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Firm-level Climate Change Exposure*

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Abstract

We introduce a method that identifies firm-level climate change exposures from conversation in earnings conference calls of more than 10,000 firms from 34 countries between 2002 and 2019. The method captures exposures related to opportunity, physical, and regulatory shocks associated with climate change. The exposure measures exhibit cross-sectional and time-series variations which align with reasonable priors, and are better in capturing firm-level variation than carbon intensities or ratings. The exposure measures relate to economic factors that prior work has identified as important correlates of climate change exposure (e.g., public climate attention). Exposure to regulatory shocks negatively correlates with firm valuations, but only in recent years.

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

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

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1. Introduction

Climate change has started to significantly affect a large number of firms in the economy.[1] While some firms face direct costs related to changes in physical climate parameters, others are adversely affected from policies and regulations implemented to combat global warming.[2] At the same time, climate change provides opportunities for some firms, for instance, for those operating in renewable energy, electric cars or energy storage. With the consequences of climate change becoming more observable, the debate has intensified about whether capital markets are paying enough attention to the financial impacts of climate change. The IMF, for example, claims that "*investors do not pay sufficient attention to climate change risks*" (IMF, 2020), causing severe danger to global financial stability.

A challenge for investors, regulators, and policy makers lies in the difficulty 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. Complications stem from different sources. First, the effects of climate change on firms are highly uncertain, because of uncertainty about how the climate will develop and because it is unclear whether, how and when policy-makers will tighten regulation (Barnett et al., 2020). Second, the effects of climate change are likely to be heterogeneous across firms, even among firms within the same industry. The reason is that many factors that plausibly affect a firm's ability to adopt to a greener economy exhibit large firm-level components (e.g., managerial skill, innovation, or financial constraints). Third, there exists no common understanding yet among academics or practitioners about how to reliably quantify firm-level climate change exposure.[3] While a firm's voluntarily disclosed carbon emissions are gaining some traction as an exposure measure,

[1] California's largest utility, PG&E, experienced in 2019 the first major bankruptcy caused by climate change (see "PG&E: The First Climate-Change Bankruptcy, Probably Not the Last", *Wall Street Journal*, January 18, 2019.)

[2] Indeed, Hugon and Law (2019) estimate that global warming affects about two-thirds of firms negatively and that managers of firms most susceptible to global warming tend to underestimate its effects on reported earnings.

[3] This is in stark contrast to other firm-level exposures, for which widely accepted measures have been developed over the years (e.g., business cycle risk or political risk).

this data exists only for a limited and selected sample (e.g., about half of all S&P 500 firms do not report their emissions). What's more, disclosed emissions reflect historic rather than future business models of firms, and they do not allow the distinction between "good" and "bad" emissions.[4]

These challenges are severe and they have the potential to impede the reallocation of resources from "brown" to "green" firms, a major task identified by policymakers around the world to achieve global climate targets in the years to come.[5] Furthermore, the lack of a firm-level exposure measure may contribute to the potential mispricing of climate risks and opportunities in capital markets (Hong et al., 2019; Daniel et al., 2017; Kumar et al., 2019), and it complicates the development of financial instruments that allow market participants to hedge the effects of climate change (Engle et al., 2020).

In this paper, we use transcripts of quarterly earnings conference calls held by publicly-listed firms to construct time-varying measures of firm-level exposure 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 presenting their views on the firm's business activities and to ask these firm officials questions about material current and future developments (Hollander et al., 2010). A major benefit of using conference calls as a source is that they are much less susceptible to "greenwashing" by management. Indeed, even if management is evading the climate change topic or window dressing their achievements, analysts will act as a counterpoint by asking probing questions. This is much different for other documents such as annual reports, ESG reports, or press releases, which exclusively reflect the views of management. To construct our measures, we build on recent work that has used such transcripts as a source for identifying the various risks and opportunities that

[4]The emissions generated by some firms support the transition to a greener economy (these firms are called "climate enablers"); an example are producers of building material that makes houses more energy efficient.

[5]According to the "Green Deal" announced by the European Commission in 2019, to achieve the current target of a 40% emissions reduction by 2030, capital (re)allocations of EUR 260bn a year are needed in the European Union alone (e.g., "Europe leads the world with its climate mission", *Financial Times*, December 12, 2019.)

firms face over time (Hassan et al., 2019, 2020a,b). In a nutshell, these studies use the proportion of the conversation during the conference call that is centered on a particular topic as a measure of the firm's exposure to that topic.[6]

Importantly, however, we modify the approach of these prior papers along several dimensions. First, we address that climate change has effects that are multifaceted, spanning issues related to physical threats, costly regulatory interventions, and new technological opportunities. Our measures therefore encapsulate exposure to upside *and* downside shocks. Second, prior studies rely on pre-specified *signal* word combinations (or "bigrams") to identify when the conversation turns to the topic of interest. Hassan et al. (2019), who study political risk, determine these bigrams by comparing training libraries of political texts with those containing 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 used. In our setting, no well-defined dictionary exists and there is also no single climate change phrase, similar to Brexit or the corona virus, that can be used to identify climate discussions in text. Creating a new dictionary from scratch, on the other hand, has been shown to be challenging and susceptible to human error (Liu et al., 2019).

