	Kyoto protocol	wind resource
costal region	natural hazard	

IA Table 3: Top-100 Bigrams Captured by Climate Change Sentiment (*CCSentiment*)

Bigrams	Sentiment	Bigrams	Sentiment	Bigrams	Sentiment
energy efficient	2766	say wind	184	gigawatt wind	117
wind power	2656	wind plant	173	operate wind	116
wind energy	2535	opportunity renewable	171	achieve energy	114
renewable energy	768	opportunity solar	166	grow wind	113
wind resource	687	opportunity wind	165	generation wind	111
electric vehicle	442	sell wind	164	especially wind	111
wind capacity	392	vehicle opportunity	164	basically wind	111
major design	382	improve air	163	turbine wind	110
friendly product	349	opportunity clean	160	total wind	109
wind park	347	portfolio wind	160	power wind	108
new energy	346	company wind	155	improvement air	107
efficient light	299	focus wind	152	particularly wind	106
clean energy	276	demand wind	150	addition stable	105
market wind	268	efficient project	149	efficiency requirement	104
come wind	264	efficient unit	149	plant wind	104
talk wind	257	efficient environmentally	145	addition wind	104
efficiency power	255	efficiency renewable	144	small wind	104
efficient build	254	mention wind	144	efficiency conservation	100
energy opportunity	251	big wind	140	motor control	99
wind facility	249	mean wind	138	install wind	99
wind wind	248	energy star	135	efficient home	97
improve environmental	235	base wind	132	friendly material	94
clean efficient	233	area wind	128	gas wind	94
build wind	227	indoor outdoor	127	efficient natural	94
solar energy	217	exist wind	126	invest wind	93
efficient power	215	innovative development	126	energy team	91
efficient energy	207	china wind	126	course wind	91
energy wind	204	renewable wind	123	wind technology	91
efficiency demand	204	production wind	122	leadership energy	89
efficiency solution	204	order wind	121	opportunity electric	89
vehicle good	192	electrical efficiency	119	overall wind	89
efficient engine	189	innovative energy	118	case wind	88
development wind	187	efficient lead	117	benefit clean	88
efficient design	184				

Notes: This table reports the top-100 bigrams associated with *CCSentiment*, which measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. The bigrams for *CCSentiment* are in turn subsets of *CCExposure*. Appendix A defines all variables in detail.

IA Table 4: Bottom-100 Bigrams Captured by Climate Change Sentiment (*CCSentiment*)

Bigrams	Sentiment	Bigrams	Sentiment	Bigrams	Sentiment
reduce emission	-924	carbon tax	-162	emission issue	-99
greenhouse gas	-848	reduction emission	-160	believe solar	-93
carbon emission	-834	air quality	-153	emission product	-93
gas emission	-769	trade scheme	-152	emission monitor	-92
energy regulatory	-720	nitrogen oxide	-151	emission year	-91
climate change	-571	air pollution	-148	reduce nox	-88
transmission grid	-419	relate electric	-147	epa regulation	-87
issue rfp	-387	obama administration	-142	far energy	-87
environmental concern	-385	environmental sustainability	-142	protection issue	-87
close megawatt	-360	increasingly stringent	-142	carbon price	-85
emission trade	-337	issue clean	-140	northern pass	-82
transmission capacity	-326	environmental quality	-138	oxide emission	-82
transmission infrastructure	-319	water resource	-137	market investigation	-80
issue request	-313	president obama	-137	factor correction	-78
carbon dioxide	-311	epa issue	-136	close population	-78
nox emission	-308	commission megawatt	-135	large displacement	-77
dioxide emission	-283	emission reduce	-135	energy plant	-75
question renewable	-265	sulfur dioxide	-135	carbon disclosure	-75
regional transmission	-239	question carbon	-133	lead pigment	-75
air emission	-234	environmental problem	-129	client resource	-74
pass house	-231	issue air	-127	transmission electric	-74
emission level	-226	believe water	-124	air pollutant	-74
energy transmission	-218	change emission	-122	emission coal	-72
reduce carbon	-204	disclosure project	-116	emission come	-72
transmission upgrade	-202	sustainability issue	-115	heavy snow	-71
clean air	-195	electric grid	-113	illinois pennsylvania	-71
concern energy	-194	california department	-110	hazardous air	-71
increasingly rely	-193	question electric	-110	energy case	-70
challenge energy	-191	energy concern	-107	regional haze	-70
particulate matt	-182	emission target	-105	emission compare	-70
mercury emission	-177	energy close	-104	energy reserve	-69
natural hazard	-176	emission rate	-101	climate issue	-69
global warm	-166	emission free	-99	commission european	-69
question clean	-165				

Notes: This table reports the bottom-100 bigrams associated with *CCSentiment*, which measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. The bigrams for *CCSentiment* are in turn subsets of *CCExposure*. Appendix A defines all variables in detail.

IA Table 5: Top-100 Bigrams Captured by Climate Change Risk (*CCRisk*)

Bigrams	Frequency	Bigrams	Frequency	Bigrams	Frequency
renewable energy	460	water resource	46	build wind	26
variable speed	351	carbon emission	46	clearly slowly	26
clean energy	301	energy reform	45	frequency motor	26
question renewable	287	energy environment	42	climate relate	25
electric vehicle	255	president obama	42	national tobacco	25
climate change	229	carbon dioxide	41	provider automation	25
natural hazard	227	air pollution	41	range avista	25
wind power	178	global warm	41	carbon footprint	24
question clean	177	prospect power	40	environmental concern	24
new energy	147	future energy	36	wind capacity	24
question carbon	140	provision residual	36	come wind	24
variable frequency	120	gas emission	35	molyneaux energy	24
wind energy	119	facilitate development	35	battery power	23
question electric	118	reduce emission	34	light bulb	23
greenhouse gas	95	policy federal	34	renewable resource	23
clean air	85	joaquin basin	33	clean water	23
solar venture	80	world population	32	regulation consumer	23
hazardous air	74	energy need	30	slowly order	23
solar energy	73	coastal area	29	utility encompass	23
energy efficient	72	variability wind	29	energy plant	22
carbon tax	69	variability power	29	snow ice	22
air pollutant	68	carbon capture	28	forest land	22
wind risk	68	president elect	28	epa regulation	22
climate risk	67	energy regulatory	27	inner mongolia	22
efficiency variable	60	build power	27	bush administration	22
state teacher	58	northern pass	27	energy involve	22
air quality	57	emission trade	27	usual remember	22
obama administration	57	energy research	27	energy program	21
carbon price	57	reduce carbon	26	market wind	21
variable energy	52	power generator	26	resource country	21
wind resource	51	electric grid	26	carbon legislation	21
solar farm	50	wind facility	26	pope pickering	21
requirement uncertainty	49	nickel metal	26	encompass expect	21
clean power	47				

Notes: This table reports the top-100 bigrams associated with *CCRisk*, which measures the relative frequency with which bigrams related to climate change occur in one sentence together with the words "risk" or "uncertainty" (or synonyms thereof). The bigrams for *CCRisk* are in turn subsets of *CCExposure*. Appendix A defines all variables in detail.