For this reason, we introduce a novel, purposeful method that can identify word combinations that signal climate change conversation in conference calls. The method builds on the finding that humans perform well when associating words to topics, but poorly when creating dictionaries from a blank slate (King et al., 2017).[7] Accordingly, our method adapts the machine learning keyword discovery algorithm proposed by King et al. (2017) to produce four (related) sets of climate change bigrams: the first set captures climate change aspects broadly defined, while the remaining three sets cover specific climate topics, that is, opportunity, physical (e.g., sea level rises, natural disasters), and regulatory shocks (e.g.,

[6]We follow these papers in defining "exposure" to a topic as the share of the conversation in transcripts 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 literatures.

[7]To the best of our knowledge, this method has not been used before in the finance or economics literature.

carbon taxes, cap and trade markets). We employ these four sets of bigrams to construct for each transcript a measure of exposure to climate change (in a broad sense), as well as three measures of exposure to the specialized "topics". The algorithm only requires human input insofar as specifying a short list of initial keyword terms that are associated with climate change.

The exposure measures count the frequency with which certain climate change bigrams occur in the transcript, scaled by the total number of bigrams in the transcript. We construe these measures as indicating the occurrence of climate change events or shocks at the firm. Our method also allows us to construct measures of the first and second moment associated with these shocks. In other words, whether the events represent (in expectation) good or bad news to the firm and whether the 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" or "uncertainty" (or their synonyms). Following prior practice (Hassan et al., 2019), we interpret these sentiment and risk measures as components of the exposure measures.

As most of our other data varies at the year level, we create for each firm annual transcript-based measures by averaging measures from quarterly transcript.[8] Our sample contains more than 80,000 annual observations originating from more than 10,000 unique firms in 34 countries over the period 2002 to 2019.

As a crucial step in verifying the validity of our measures, we conduct a human audit of the identified bigrams that signify discussion of the different dimension of climate change. We find that 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 are

[8]Note, however, that our publicly available data set provides climate change scores at the firm-quarter granularity, allowing researchers and policy makers to trace the over-time variation in exposure at this higher frequency.

reminiscent of 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 words 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 we verify that the call fragments are indeed centered on salient climate issues.

We then examine the aggregate patterns in our measures of climate change exposure by documenting their development over time and in the cross-section. The time-series dynamics for the broadly-defined exposure measure reveals that discussions of climate change issues increase remarkably over time until around 2011. Perhaps surprisingly, this rise starts already in the mid 2000s. There is some modest decline up to the largely unsuccessful 2012 Doha Climate Summit, with a leveling off at a high level (compared to the years before 2011) in the subsequent years. We observe a renewed increase in climate change exposure since the Paris Agreement in 2015 and the 2016 Trump election. Climate change exposure reaches its highest overall level at the end of the sample in 2019.

A similar exercise in which we aggregate our measures by taking sector averages shows that the sectors with the highest overall 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 both opportunities (e.g., renewable energy) and regulatory risks (e.g., carbon taxes) related to climate change.[9] Physical climate change exposure is highest for the sectors Paper & Allied Products, Heavy Construction, and Insurance. Importantly, for all of our measures, we find large within-industry variation, indicating that firms will benefit or suffer in various degrees from climate change. The large within-industry variation underscores the need for a (time-varying) *firm-level* measures of climate change exposure.[10] Indeed, further analyses

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

[10]A case in point are again utilities, which exhibit, for example, large within-industry heterogeneity in

show that even the identity of firms exposed to climate change within a sector changes over time; climate change exposure is not in all cases a persistent firm-level characteristic. Further, exposure to climate change varies substantially 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.

To bolster our claim that our measures quantify variation in exposure to climate change shocks *at the firm level*, we conduct an analysis of variance. We find that between 70.4 and 96.8% of variation in our exposure measures plays out at the firm level (rather than at the level of the country, industry or over-time), only half of this firm-level variation is persistent, suggesting that, within an industry over time, different firms are exposed to climate change.[11] We then compare the results of this analysis with a similar decomposition exercise for two important alternative measures of firm-level exposure to climate change. These alternatives are a firm's carbon intensity (emissions scaled by assets) as well as its carbon risk rating. The carbon risk rating is constructed by proxy-advisory firm ISS with the objective to provide investors with a comprehensive assessment of the carbon-related performance of firms. ISS plans to include information from its rating into its voting recommendations, with the objective to "*incorporate climate-related considerations systematically into their engagement and proxy voting strategies.*"[12] The firm-level variation for carbon intensities and the ISS measures are 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 the finance literature (Bolton and Kacperczyk, 2020b,a; Ilhan et al., 2020; De Haas and Popov, 2020), are driven mostly by industry fixed effects.