IA Table 6: Initial Bigrams for Searching Climate Change Topic Bigrams

Initial Opportunity Bigrams				
heat power	new energy	plug hybrid	rooftop solar	renewable electricity
renewable energy	wind power	renewable resource	sustainable energy	wave power
electric vehicle	wind energy	solar farm	hybrid car	geothermal power
clean energy	solar energy	electric hybrid		
Initial Regulatory Bigrams				
greenhouse gas	gas emission	carbon tax	emission trade	carbon reduction
reduce emission	air pollution	carbon price	dioxide emission	carbon market
carbon emission	reduce carbon	environmental standard	epa regulation	mercury emission
carbon dioxide	energy regulatory	nox emission	energy independence	
Initial Physical Bigrams				
coastal area	forest land	storm water	natural hazard	water discharge
global warm	sea level	heavy snow	sea water	ice product
snow ice	nickel metal	air water	warm climate	

IA Table 7: Top-100 Opportunity Climate Change Bigrams ($CCExposure^{Opp}$)

Bigrams	Exposure	Risk	Sentiment	Bigrams	Exposure	Risk	Sentiment
renewable energy	12406	460	768	grid technology	249	6	45
electric vehicle	6732	255	442	geothermal power	249	17	1
clean energy	4815	301	276	type energy	246	6	-11
new energy	3751	147	346	solar program	245	5	37
wind power	3673	178	2656	vehicle development	243	13	0
wind energy	3611	119	2535	energy important	243	5	8
solar energy	2153	73	217	install solar	242	6	14
plug hybrid	890	19	34	vehicle battery	242	5	33
heat power	835	18	46	energy vehicle	242	16	16
renewable resource	800	23	10	energy bring	240	8	35
solar farm	753	50	34	vehicle space	233	9	-3
battery electric	659	16	11	opportunity clean	231	6	160
electric hybrid	476	14	49	demand wind	227	6	150
reinvestment act	460	15	-1	vehicle good	226	8	192
issue rfp	443	6	-387	medical electronic	226	5	16
construction megawatt	435	13	0	incremental content	224	4	18
rooftop solar	434	20	19	supply industrial	223	7	-14
grid power	421	17	-56	energy target	223	10	6
recovery reinvestment	395	9	11	term electric	221	8	-16
solar generation	394	20	64	power world	220	5	38
energy standard	384	7	-27	vehicle small	216	5	11
sustainable energy	376	9	45	renewable electricity	216	14	18
vehicle charge	374	9	38	wave power	214	10	13
guangdong province	360	11	-3	carbon neutral	213	3	-16
hybrid car	341	17	6	auction new	211	15	-9
charge infrastructure	323	5	2	cost renewable	210	9	-25
micro grid	322	7	9	vehicle talk	210	11	-23
grid connect	319	10	23	vehicle offer	210	9	14
clean efficient	308	6	233	customer clean	210	8	12
carbon free	306	15	2	power solar	209	13	62
hybrid technology	306	9	-1	vehicle opportunity	208	8	164
generation renewable	303	10	16	community solar	208	5	-10
energy wind	295	12	204	energy goal	207	3	37
battery charge	290	3	25	vehicle hybrid	207	6	10
gas clean	289	12	-25	invest renewable	207	12	15
vehicle lot	287	7	9	incorporate advance	206	5	20
vehicle place	286	7	-12	talk solar	203	8	3
meet energy	286	6	14	ton carbon	202	2	-50
vehicle type	281	11	2	small hydro	202	5	6
vehicle future	276	15	6	base solar	202	9	24
energy commitment	276	6	29	target gigawatt	201	7	33
electronic consumer	275	8	20	charge network	201	20	-43
expand energy	269	8	29	capacity generation	201	9	-5

IA Table 7 continued

Bigrams	Exposure	Risk	Sentiment	Bigrams	Exposure	Risk	Sentiment
gigawatt install	266	3	11	vehicle add	200	6	6
bus truck	264	4	16	vehicle infrastructure	200	6	15
ton waste	263	1	-38	solar array	198	8	-26
energy research	258	27	-8	energy auction	198	14	-15
focus renewable	257	10	32	product hybrid	192	6	44
pure electric	256	4	-26	product solar	192	5	28
ev charge	255	-47	33	exist wind	192	9	126

Notes: This table reports the top-100 bigrams associated with $CCExposure^{Opp}$, which measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. For each of these bigrams, we also report how frequently they are associated with $CCRisk^{Opp}$ and $CCSentiment^{Opp}$. Appendix A defines all variables in detail.

IA Table 8: Top-100 Regulatory Climate Change Bigrams ($CCExposure^{Reg}$)

Bigrams	Exposure	Risk	Sentiment	Bigrams	Exposure	Risk	Sentiment
greenhouse gas	2341	95	-848	produce carbon	128	4	-34
reduce emission	1567	34	-924	clean job	126	3	-46
carbon emission	1273	46	-834	efficient natural	124	1	94
carbon dioxide	1247	41	-311	emission monitor	124	1	-92
gas emission	1166	35	-769	emission issue	123	7	-99
air pollution	1063	41	-148	quality permit	122	1	-27
reduce carbon	1004	26	-204	product carbon	122	3	-26
energy regulatory	921	27	-720	china air	122	3	3
carbon tax	792	69	-162	reduce sulfur	121	7	-50
carbon price	760	57	-85	available control	121	9	-34
environmental standard	496	10	-13	emission rate	119	5	-101
nox emission	418	11	-308	regulation low	118	13	-27
emission trade	412	27	-337	capture sequestration	118	2	-3
dioxide emission	396	18	-283	nation energy	117	4	-3
epa regulation	370	22	-87	emission year	115	3	-91
energy independence	350	14	31	efficient combine	115	1	75
carbon reduction	338	10	16	carbon economy	114	7	-6
know clean	276	8	-22	comply environmental	114	8	-21
standard requirement	268	10	-33	glacier hill	111	0	-43
development renewable	267	5	24	hill wind	110	2	0
carbon market	259	15	-7	nox sox	110	3	-37
trade scheme	232	15	-152	tax australia	106	4	-17
deliver clean	228	4	6	way comply	105	1	2
mercury emission	220	4	-177	emission intensity	103	0	-62
reduce air	218	4	-24	oxide emission	101	2	-82
save technology	193	10	26	emission improve	101	2	0
talk clean	190	5	-9	emission increase	100	3	-65
energy alternative	188	7	9	install low	99	1	0
place energy	176	13	11	commission public	97	10	-78
reduce nox	175	1	-88	castle peak	97	23	-41
air resource	169	1	-45	capture carbon	97	3	1
target energy	166	4	17	wait commission	96	2	-90
change climate	163	7	-10	emission compare	92	0	-70
impact climate	163	11	-12	clean electricity	92	2	-11
issue air	157	9	-127	high hydrocarbon	92	6	5
promote energy	153	3	48	emission come	88	2	-72
emission free	152	4	-99	weight fuel	87	0	6
implement energy	151	1	24	stability reserve	87	4	38
recovery pollution	149	0	4	quality regulation	86	6	-23
control regulation	146	13	-36	request public	86	4	-40
florida department	144	7	-34	additive process	86	1	-12
commission license	141	8	-128	gas carbon	84	2	-10
gas regulation	140	15	-24	epa requirement	83	3	-11

IA Table 8 continued

Bigrams	Exposure	Risk	Sentiment	Bigrams	Exposure	Risk	Sentiment
appeal district	139	3	-61	liter diesel	83	2	3
source electricity	139	3	17	meet reduction	81	3	-15
effective energy	138	1	83	talk climate	81	3	-3
nitrous oxide	138	1	-44	expect carbon	80	2	-10
impact clean	134	7	-20	emission ton	80	1	-62
think carbon	134	7	-21	ambient air	80	5	-25
global climate	132	8	-13	know carbon	79	5	-11

Notes: This table reports the top-100 bigrams associated with $CCExposure^{Reg}$, which measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. For each of these bigrams, we also report how frequently they are associated with $CCRisk^{Reg}$ and $CCSentiment^{Reg}$. Appendix A defines all variables in detail.

IA Table 9: Top-50 Physical Climate Change Bigrams ($CCExposure^{Phy}$)

Bigrams	Exposure	Risk	Sentiment	Bigrams	Exposure	Risk	Sentiment
coastal area	738	29	-61	ice control	128	5	27
global warm	671	41	-166	inland area	127	2	6
snow ice	481	22	-43	non coastal	115	6	-13
friendly product	447	13	349	storm january	105	1	-28
forest land	426	22	-53	sale forest	93	3	-8
area florida	367	7	-45	value forest	80	6	-6
sea level	365	17	-55	land forest	79	4	-13
provide water	364	5	-14	particularly coastal	66	1	9
nickel metal	362	26	12	golf ground	58	0	24
supply water	297	13	-57	especially coastal	58	2	-1
storm water	262	5	-52	sewer overflow	52	0	0
heavy snow	252	11	-71	combine sewer	52	0	-2
air water	251	6	-14	area coastal	52	2	0
natural hazard	227	227	-176	large desalination	50	3	-1
sea water	218	6	-29	plant algeria	50	1	-5
warm climate	213	7	5	warm product	47	1	9
water discharge	211	7	-59	solution act	47	0	-1
ice product	198	8	23	fluorine product	47	0	15
security energy	194	7	-3	area inland	43	3	0
water act	182	14	-64	fight global	41	1	-9
management district	174	1	4	sell forest	39	1	-6
weather snow	154	2	-21	exposure coastal	34	4	-6
service reliable	148	1	30	city coastal	34	2	1
management water	138	2	-9	marina east	28	0	18
ability party	134	32	31	day desalination	23	0	-8

Notes: This table reports the top-50 bigrams associated with $CCExposure^{Phy}$, which measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. For each of these bigrams, we also report how frequently they are associated with $CCRisk^{Phy}$ and $CCSentiment^{Phy}$. Appendix A defines all variables in detail.

IA Table 10: Top-5 Firms by Opportunity Climate Change Exposure

Firm	**HQ**	**SIC**	**Time**	**Assets ($ millions)**	**Bigrams**	**Top Snippet**
China Ming Yang Wind Power Group Ltd	China	3511	2014Q4	2,040	energy wind; geothermal power; power solar; renewable energy; wind power	on november 19, the state council announced the action plan of energy development strategy from 2014 to 2020, which is to optimize the energy structure, to enlarge the shares of renewable energies, such as wind power, solar power and geothermal power, as well as the share of nuclear in energy consumption.
China Longyuan Power Group Corp Ltd	China	4911	2014Q2	18,965	power thermal; wind power	the second question is, can you provide your operating cost breakdown among wind power and thermal power?
Xinjiang Goldwind Science & Technology Co Ltd	China	3511	2018Q4	11,873	forecast gigawatt; gigawatt onshore; wind power	the forecast was 66.4 gigawatts for onshore wind power in 2019, an increase of 21.6% year-on-year, and 6.3 gigawatts for offshore wind power in 2019, an increase of 75% year-on-year.
ECOtality Inc	U.S.	3621	2008Q4	9	electric transportation; electric vehicle; home charge; vehicle fast	while we believe that home charging systems will play a dominant role in the fueling of electric vehicles, we firmly believe that the ability to quickly and conveniently recharge vehicles on the go via a fast-charge station, is pivotal to the mass consumer acceptance of electric transportation.
ALLETE Inc	U.S.	4911	2018Q4	5,165	clean sustainable; energy landscape; support clean; sustainable energy	these transformative projects represent significant capital investments in support of cleaner and more sustainable energy sources as mp answers the call to transform the nation's energy landscape.

IA Table 11: Top-5 Firms by Regulatory Climate Change Exposure

Firm	HQ	SIC	Time	Assets ($ millions)	Bigrams	Top Snippet
Korea Electric Power Corp	South Korea	4911	2016Q2	126	gas emission; greenhouse gas	but considering the greenhouse gas emission cost and the energy industry investment, we believe the tariff calculation should be based off of mid- to long-term performance rather than short-term performance.
Vacon Oy	Finland	3671	2007Q2	145	carbon dioxide; dioxide emission	it might be a surprise for some of us that about 65% of the electricity is produced by burning fossil fuels like oil, coal and gas and thus lot of carbon dioxide emissions are created.
CECO Environmental Corp	U.S.	3499	2011Q3	74	epa regulation	but our business is diversifying enough that we are going to do well without the epa regulations kicking-in.
Rentech Inc	U.S.	851	2007Q4	156	capture sequestration; carbon dioxide; dioxide emission	carbon capture and sequestration enables the carbon dioxide emissions from the product production of the fuels from the rentech process to be comparable or comparable to or lower than those generated in the production of petroleum derived diesel.
Fuel Tech Inc	U.S.	3564	2010Q3	100	emission trade; mercury emission; nox sox	this bill addresses nox and sox emissions on a national level, with two separate trade zones, and a cap on mercury emissions with no trading through amendments to the clean air act.

IA Table 12: Top-5 Firms by Physical Climate Change Exposure

Firm	**HQ**	**SIC**	**Time**	**Assets ($ millions)**	**Bigrams**	**Top Snippet**
Cincinnati Financial Corp	U.S.	6331	2005Q4	16,003	coastal area; exposure coastal	we would expect that because of exposures we have in coastal areas, that is going to affect things as far as the kind of premiums we would pay for catastrophe reinsurance, things of that nature.
Abtech Holdings Inc	U.S.	3822	2015Q2	1	storm water	in addition, over the past year, a number of municipalities have implemented storm water utilities or assess storm water fees intended to provide the funding needed to implement effective storm water treatment systems.
Westrock MWV LLC	U.S.	2653	2007Q1	9,171	forest land; value forest	i can tell you this morning that we have already determined that much of our land in alabama and georgia, as well as some in west virginia, has the most value as forest land, and with that in mind, we plan to sell this land, roughly about 300,000 acres during 2007.
UPM-Kymmene Oyj	Finland	2611	2014Q1	24,774	forest land; sale forest; value forest	but, as we have mentioned here, part of the value change in the last quarter that we recorded in the increase in fair value for our forests came from the sale of forest land.
Inficon Holding AG	Switzerland	3823	2017Q4	269	security energy	looking at the end market development, all markets except security & energy markets increased in q3.