We find that our climate change exposure measures, on the one hand, and the carbon

terms of renewable energy capacity or reliance on fossil fuels, resulting in a divergence of both risks and opportunities within the sector.

[11] At 96.8%, firm-level variation is by far highest for firm exposure to physical shocks, which is reasonable as such shocks largely depend on firm-specifics (e.g., the exact location of a firm's production sites within a country, the supply chain specifics, or insurance policies).

[12] See https://www.issgovernance.com/iss-launches-climate-voting-policy/

intensity and ISS measures, on the other hand, overlap to some extent—as expected given that all aim to capture dimensions of climate change exposure of firms. Carbon intensities appear to correlate mostly with our measures of opportunity and regulatory shocks. The ISS rating reflects our measures of opportunities more than those of regulatory or physical events. Together with the variance decomposition results, this suggests that both of these alternatives are more specialized than our (more comprehensive) measure.[13]

Our sample allows us to explore the role of important economic factors that prior work has identified as potentially being related to firm-level climate change exposure. As these factor vary at the time, firm, and country level, documenting correlations between them and the exposure measures allows us to 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 et al., 2020) and the costs of insurance again carbon tail risk (Ilhan et al., 2020). We document that times of higher climate change attention are associated with a rise in firms' exposures to regulatory and physical climate shocks, while attention is unrelated to opportunity shocks. We proxy for attention by using the time-varying measure of climate change news developed in Engle et al. (2020). A reason for the asymmetry in results could be that the media is paying more attention to environmental rules and physical threats to economic activity than to the opportunities climate change might offer to businesses. Participants in conference calls that follow the media may therefore have a higher propensity to address such topics.

Second, we find that firm-level institutional ownership is negatively related to climate change exposure. This effect is particularly strong in the recent years and it originates primarily from a negative association between institutional ownership and exposure to regulatory *and* opportunity shocks. This finding is consistent with an interpretation whereby institutional investors started to underweight (or divest) firms with high climate change ex-

[13] Some disagreement across measures is not unique to our climate setting and it resembles the divergence documented for ESG ratings (Berg et al., 2020; Gibson et al., 2020).

posure, apparently without distinguishing much between firms with upside and downside exposures.

Third, we show that *voluntary* information exchanges between management and financial analysts during conference calls do not appear to be affected by variation across countries in terms of mandatory ESG disclosure standards. This nonresult is comforting inasmuch as it indicates that our measures of *voluntary* information exchange are not unduly affected by variation across countries in *mandatory* disclosure standards.

In a last step, we explore whether our exposure measures exhibit associations with firms' market valuations. We find that firm exposure to regulatory shocks is negatively associated with valuations changes. Interestingly, we can document such an effect only for the second half of the sample, i.e., the years during which climate change exposure attains relatively high levels (since 2011). At the same time, we cannot detect that changes in firm valuations reflect firm-level exposures to opportunity shocks; markets may hence undervalue firms with high exposures to such shocks, bolstering the survey evidence in Krueger et al. (2020).

We relate to two strands of literature. With respect to our methodology, as explained above, we build on studies that use the occurrence of bigrams in earnings calls (Hassan et al., 2019, 2020a,b). In terms of substance, our most direct contribution is to the burgeoning climate finance literature, especially to papers that study climate risk disclosure and firm-level climate risks. Solomon et al. (2011) show that institutional investors use channels of discourse with portfolio firms to compensate for the inadequacies of public climate reporting. Matsumura et al. (2014) find that markets discount firms that do not disclose emissions through the CDP, although Griffin et al. (2017) suggests that the differences may not arise from CDP disclosure. Matsumura et al. (2018) analyze voluntary 10-K climate risk disclosures and find that disclosing firms have lower costs of equity. Ilhan et al. (2020) study the preferences of institutional investors with respect to climate risk disclosures. Further, Flammer et al. (2019) 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 their plans for emission abatement. Krueger (2015) reports beneficial valuation effects of the introduction of mandatory greenhouse-gas (GHG) disclosures in the U.K., and Jouvenot and Krueger (2019)) document strong reductions in carbon emissions as a result of the disclosure requirement.