IA Table 13: Industry Distribution of Carbon Intensity and ISS Carbon Risk Rating

Carbon Intensity					*ISS Carbon Risk Rating*				
Industry (SIC2)	Mean	STD	Median	Obs.	Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries					Bottom-10 Industries				
32 Stone, Clay, & Glass Products	1048.2	952.8	556.8	110	13 Oil & Gas Ext	1.398	0.214	1.358	195
49 Electric, Gas, & Sanitary Services	748.7	826.7	352.6	392	29 Petroleum Refinery	1.461	0.385	1.352	149
45 Transportation by Air	589.4	363.5	708.5	85	65 Real Estate	1.533	0.291	1.425	311
42 Trucking & Warehousing	539.2	442.2	451.6	70	50 Wholesale Trade—Durable Goods	1.572	0.345	1.463	190
33 Primary Metal	523.3	687.8	340.3	56	15 Building Cons	1.602	0.278	1.536	82
44 Water Transport	330.4	337.3	263.0	43	47 Transportation Services	1.649	0.361	1.512	98
29 Petroleum Refinery	260.4	117.3	236.6	113	45 Transportation by Air	1.653	0.280	1.679	137
26 Paper & Allie Products	210.7	187.5	175.6	116	51 Wholesale Trading—Nondurable Goods	1.660	0.340	1.637	208
13 Oil & Gas Extraction	174.2	267.2	126.1	131	87 Engineering & Management Services	1.696	0.414	1.631	158
Bottom-10 Industries					Top-10 Industries				
39 Miscellaneous Manufacturing Industries	5.7	2.4	4.8	21	28 Chemicals & A	1.903	0.509	1.904	836
80 Health Services	4.6	7.1	1.9	38	70 Hotels & Other Lodging Places	1.917	0.476	2.001	65
27 Printing & Publishing	4.3	11.7	1.7	38	25 Furniture & Fixings	1.931	0.507	1.842	28
48 Communication	3.5	6.2	1.4	219	53 General Merchandise	1.946	0.472	1.945	83
56 Apparel & Accessory Stores	2.5	2.0	2.0	42	56 Apparel & Accessory Stores	2.019	0.424	2.033	63
65 Real Estate	2.4	2.8	1.3	76	35 Industrial Machinery & Equipment	2.045	0.650	1.934	408
78 Motion Pictures	0.8	0.8	0.4	23	26 Paper & Allied Products	2.163	0.455	2.138	103
63 Insurance Carriers	0.2	0.2	0.1	169	49 Electric, Gas, & Sanitary Services	2.217	0.639	2.178	532
62 Security & Commodity Brokers	0.1	0.2	0.0	86	36 Electronic & Other Electric Equipment	2.241	0.818	2.078	518
60 Depository Institutions	0.1	0.1	0.0	294	40 Railroad Transport	2.590	0.235	2.677	47

Notes: This table reports firms' *Carbon Intensity* and *ISS Carbon Risk Rating* for the top-10 and bottom-10 industries. Statistics are reported at the firm-year level across different SIC2 industries. We rank sectors by the average values of the climate change measures. *Carbon Intensity* measures Scope 1 carbon emissions divided by total assets. *ISS Carbon Risk Rating* is constructed by ISS and provides an assessment of the carbon-related performance of companies. Appendix A defines all variables in detail.

IA Table 14: Industry Distribution of Climate Change Sentiment & Risk

Panel A. $CCSentiment$ ($\times 10^3$)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
16 Heavy Construction, Except Building	0.281	1.639	0.000	450
35 Industrial Machinery & Equipment	0.247	1.719	0.000	2305
36 Electronic & Other Electric Equip.	0.201	0.867	0.000	5896
40 Railroad Transportation	0.117	0.665	0.001	182
52 Building Material	0.105	0.447	0.000	38
75 Auto Repair Services	0.061	0.372	0.000	121
15 General Building Contractors	0.051	0.399	0.000	690
54 Food Stores	0.048	0.255	0.000	215
57 Home Furniture	0.039	0.167	0.000	136
34 General Building Contractors	0.039	0.622	0.000	925
Bottom-10 Industries				
44 Water Transport	-0.047	0.461	0.000	784
14 Nonmetallic Minerals, Except Fuels	-0.060	0.386	0.000	182
26 Paper & Allied Products	-0.069	0.419	0.000	705
07 Agricultural Services	-0.096	0.472	0.000	164
46 Pipelines, Except Natural Gas	-0.101	0.484	0.000	309
10 Metal Mining	-0.116	0.474	0.000	1245
67 Holding & Other Investment Offices	-0.118	0.492	0.000	101
17 Construction	-0.122	1.251	0.000	167
49 Electric, Gas, & Sanitary Services	-0.258	1.952	-0.263	2675
12 Coal Mining	-0.310	0.625	-0.202	285

Panel B. $CCSentiment^{Opp}$ ($\times 10^3$)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
16 Heavy Construction, Except Building	0.248	1.186	0.000	450
35 Industrial Machinery & Equipment	0.207	1.278	0.000	2305
49 Electric, Gas, & Sanitary Services	0.174	1.254	0.000	2675
36 Electronic & Other Electric Equip.	0.110	0.591	0.000	5896
08 Forestry	0.067	0.333	0.000	27
29 Petroleum Refining	0.051	0.390	0.000	685
87 Engineering & Management Services	0.049	0.441	0.000	1216
34 Fabricated Metal Products	0.048	0.385	0.000	925
37 Transportation Equipment	0.045	0.384	0.000	1401
40 Railroad Transportation	0.039	0.299	0.000	182
Bottom-10 Industries				
62 Security & Commodity Brokers	-0.003	0.109	0.000	1280
10 Metal Mining	-0.013	0.214	0.000	1245
46 Pipelines, Except Natural Gas	-0.015	0.242	0.000	309
26 Paper & Allied Products	-0.017	0.237	0.000	705
17 Construction	-0.018	0.314	0.000	167
41 Local & Interurban Passenger Transit	-0.025	0.235	0.000	82
07 Agricultural Services	-0.028	0.245	0.000	164
01 Agricultural Production – Crops	-0.030	0.207	0.000	107
12 Coal Mining	-0.030	0.214	0.000	285
67 Holding & Other Investment Offices	-0.049	0.253	0.000	101