Research on climate risks has focused on carbon emissions (or intensities), with a strong emphasis on the "downside" rather than "upside" effects. Bolton and Kacperczyk (2020a,b) show that investors demand a compensation for investing in firms with high carbon intensities as they are perceived as more risky. Görgen et al. (2019) calculate exposure (carbon betas) to a carbon risk factor, which is constructed using carbon and climate transition-related information from ESG databases. Ilhan et al. (2020) find that high carbon intensities are priced in the option market and associated with higher tail risk. There is also evidence that greater climate risk leads to lower firm leverage, with firms decreasing their demand for debt and lenders reducing their lending to firms with the greatest risk (Ginglinger and Moreau, 2019). Consistent with this evidence, Delis et al. (2019) find that banks began to price carbon risk into their loans after the 2015 Paris Agreement, and Selzer et al. (2019) show that credit ratings and yield spreads change for polluting firms.

2. Data

2.1. Data on Earnings Calls

We use transcripts of quarterly earnings conference calls held by publicly-listed firms to construct our time-varying measures of firm-level exposure to climate change. Earnings calls allow financial analysts and other market participants to listen to senior management presenting their views on the company's state of affairs and to 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 et al., 2010). As most of our other data varies at the year level, we create for each firm a series of 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 from this database 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 provided in Appendix A and summary statistics in Table 1. OA 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' carbon emissions from the CDP, formerly known as the Carbon Disclosure Project. These data are collected by the CDP on behalf of institutional investors representing over $100 trillion in assets under management. Reporting to the CDP is voluntary, which raises concerns about selection bias in their data set. The CDP data include information on three types of emissions. Scope 1 emissions are direct emissions, which originate from the combustion of fossil fuels or from releases during manufacturing. Scope 2 emissions are indirect emissions from the consumption of electricity or steam, and Scope 3 emissions are emissions that occur in the value chain of a firm. The CDP translates all greenhouse gases into carbon dioxide equivalents. We focus on Score 1 emissions because they are directly owned and controlled by firms, and scale these emissions by total assets to obtain a measure of $Carbon\,Intensity$. Our CDP sample includes 6,009 firm-year observations from 1,287 unique firms located in all 34 sample countries. The emissions of these firms were generated 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 provide investment professionals and banks with an assessment of the carbon-related performance of firms.[14] ISS ESG, which claims to be the world's leading provider of ESG solutions for investors, is the responsible investment division of Institutional Shareholder Services (ISS) Inc. ISS is a dominant player in the area of corporate governance and provides proxy voting advice to institutional investors.

$ISSCarbonRiskRating$ is available at the annual frequency and constructed from several factors, such as the carbon impact of a firm's product portfolio (e.g., revenue shares of products associated with a positive or negative climate impacts) or carbon emission reduction targets and action plans. Similar to our approach, ISS aims at capturing both the upside and downside exposure of firms with respect to climate change. To reflect this spectrum, the rating scores vary between 1 (poor performance) and 4 (excellent performance). The data are collected by ISS from publicly available sources such as annual reports, ESG reports or newspaper articles, but also from interviews with firm management. Our ISS sample contains 9,995 firm-year observations, originating from 3,306 firms in all 34 countries. The rating is available for the years 2015 to 2019. Firm coverage has significantly increased over the sample period, from 1,493 sample firms in 2015 to 3,032 firms in 2019.[15]

2.4. Other Data

We obtain additional data from a variety of sources to validate our measures and to exploit its time-series and cross-sectional variations.

Climate Policy Regulation. To validate our measures, we use an index constructed by Germanwatch, which evaluates the climate policy regulations of a country. The index, *Climate Policy Regulation*, covers, for example, a country's policies on the promotion of renewable energies, measures to reduce carbon emissions, the ambition level and "2 degree" compatibility of a country's Nationally Determined Contributions, and its progress towards reaching these goals. The index varies at the country-year level and ranges between 0 and 20;

[14] To the best of our knowledge, we are the first academic study that uses these rating scores.

[15] Sustainalytics provides a similar rating of firm-level carbon risk, which is included in Morningstar. However, this rating is available for a much shorter time period (since 2017).

higher numbers reflect better climate policy regulations in a country. The data are available for 29 sample countries over the years 2007-2019 (not for Bermuda, Chile, Hong Kong, Israel, and Singapore). Data from Germanwatch has previously been used in Atanasova and Schwartz (2019) and Delis et al. (2019).

Extreme Temperatures. We further validate our measures by using information on 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 how often extreme temperature episodes occurred. The resulting variable, $ExtremeTemperature$ ranges between 0 and 3 and is available for all countries over the years 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 has varied between 2002 and 2017. The index, *Media Attention*, is constructed by measuring positive and negative news in the *Wall Street Journal* on the topic of climate change. 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. The measure has recently been used in Ilhan et al. (2020).

Institutional Ownership. We measure the percentage ownership by institutional investors using data from Thomson Reuters. These data are available only for firms in North America, for the period 2002 to 2019.