IA Table 14 continued

Panel C. $CCSentiment^{Reg}$ $(\times 10^3)$

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
57 Home Furniture	0.004	0.032	0.000	136
54 Food Stores	0.004	0.049	0.000	215
59 Miscellaneous	0.001	0.006	0.000	342
58 Eating & Drinking Places	0.000	0.060	0.000	196
21 Tobacco	0.000	0.000	0.000	85
82 Educational Services	-0.001	0.013	0.000	415
83 Social Services	-0.001	0.008	0.000	96
56 Apparel & Accessory Stores	-0.001	0.017	0.000	347
60 Depository Institutions	-0.001	0.021	0.000	3585
27 Printing & Publishing	-0.002	0.029	0.000	1309
Bottom-10 Industries				
34 Fabricated Me	-0.028	0.191	0.000	925
76 Miscellaneous Repair Services	-0.031	0.160	0.000	34
55 Automative Dealers & Service	-0.032	0.186	0.000	283
33 Primary Metal	-0.033	0.168	0.000	748
29 Petroleum Refining	-0.035	0.144	0.000	685
17 Construction	-0.044	0.171	0.000	167
32 Stone, Clay, & Glass Products	-0.052	0.262	0.000	577
12 Coal Mining	-0.056	0.141	0.000	285
49 Electric, Gas, & Sanitary Services	-0.164	0.409	0.000	2675
08 Forestry	-0.202	0.394	0.000	27

Panel D. $CCSentiment^{Phy}$ $(\times 10^3)$

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
40 Railroad Transport	0.008	0.072	0.000	182
35 Industrial Machinery & Equipment	0.006	0.095	0.000	2305
30 Rubber & Miscellaneous Plastics Products	0.004	0.033	0.000	568
53 General Merchandise Stores	0.003	0.027	0.000	291
31 Leather & Leather Products	0.002	0.025	0.000	112
37 Transportation Equipment	0.002	0.044	0.000	1401
25 Furniture & Fixtures	0.002	0.041	0.000	310
15 General Building Contractors	0.001	0.043	0.000	690
47 Transportation by Air	0.001	0.021	0.000	574
51 Wholesale Trade – Nondurable Goods	0.001	0.032	0.000	2031
Bottom-10 Industries				
22 Textile Mill Products	-0.004	0.063	0.000	99
55 Automative Dealers & Service Stations	-0.004	0.067	0.000	283
75 Auto Repair S	-0.005	0.040	0.000	121
29 Petroleum Refining	-0.006	0.042	0.000	685
49 Electric, Gas, & Sanitary Services	-0.007	0.060	0.000	2675
10 Metal Mining	-0.007	0.072	0.000	1245
26 Paper & Allied Products	-0.010	0.096	0.000	705
01 Agricultural Production – Crops	-0.010	0.058	0.000	107
12 Coal Mining	-0.010	0.084	0.000	285
08 Forestry	-0.021	0.069	0.000	27

IA Table 14 continued

Panel E. $CCRisk$ ($\times 10^3$)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
49 Electric, Gas, & Sanitary Services	0.289	0.558	0.115	2675
16 Heavy Construction, Except Building	0.118	0.317	0.000	450
12 Coal Mining	0.115	0.274	0.000	285
29 Petroleum Refining	0.069	0.160	0.000	685
37 Transportation Equipment	0.067	0.200	0.000	1401
35 Industrial Machinery & Equipment	0.066	0.240	0.000	2305
87 Engineering & Management Services	0.060	0.190	0.000	1216
36 Electronic & Other Electric Equipment	0.053	0.206	0.000	5896
61 Non-Depository Institutions	0.052	0.492	0.000	667
34 Fabricated Metal Products	0.052	0.190	0.000	925
Bottom-10 Industries				
23 Apparel & Oth	0.007	0.045	0.000	194
56 Apparel & Accessory Stores	0.006	0.031	0.000	347
59 Miscellaneous	0.005	0.027	0.000	342
57 Home Furniture	0.005	0.032	0.000	136
78 Motion Pictures	0.003	0.021	0.000	417
22 Textile Mill Products	0.003	0.021	0.000	99
31 Leather & Leather Products	0.003	0.020	0.000	112
53 General Merchandise Stores	0.002	0.017	0.000	291
58 Eating & Drinking Places	0.002	0.016	0.000	196
76 Miscellaneous Repair Services	0.000	0.000	0.000	34

Panel F. $CCRisk^{Opp}$ ($\times 10^3$)

Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries				
49 Electric, Gas, & Sanitary Services	0.130	0.357	0.000	2675
75 Auto Repair, Services, & Parking	0.123	0.290	0.000	121
16 Heavy Construction, Except Building	0.047	0.180	0.000	450
37 Transportation Equipment	0.037	0.126	0.000	1401
55 Automative Dealers & Service Stations	0.036	0.113	0.000	283
35 Industrial Machinery & Equipment	0.034	0.145	0.000	2305
34 Fabricated Metal Products	0.033	0.380	0.000	925
36 Electronic & Other Electric Equipment	0.029	0.144	0.000	5896
08 Forestry	0.025	0.097	0.000	27
29 Petroleum Refining	0.022	0.083	0.000	685
Bottom-10 Industries				
39 Miscellaneous Manufacturing Industries	0.002	0.022	0.000	121
70 Hotels	0.002	0.017	0.000	542
83 Social Services	0.002	0.011	0.000	96
78 Motion Pictures	0.002	0.013	0.000	417
21 Tobacco	0.001	0.010	0.000	85
56 Apparel & Accessory Stores	0.001	0.009	0.000	347
59 Miscellaneous	0.001	0.010	0.000	342
53 General Merchandise Stores	0.001	0.009	0.000	291
58 Eating & Drinking Places	0.000	0.000	0.000	196
76 Miscellaneous Repair Services	0.000	0.000	0.000	34