Country Mandatory ESG Disclosure. We use data collected by Krueger et al. (2020) to identify whether and when countries introduced mandatory ESG disclosure. The primary purpose of such regulation is to enhance the disclosure of corporate nonfinancial information to investors. Disclosure on ESG issues covers topics such as climate change, modern slavery, illegal logging, or water scarcity. Krueger et al. (2020) identify 14 countries that mandate firms to disclose ESG information during the period from 2000 to 2017. Out of these 14 countries, 12 countries (Australia, Brazil, China, France, Hong Kong, India, Italy, Norway, Singapore, South Africa, Spain, 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

Our objective is to quantify a firm's exposure to climate change. We build on recent work that has identified transcripts of conference calls as a source for identifying the various risks and opportunities facing firms (Hassan et al., 2019, 2020a,b). These prior studies use the proportion of the conversation during a conference call that is centered on a particular topic as a measure of the firm's exposure to that topic. We face at least two challenges applying the selfsame logic to quantifying climate change exposure.

First, the effects of climate change are multifaceted, spanning issues emerging from regulatory interventions to imminent "physical threats", for example, to a firm's plant, property, and equipment, owing to the increased probability of extreme weather events. What's more, new technologies and market opportunities provide some firms with a potential upside to climate change developments. An ideal measure therefore needs to encapsulate all of these facets to arrive at firmer conclusions about a firm's exposure to environmental changes. Ideally, the measure should also allow the decomposition of a firm's (composite) exposure to its contributing factors.

Second, prior studies identify when the conversations in earnings calls turns to the topic of interest by relying on pre-specified *signal* bigrams. These word combinations, in turn, are compiled in either 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 those containing nonpolitical texts (e.g., accounting textbooks and novels). In contrast, in Hassan et al. (2020a,b), who study Brexit and Covid-19, respectively, the words used to identify discussions about these shocks are self-evident and no training libraries are used. However, neither of these two approaches yields satisfactory results in identifying climate change bigrams. For example, using training libraries that consist of climate change reports issued by research institutions and/or professional investors fails to achieve our goals, because people tend to discuss climate change in conjunction with other topics, such as (new) technologies, government regulation, and tax credits. Accordingly, text documents in the training library reflect mixtures of genuine climate change discussions and conversations about extraneous topics. The same will hold true for the conference call transcript. Using a training library, the algorithm will then identify word combinations that are unrelated to climate change (but instead signal for example tax policies) as if these are climate change bigrams. What's more, when taking these bigrams to the earnings call transcripts, too many extraneous discussions are wrongly classified as climate change exposure. Thus, the method used in Hassan et al. (2019) yields a set of word combinations which contains more "false positives" than valid climate change word combination.[16] That said, Hassan et al. (2020a,b)'s method falls short in our context too inasmuch as there is no clear climate change equivalent to "Brexit" or "Corona" word combinations. While researchers could, in principle, attempt to create a comprehensive word list, prior work has suggested that humans tend to overlook important phrases in such tasks (King et al., 2017). For this reason, we introduce to the economics and finance literature a novel, purposeful method that can identify word combinations that signal climate change conversation in conference calls.

3.2. Discovery of Climate Change Bigrams

We adapt the machine learning keyword discovery algorithm proposed by King et al. (2017) to produce a set of climate change bigrams $\mathbb{C}$. The algorithm helps us to overcome challenges in applying either of the two methods mentioned above to quantify climate change exposure. First, the algorithm does *not* need a comprehensive "climate change" training library as

[16] Ultimately, the challenge researchers face is that they need to identify a library of non-climate change documents that can help filter out a "clean" list of climate change bigrams without picking up related topics. In practice, given the commingling of climate change with other topics, this is hard to achieve.

input. By contrast, it only requires the researcher to draw up a small set of "initial" bigrams (listed in OA Table 2). These initial bigrams are chosen such that they unambiguously relate to climate change. The algorithm uses these initial bigrams to search for new bigrams that also likely indicate conversation about climate change—and does so directly in the earnings call transcripts themselves. Second, as each initial bigram is connected with a specific group of new bigrams discovered through the application of the search algorithm, the researcher can easily decompose the measure of climate change exposure (based on the presence of these bigrams) into its constituent parts.

The "initial" set of bigrams allows the algorithm to identify from the transcripts those sentences of interests that clearly talk about climate change. Relying on several supervised learning methods, the algorithm can then extract features, i.e., bigrams, beyond the set of "initial" bigrams, that predict climate change from the identified sentences of interests. Finally, it constructs a model predicting whether a sentence is related to climate change or not. We apply this prediction model to sentences *not* including any "initial" bigrams and learn from whether or not the predicted sentences are climate-change-related. In order to discover new climate change bigrams, we reverse-engineer the machine learning process and trace back those bigrams that best discriminate the climate-change-related sentences from other sentences. The resultant set of climate change bigrams $\mathbb{C}$ includes both the "initial" bigrams and the newly found bigrams from the machine learning algorithm.[17].

The benefit of our approach is that the algorithm generates various meaningful climate change bigrams based on the "initial" bigram set. First, the algorithm extends the rather broadly specified initial bigrams into more specialized word combinations. For example, "rooftop solar" and "photovoltaic panel" are based on the initial bigram "solar energy"; "nuclear power" or "event fukushima" relate to "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 such as "kibby wind"; "joaquin valley"; and

[17]We summarize the technical details about the bigram searching algorithm, including how we define the set of initial bigrams, in Online Appendix A as well as in OA Table 2 (list of initial bigrams)

"coughlin power", which are related to climate change and of interest to call participants. At the same time, these bigrams illustrate the challenges of using training libraries or pre-specified word list to identify climate change talk; few researchers would have the detailed institutional and/or field knowledge to recognize these words as related to climate change.

We adapt the bigram-searching algorithm to discover three unique sets of climate change bigrams, $\mathbb{C}^{Opp}$, $\mathbb{C}^{Phy}$, and $\mathbb{C}^{Reg}$ from $\mathbb{C}$, which capture opportunity, physical, and regulatory shocks related to climate change, respectively. To this end, we feed a set of "initial" bigrams reflecting the three specific climate change topic to the searching algorithm, and then allow the algorithm to discover bigrams that are mostly related to each one of these. [18] For each topic, we tailor-make the set of initial bigrams based on the top-500 bigrams in $\mathbb{C}$ that most frequently occur in conference calls. We then re-perform the searching algorithm to find a broader set of bigrams for each topic. As the topics-based searching algorithm can also yield some general climate change bigrams, we drop bigrams appearing in more than one topic; this step further guarantees that we have topic measures that do not overlap. Last, we take the intersection between $\mathbb{C}$ and each set of topic bigrams to obtain the set of opportunity climate change bigrams $\mathbb{C}^{Opp}$, the set of physical climate change bigrams $\mathbb{C}^{Phy}$, and the set of regulatory climate change bigrams $\mathbb{C}^{Reg}$.

3.3. Construction of Climate Change Exposure Measures

Using these these four set of bigrams, we construct for each transcript a measure of exposure, sentiment, and risk. To simplify the exposition, we take 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 related 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. To do so, we take the

[18] See OA Table 7 for the list of initial bigrams for topic search.

set of climate bigrams $\mathbb{C}$ to the conference call transcript of firm i in quarter t and count the frequency with which these bigrams occur. We then scale the total count by the total 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 contained in the conference call transcripts of firm i in quarter t and $1[\cdot]$ is the indicator function.

Next, we create a measure of climate change sentiment (*CCSentiment*) by counting the number of climate change bigrams, conditioning on the presence of the positive and negative tone words summarized in Loughran and McDonald (2011). We then standardize again by the total 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 $\mathcal{T}(b)$ assigns sentiment to each 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 *together* with the words “risk” or “uncertainty” (or synonyms thereof) in one sentence:

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

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

As most of our other data varies at the year level, we create for each firm annual transcript-based measures 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 $\mathbb{C}^{Phy}$ by scoring each conference call transcript using the same method. We label these topics-based measures by adding the superscripts of 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.[19] First, we consider the face validity of the bigrams used to construct $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively.

Table 2 shows the top-100 bigrams in $\mathbb{C}$ with the highest frequency of occurrence in the transcripts (an expanded list of the top-200 bigrams is in OA Table 3). Top bigrams associated with $CCExposure$, the broad exposure measure, capture aspects related to opportunities and potential risks associated with climate change. Specifically, the top-20 bigrams include opportunity-related word-pairs such as "carbon capture" or "rooftop solar", but also more risk-related terms such as "environmental concern" or "reduce emissions". OA Table 4 shows the top-100 bigrams and OA Table 5 the bottom-100 bigrams for $CCSentiment$. OA Table 6 reports the top bigrams for $CCRisk$.

Turning to the three topics-based measures, using initial bigrams that include "wind power", "solar energy", and "new energy", we find bigrams associated with $CCExposure^{Opp}$ that refer to new (green) technologies, such as "nuclear renewable", "pv panel", or "carbon free". Several word combinations appear to be linked to developments in "electric vehicles"

[19]For brevity, we focus on the climate change *exposure* measures in our discussion. We also subject the corresponding *sentiment* and *risk* measures to the same tests, a summary of which is reported in the Online Appendix.

and include "charge infrastructure" and "battery electric" (see OA Table 8). In a similar vein, in our measure of regulatory exposure, $CCExposure^{Reg}$, using bigrams such as "carbon tax", "air pollution", and "air quality", which are reminiscent of regulatory and/or governmental interventions associated with climate change and the goal to reduce carbon emissions, we find bigrams that are often word combinations that explicitly include synonyms for regulation, as in "epa regulation", "control regulation", "energy regulatory", and "environmental standard" (see OA Table 9). Turning to the list of prominent bigrams for $CCExposure^{Phy}$, we use initial bigrams such as "natural hazard" or "sea level" to identify phrases that are intuitively linked to the physical aspects of climate change, such as "island coastal", "hurricane ice", "large desalination", and "land forest" (see OA Table 10).