IA Table 14 continued

Panel G. $CCRisk^{Reg}$ ($\times 10^3$)					Panel H. $CCRisk^{Phy}$ ($\times 10^3$)				
Industry (SIC2)	Mean	STD	Median	Obs.	Industry (SIC2)	Mean	STD	Median	Obs.
Top-10 Industries					Top-10 Industries				
08 Forestry	0.029	0.102	0.000	27	26 Paper & Allied Products	0.006	0.038	0.000	705
49 Electric, Gas, & Sanitary Services	0.021	0.107	0.000	2675	64 Insurance Agents, Brokers, & Service	0.003	0.016	0.000	204
12 Coal Mining	0.015	0.057	0.000	285	40 Railroad Transportation	0.003	0.027	0.000	182
29 Petroleum Refinery	0.006	0.044	0.000	685	41 Local & Interurban Passenger Transit	0.002	0.022	0.000	82
32 Stone, Clay, & Glass Products	0.005	0.035	0.000	577	87 Engineering & Management Services	0.002	0.030	0.000	1216
46 Pipelines, Except Natural Gas	0.004	0.045	0.000	309	75 Auto Repair, Services, & Parking	0.002	0.016	0.000	121
16 Heavy Construction	0.004	0.043	0.000	450	63 Insurance Carriers	0.002	0.021	0.000	2557
10 Metal Mining	0.003	0.035	0.000	1245	12 Coal Mining	0.002	0.014	0.000	285
33 Primary Metal	0.003	0.036	0.000	748	15 General Building Contractors	0.002	0.022	0.000	690
79 Amusement & Recreation Services	0.003	0.023	0.000	553	35 Industrial Machinery & Equipment	0.002	0.024	0.000	2305
Bottom-10 Industries					Bottom-10 Industries				
52 Building Material	0.000	0.000	0.000	38	56 Apparel & Accessory Stores	0.000	0.000	0.000	347
54 Food Stores	0.000	0.000	0.000	215	57 Home Furniture	0.000	0.000	0.000	136
56 Apparel & Accessory Stores	0.000	0.000	0.000	347	58 Eating & Drinking Places	0.000	0.000	0.000	196
57 Home Furniture	0.000	0.000	0.000	136	62 Security & Commodity Brokers	0.000	0.000	0.000	1280
59 Miscellaneous	0.000	0.000	0.000	342	67 Holding & Other Investment Offices	0.000	0.000	0.000	101
64 Insurance Agents, Brokers, & Service	0.000	0.000	0.000	204	72 Personal Serves	0.000	0.000	0.000	383
67 Holding & Other Investment Offices	0.000	0.000	0.000	101	76 Miscellaneous	0.000	0.000	0.000	34
75 Auto Repair, Services, & Parking	0.000	0.000	0.000	121	78 Motion Pictures	0.000	0.000	0.000	417
76 Miscellaneous Repair Services	0.000	0.000	0.000	34	80 Health Services	0.000	0.000	0.000	1265
82 Educational Services	0.000	0.000	0.000	415	83 Social Services	0.000	0.000	0.000	96

Notes: This table reports firms' climate change sentiment/risk measures for the top-10 and bottom-10 industries. Statistics are reported at the firm-year level across different SIC2 industries. We rank sectors by the average values of the climate change measures. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). For all measure, we average values of the four analyst earnings conference calls during the year. We report only those industries for which we have at least 30 firm-year observations. Appendix A defines all variables in detail.

IA Table 15: Climate Change Sentiment/Risk, Climate Policy Regulation, and Extreme Temperatures

Panel A. Climate Policy Regulation and Climate Change Sentiment				
	$CCSentiment$	$CCSentiment^{Opp}$	$CCSentiment^{Reg}$	$CCSentiment^{Phy}$
	(1)	(2)	(3)	(4)
Climate Policy Regulation	0.002***	0.001***	-0.000	0.000
	(2.63)	(2.75)	(-1.08)	(0.19)
Obs.	61635	61635	61635	61635
adj. R-sq.	0.000	0.000	0.000	-0.000
Panel B. Extreme Temperatures and Climate Change Sentiment				
	$CCSentiment$	$CCSentiment^{Opp}$	$CCSentiment^{Reg}$	$CCSentiment^{Phy}$
	(1)	(2)	(3)	(4)
Extreme Temperatures	-0.007	-0.004	-0.000	-0.001*
	(-1.30)	(-1.29)	(-0.07)	(-1.88)
Obs.	70058	70058	70058	70058
adj. R-sq.	0.004	0.006	0.004	0.001
Panel C. Climate Policy Regulation and Climate Change Risk				
	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)
Climate Policy Regulation	0.001***	0.001***	0.000	-0.000
	(3.28)	(4.04)	(0.34)	(-0.21)
Obs.	61635	61635	61635	61635
adj. R-sq.	0.001	0.001	-0.000	-0.000
Panel D. Extreme Temperatures and Climate Change Risk				
	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)
Extreme Temperatures	0.000	-0.000	0.000	0.000
	(0.01)	(-0.45)	(1.09)	(1.23)
Obs.	70058	70058	70058	70058
adj. R-sq.	0.011	0.009	0.004	0.001
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes

IA Table 15 continued

Notes: Regressions are estimated at the firm-year level. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). *Climate Policy Regulation* is an index that evaluates climate policies and regulations in a country-year. *Extreme Temperatures* is the frequency with which extreme temperature episodes occur in a country-year. In Panels B and D, we include country fixed effects to absorb average country effects with respect to local or topography. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

IA Table 16: Top-100 Unigrams and Bigrams Captured by $CCExposure^{Pre}$

Uni/Bigrams	Frequency	Uni/Bigrams	Frequency	Uni/Bigrams	Frequency
market	17544103	model	2001080	unite	629446
increase	14970914	reduction	1996276	policy	601675
time	11692361	effect	1858837	live	597283
cost	10859899	potential	1856623	land	579838
term	10657730	set	1488305	national	573457
result	10641355	gas	1451438	party	568902
high	9169480	international	1435193	natural	554054
impact	6268987	world	1431945	weather	549623
numb	6142340	global	1347214	develop	543605
net	6072625	event	1321049	establish	503503
include	5759823	measure	1286049	response	497536
level	5721097	country	1256599	water	471644
base	5480688	plant	1170860	define	364441
project	3916586	region	1170156	implementation	358107
area	3592111	pressure	1160599	wind	329958
balance	3380873	trade	1147381	air	310867
report	3285818	power	1138307	scenario	266144
future	3176099	energy	1087009	chemical	239582
development	3138177	condition	1083963	feedback	211825
range	3105648	economic	1057331	assessment	203180
benefit	3003483	relative	1036103	environmental	177854
current	2867933	organic	990337	solar	176807
process	2863112	cycle	906090	mass	176775
activity	2821574	produce	897265	social	156769
average	2713741	form	893457	human	140288
production	2587122	develope	879222	mechanism	131122
group	2411108	refer	854675	layer	126108
technology	2389519	action	850100	sea	120514
reduce	2331115	resource	815852	concentration	115268
place	2241794	fuel	742624	framework	108903
state	2148884	source	705250	surface	105963
capacity	2046741	industrial	680506	carbon	95668
environment	2034060	occur	678205	protocol	85538
unit	2008355				

Notes: This table reports the the top-100 unigrams and bigrams associated with $CCExposure^{Pre}$, which measures the relative frequency with which the pre-specified list of unigrams and bigrams from Engle et al. (2020) appear in the transcripts of earnings calls.

IA Table 17: Climate Change Metrics: Pre-specified Keywords vs. Machine Discovered Keywords

Panel A. Summary Statistics for Measures based on Pre-Specified Keywords						
	Mean	STD	25%	Median	75%	Obs.
$CCExposure^{Pre}$	0.054	0.010	0.048	0.053	0.060	80221
$CCSentiment^{Pre}$	-0.002	0.006	-0.005	-0.002	0.001	80221
$CCRisk^{Pre}$	0.003	0.002	0.002	0.003	0.004	80221

Panel B. Correlations with Measures based on Pre-Specified Keywords	
Corr($CCExposure^{Pre}$; $CCExposure$)	0.36
Corr($CCSentiment^{Pre}$; $CCSentiment$)	0.23
Corr($CCRisk^{Pre}$; $CCRisk$)	0.15

Panel C. Quartile Overlap with Measures based on Pre-Specified Keywords					
			$CCExposure$		
$CCExposure^{Pre}$	Q1	Q2	Q3	Q4	All
Q1	8%	8%	6%	2%	25%
Q2	7%	8%	7%	4%	25%
Q3	6%	6%	7%	6%	25%
Q4	4%	3%	5%	13%	25%
All	25%	25%	25%	25%	100%

Notes: This table shows in Panel A summary statistics for exposure, sentiment, and risk measures constructed based on the pre-specified list of unigrams and bigrams from Engle et al. (2020). Panel B shows rank correlations of these measures with our measures that are based on bigrams constructed with a keyword discovery algorithm. Panel C shows the quartile overlaps between firm-year observation sorted based on $CCExposure$ and $CCExposure^{Pre}$, respectively.

IA Table 18: Climate Change Sentiment/Risk and Firm Characteristics

	$CCSent.$	$CCSent.^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Sales\,Growth$	-0.001	-0.000	-0.000	0.000	-0.000	-0.000*	-0.000	0.000
	(-1.31)	(-0.67)	(-0.22)	(1.44)	(-1.29)	(-1.79)	(-0.36)	(0.46)
$Log(Assets)$	-0.002	-0.001	-0.001***	0.000	0.001	-0.000	0.000**	0.000
	(-1.05)	(-1.42)	(-3.32)	(0.33)	(1.23)	(-0.10)	(2.43)	(0.15)
$Debt/Assets$	0.003	0.002*	0.000	0.000***	0.000	0.000	-0.000*	-0.000
	(1.40)	(1.65)	(1.16)	(2.73)	(0.75)	(1.24)	(-1.86)	(-0.39)
$Cash/Assets$	0.004	0.003	-0.000	0.000	0.001	0.001*	-0.000	0.000
	(1.05)	(1.37)	(-0.34)	(0.95)	(1.53)	(1.71)	(-0.16)	(0.58)
$PPE/Assets$	-0.002	-0.001	0.000	-0.000	0.001	0.001	-0.000*	0.000
	(-0.72)	(-0.43)	(0.07)	(-0.88)	(1.10)	(1.31)	(-1.74)	(0.21)
$EBIT/Assets$	0.007	-0.003	0.002***	-0.000	-0.005***	-0.003***	-0.000*	-0.000
	(1.31)	(-0.74)	(2.80)	(-0.70)	(-4.97)	(-3.30)	(-1.84)	(-1.42)
$Capex/Assets$	0.005	0.014	0.000	-0.000	-0.000	-0.000	0.001*	0.000*
	(0.33)	(1.30)	(0.06)	(-0.27)	(-0.14)	(-0.12)	(1.67)	(1.91)
$R\&D/Assets$	-0.074***	-0.058***	-0.009	-0.001	-0.016***	-0.007***	0.000	-0.001**
	(-3.70)	(-5.62)	(-1.29)	(-0.47)	(-4.22)	(-2.59)	(0.63)	(-2.39)
Industry × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	65932	65932	65932	65932	65932	65932	65932	65932
adj. R-sq.	0.027	0.020	0.057	0.006	0.106	0.056	0.021	0.000

IA Table 18 continued

Notes: Regressions are estimated at the firm-year level. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). For all measure, we average values of the four analyst earnings conference calls during the year. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

IA Table 19: Coverage Comparison: Climate Change Exposure vs. Carbon Intensity/ISS Carbon Risk Rating

		Carbon Intensity			*ISS Carbon Risk Rating*		
		Missing	Nonmissing	Obs	Missing	Nonmissing	Obs.
CCExposure	Zero	18303	698	19001	17189	1812	19001
		(22.8%)	(0.9%)	(23.7%)	(21.4%)	(2.3%)	(23.7%)
	Nonzero	55909	5311	61220	53037	8183	61220
		(69.7%)	(6.6%)	(76.3%)	(66.1%)	(10.2%)	(76.3%)
	Obs.	74212	6009	80221	70226	9995	80221
		(92.5%)	(7.5%)	(100%)	(87.5%)	(12.5%)	(100%)

Note: This table cross-tabulates the number of observations (and frequencies) for *CCExposure* and *Carbon Intensity* as well as well as *ISS Carbon Risk Rating*. For *CCExposure* we report the number of observations for which the variable is zero (no exposure) or nonzero (positive exposure). For the other two measures, we report the number of observations for which they are missing or nonmissing. We also report the frequency of each cross-tabulated cell relative to the total number of observations in the sample.

IA Table 20: Climate Change Sentiment/Risk, Carbon Intensity, and ISS Carbon Risk Ratings

Panel A. Carbon Intensity and Climate Change Sentiment/Risk

	$CCSent.$	$CCSent.^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Carbon Intensity (x100)	-0.024***	-0.000	-0.011***	-0.000	0.008***	0.001	0.002**	0.000
	(-3.43)	(-0.14)	(-4.04)	(-1.33)	(5.78)	(1.27)	(2.34)	(0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5404	5404	5404	5404	5404	5404	5404	5404
adj. R-sq.	0.026	-0.008	0.096	-0.017	0.242	0.172	0.030	0.028

Panel B. ISS Carbon Risk Rating and Climate Change Sentiment/Risk

	$CCSent.$	$CCSent.t^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ISS Carbon Risk Rating	-0.024***	-0.000	-0.011***	-0.000	0.008***	0.001	0.002**	0.000
	(-3.43)	(-0.14)	(-4.04)	(-1.33)	(5.78)	(1.27)	(2.34)	(0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8747	8747	8747	8747	8747	8747	8747	8747
adj. R-sq.	0.129	0.202	0.256	0.136	0.326	0.293	0.359	-0.004

IA Table 20 continued

Notes: Regressions are estimated at the firm-year level. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). For all measure, we average values of the four analyst earnings conference calls during the year. *Carbon Intensity* measures Scope 1 carbon emissions divided by total assets. *ISS Carbon Risk Rating* is constructed by ISS nd provides an assessment of the carbon-related performance of companies. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

IA Table 21: Economic Correlates of Climate Change Sentiment/Risk

Panel A. Effects of Media Attention to Climate Change

	$CCSent.$	$CCSent.^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Media Attention	0.335	1.556	-3.064**	-0.005	-0.226	-0.146	-0.096	0.071
	(0.06)	(0.42)	(-2.40)	(-0.01)	(-0.20)	(-0.21)	(-0.46)	(0.73)
Obs	56445	56445	56445	56445	56445	56445	56445	56445
adj. R-sq.	0.032	0.019	0.061	0.007	0.106	0.064	0.020	0.001

Panel B. Effects of Institutional Ownership

	$CCSent.$	$CCSent.^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institutional Ownership	-0.016	-0.018**	0.009***	-0.001**	-0.009***	-0.007***	-0.001***	0.000
	(-1.22)	(-2.39)	(4.24)	(-2.32)	(-3.62)	(-4.71)	(-3.09)	(1.05)
Obs	43100	43100	43100	43100	43100	43100	43100	43100
adj. R-sq.	0.051	0.016	0.082	0.013	0.100	0.041	0.036	0.002