For the high scoring firms we also provide "snippets", i.e., text fragments taken from the point in the respective earnings call transcript that the algorithm identifies as the moment when call participants are discussing climate change. We report details in Table 3. The five highest scoring firms on $CCExposure$ are headquartered in the U.S. and China. Consider for example, Ocean Power Technologies Inc, a U.S. company which turns (ocean) wave power into electricity for offshore applications. In its fourth quarter 2008 earnings call, bigrams such as "energy requirement", "powerbuoy wave", "wave condition", and "wave power" featured heavily. Turning to the top "snippet" from the call, we observe the participants discussing the demand for the company's trademark technology (the PowerBuoy®) in relation to heightened attention for renewable energy requirements. Similarly, the 2014 (fourth quarter) call of the China Ming Yang Wind Power Group Ltd, uses bigram that include "distribute renewable" and "wind power". Its top snippet discusses the management's expectations regarding the attainability of distributed renewable energy objectives. Not surprisingly, firms in this top list 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 do so to discuss how their infrastructure projects are central to delivering new sources of energy to customers. OA Tables 11 - 13 present more examples of snippets, focusing on the top-scoring firms of each of our three topic-related measures.

Together, this first validation exercise provides support for the idea that our algorithm identifies bigrams that signify discussion of the different dimensions of climate change. It is important to note, however, that our exposure measures are constructed at the *transcript* level and each of these bigrams contributes only little to the final score on the exposure measures. For this reason, we shift attention in what follows to the properties of the final measures constructed using the full set of possible climate change bigrams.

4.2. Times-Series Patterns of Measures

Accordingly, in our next step, we examine the *aggregate* properties of our broad exposure measure as well as of the three more specialized topic measures. We do so in different ways. First, we compute the cross-sectional means of each measure and plot these over time in Figure 1, Panel A-D (the figures use quarterly transcript data to illustrate the time-series changes more precisely). The figures also highlight some key moments in the public awareness of climate change during this time period, ranging from policy events to natural disasters. For expositional purposes, 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 remarkably over time, especially in the mid 2000s. The strong rise in the early years of the sample is somewhat surprising, as it indicates that earnings calls started to address issues related to climate change earlier than maybe expected. Reaching a plateau around the year 2011, we observe some small decline in the period up to the 2012 Doha Climate Summit, widely perceived as being unsuccessful in addressing climate change, and a leveling off in the subsequent years (but at a high level compared to the pre-2011 period). We note a renewed increase in climate change exposure since the 2015 Paris Agreement and the 2016 Trump election. Climate change exposure reaches its peak at the end of sample period.

We next turn towards understanding how this aggregate pattern reflects changes in the individual topics-based measures. Interestingly, the dynamics of the three topics vary to some extent differently over time. In Panel B, the time-series changes for $CCExposure^{Opp}$ resemble those of the aggregate measure; it is clearly upward trending, especially in the beginning of the sample period. In Panel C, $CCExposure^{Reg}$ also trends upwards between 2002 and 2008, but it varies around a markedly lower level between 2012 and 2017. Since then and especially towards the end of the sample, the measure of regulatory aspects increases substantially again, as has 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, there are also better (worse) opportunities for firms. This is consistent with priors, as, for example, regulation to limit carbon emissions simultaneously triggers new business opportunities for firms in renewable energy or battery technology.

Quite differently from the previous patterns, $CCExposure^{Phy}$ in Panel D displays large swings over time, revolving around a long-term mean of around 0.0125. There appears to be neither an upwards nor downwards trend in the time-series of the mean of this measure. OA Figure 1 provides additional figures, bifurcating climate change exposure into sentiment and risk scores. The perhaps 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 average values of our four exposure measures by industry sector (at the two-digit SIC code level, across all sample years) and present a ranking based on these means in Table 4.[20] In Panel A, using the broad exposure measure, the sectors with the highest

[20]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 OA Table 14. OA Table 15 reports the industry ranking for the sentiment and risk measures, respectively.

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).

Turning to the topics-based measures, we find utility companies topping the list also for $CCExposure^{Opp}$ (Panel B) and $CCExposure^{Reg}$ (Panel C). Coal Mining displays high exposure to regulatory and physical climate shocks (Panels C and D). While the high regulatory exposure of the coal mining sector is plausible given the large carbon emissions that result from burning coal, the high physical exposure is more subtle. One explanation is that it 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, has large exposure to physical shocks such as storms, flooding, or draughts. The table moreover lists those industries which appear *not* to have material (measured) exposure to climate change. Such industries include educational services or hotels for $CCExposure^{Opp}$ and $CCExposure^{Reg}$, and communications for $CCExposure^{Phy}$, among others.