Panel C. Effects of Mandatory ESG Disclosure

	$CCSent.$	$CCSent.^{Opp}$	$CCSent.^{Reg}$	$CCSent.^{Phy}$	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mandatory ESG Disclosure	-0.011	-0.016	0.002	-0.001	0.001	-0.002	0.000	0.000
	(-0.58)	(-1.39)	(0.45)	(-0.60)	(0.24)	(-0.74)	(0.57)	(0.07)
Obs.	65932	65932	65932	65932	65932	65932	65932	65932
adj. R-sq.	0.027	0.020	0.057	0.006	0.106	0.056	0.021	0.000
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

IA Table 21 continued

Notes: Regressions are estimated at the firm-year level. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). For all measure, we average values of the four analyst earnings conference calls during the year. $Median\ Attention$ is an index developed in Engle et al. (2020) that captures climate change news in the $Wall\ Street\ Journal$. $Institutional\,Ownership$ is the percentage ownership by institutional investors. $Mandatory\,ESG\,Disclosure$ is a dummy variable constructed in Krueger et al. (2021) that takes the value one if a country has mandatory ESG disclosure; and zero otherwise. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

IA Table 22: Climate Change Sentiment/Risk and Firm Valuations

	Δ *Tobin's Q* After 2011 (1)	Δ *Tobin's Q* Before 2011 (2)	Δ *Tobin's Q* After 2011 (3)	Δ *Tobin's Q* Before 2011 (4)
$CCSentiment^{Opp}$	0.117*	-0.037		
	(1.66)	(-0.56)		
$CCSentiment^{Reg}$	0.546	-0.307		
	(1.48)	(-1.05)		
$CCSentiment^{Phy}$	1.790**	0.641		
	(2.12)	(0.65)		
$CCRisk^{Opp}$			0.047	0.330
			(0.20)	(1.10)
$CCRisk^{Reg}$			-5.790***	0.530
			(-3.65)	(0.70)
$CCRisk^{Phy}$			2.336	-2.611*
			(1.22)	(-1.72)
Sales Growth	-0.018	-0.025***	-0.019	-0.025***
	(-0.81)	(-2.70)	(-0.85)	(-2.71)
Log(Assets)	0.091***	0.031	0.091***	0.032
	(2.74)	(0.91)	(2.74)	(0.94)
Debt/Assets	-0.118	0.254*	-0.118	0.255*
	(-1.29)	(1.71)	(-1.29)	(1.71)
Cash/Assets	0.225	0.467	0.225	0.468
	(1.29)	(1.32)	(1.30)	(1.32)
PPE/Assets	0.191	0.206	0.189	0.205
	(1.25)	(0.89)	(1.24)	(0.88)
EBIT/Assets	-0.775**	-1.238*	-0.776**	-1.239*
	(-2.56)	(-1.69)	(-2.56)	(-1.69)
Capex/Assets	-0.964*	-0.838	-0.957*	-0.835
	(-1.67)	(-0.66)	(-1.66)	(-0.66)
R&D/Assets	1.483	-2.602*	1.464	-2.597*
	(1.13)	(-1.96)	(1.11)	(-1.95)
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Obs.	25107	28694	25107	28694
Adj. R-sq	0.039	0.058	0.039	0.058

IA Table 22 continued

Notes: Regressions are estimated at the firm-year level. $\Delta Tobin'sQ$ is the year-on-year change in Tobin's Q. $CCSentiment$ measures the relative frequency with which bigrams related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in one sentence together with positive and negative tone words. $CCSentiment^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks occur in one sentence together with positive and negative tone words. The risk measures are defined accordingly, but for bigrams mentioned together with the words "risk" or "uncertainty" (or synonyms thereof). For all measure, we average values of the four analyst earnings conference calls during the year. We separate the sample into the years before (and including) 2011 and the years after 2011. Appendix A defines all variables in detail. t-statistics, based on standard errors clustered by industry-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

IA Table 23: Climate Change Metrics: Presentation vs. Q&A

Panel A. Summary Statistics of Presentation and Q&A Section

Presentation Section	Mean	STD	Median	Obs.
$CCExposure$ ($\times 10^3$)	1.042	2.875	0.240	78672
$CCExposure^{Opp}$ ($\times 10^3$)	0.644	1.920	0.000	78672
$CCExposure^{Reg}$ ($\times 10^3$)	0.430	1.567	0.000	78672
$CCExposure^{Phy}$ ($\times 10^3$)	0.270	1.120	0.000	78672
$CCSentiment$ ($\times 10^3$)	0.023	0.853	0.000	78672
$CCRisk$ ($\times 10^3$)	0.033	0.189	0.000	78672

Q&A Section	Mean	Std.Dev.	Median	Obs.
$CCExposure$ ($\times 10^3$)	0.056	0.324	0.000	78672
$CCExposure^{Opp}$ ($\times 10^3$)	0.033	0.292	0.000	78672
$CCExposure^{Reg}$ ($\times 10^3$)	0.013	0.131	0.000	78672
$CCExposure^{Phy}$ ($\times 10^3$)	0.010	0.104	0.000	78672
$CCSentiment$ ($\times 10^3$)	-0.018	0.168	0.000	78672
$CCRisk$ ($x10^3$)	0.002	0.036	0.000	78672

Panel B. Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CCExposure^{Opp}$ ($\times 10^3$) $Pres.$	(1)	0.66	1					
$CCExposure^{Reg}$ ($\times 10^3$) $Pres.$	(2)	0.87	0.61	1				
$CCExposure^{Phy}$ ($\times 10^3$) $Pres.$	(3)	0.58	0.78	0.63	1			
$CCExposure$ ($\times 10^3$) $Q\&A$	(4)	0.54	0.35	0.31	0.21	1		
$CCExposure^{Opp}$ ($\times 10^3$) $Q\&A$	(5)	0.25	0.35	0.16	0.16	0.37	1	
$CCExposure^{Reg}$ ($\times 10^3$) $Q\&A$	(6)	0.14	0.07	0.05	0.03	0.07	0.03	1
$CCExposure^{Phy}$ ($\times 10^3$) $Q\&A$	(7)	0.06	0.11	0.03	0.03	0.02	0.02	0.31

Panel C. $CCExposure$ Only in Q&A Section

	Obs.
$CCExposure$	170
$CCExposure^{Opp}$	145
$CCExposure^{Reg}$	1195
$CCExposure^{Phy}$	1006

Notes: This table provides summary statistics of some of our key climate change measures across the management presentation and Q&A section of the conference calls. Panel A presents means, standard deviations, and medians separately for the management presentation and Q&A section. The number of observations differs from Table 1 as in some cases there are no Q&A sections, which we code as missing for this table. Panel B reports correlations across some of the key climate change measures. Panel C shows the number of firm-year observations in which climate change exposure is positive in the Q&A section, and zero in the management presentation section.

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