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. We explore this within-industry variation below, but provide some additional evidence to corroborate this observation for a key sector, utilities, in OA Figure 2, Panel A-D. Using histograms the figure's 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.[21]

The large within-industry variation underscores the need for a (time-varying) *firm-level* measure of climate change exposure. But it also has important implications for investors

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

as it illustrates differential firm-level exposure within a sector for climate opportunities *as well as* regulatory and physical climate shocks. Moving forward, individual sectors will therefore likely have "winners" and "losers". A consequence for investors is that they may be able to address climate risks and opportunities by keeping a broad industry diversification (rather than banning some industries entirely), and then perform a negative (or exclusionary) screening of firms identified as climate change "losers". This observation echoes recent arguments by academics (Andersson et al., 2016) as well as 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 also compute average values of climate change exposure by country. Figure 2 documents several noteworthy patterns. First, total exposure to climate change (Panel A) varies substantially across countries, attaining on average the highest scores for firms in Spain, Austria, and Chile, and the lowest in Israel. In Panel B, Spain leads the ranking for $CCExposure^{Opp}$, outpacing New Zealand and Austria. The high ranking for firms in Spain likely originates 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. Second, regulatory exposure (Panel C) is particularly manifest for firms in New Zealand, Australia, South Africa, Singapore, and Hong Kong, but also in the EU and the U.K.[22] Third, firms in countries such as Finland, Singapore, and Sweden have high $CCExposure^{Phy}$, consistent with being economies that either rely on or are constrained by natural resources vulnerable to climate change.[23]

[22] 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 closely cooperates with the EU on climate regulation. Among other things, it plans to fully decarbonise its electricity production by 2050.

[23] Examples are the effects of sea level rises on firms in Singapore, and effects of changes in precipitation and temperature on firms producing forest products in Finland or Sweden, whose economies are very dependent on such products (it remains highly uncertain among scientists whether climate changes positively or negatively affects forest growth (CCSP, 2008), which is also reflected in the high scores of $CCRisk$ in OA Figure 3 for

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

4.5. Climate Change Regulation and Extreme Temperature

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

First, we consider in Table 5, Panel A, firm-level regressions to explore the association between our exposure measures and the index constructed by Germanwatch to evaluate policies and regulations with respect to climate change in a country. As explained above, *Climate Policy Regulation* reflects issues such as subsidies for renewable energies or regulation to reduce carbon emissions. The estimates in Column (1) reveal a positive association between the index and $CCExposure$, indicating that more climate change bigrams occur in transcripts of firms located in countries with more climate-friendly policies and regulations. However, the explanatory power of *Climate Policy Regulation* is modest only, 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 topics in Columns (2) to (4), we find that the

these two countries).

aggregate effect originates mostly from firm-level exposure to opportunity and regulatory shocks (not from physical shocks). The economic magnitudes are reasonable. For example, a one-standard deviation shock to *Climate Policy Regulation* is associated with an increase in $CCExposure^{Reg}$ by (5.131 x 0.008=) 0.041 or 10% of the variable's mean.[24]

Second, we examine in Table 5, Panel B, the association between the exposure measures and a country-level proxy for the physical impact of climate change (the frequency of extreme temperature events in the prior year).[25] The estimates provide some weak, but suggestive evidence supporting the validity of our measures. Most notable is that $CCExposure^{Reg}$ in Column (3) shows virtually no association with *Extreme Temperatures*, neither statistically nor economically, while there seems to be some positive association in Column (4) for $CCExposure^{Phy}$ (the effect is marginally insignificant with a t-stat of 1.65; the effect does become statistically significant when we condition on sentiment in OA Table 16). The weak explanatory power of the temperature variable, which varies at the level of the country of a firm's headquarters location, may also arise because actual 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. Summary of Validation Exercise

The evidence in this section supports the validity of our approach. Our algorithm identifies word combinations in earnings call transcripts that describe different facets of climate change well, and by counting the occurrence of climate change bigrams in transcripts, we can construct various climate change exposure measures. Moreover, our topics-based measures exhibit cross-sectional and time-series variation which align with reasonable priors.

[24] 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 for business opportunities (e.g., the promotion of renewable energy) or how they affect costs (e.g., carbon pricing). At the same time, they should not directly lead to discussions about a firm's exposure to extreme weather events or draughts. The difference in patterns also underpins our claim that the proposed climate change exposure measures capture distinct dimensions along which firms can be exposed to climate change.

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

Yet, aggregating the scores on our climate change exposure measures, whether over time, by industry or by country, potentially masks measurement error at the firm level. To examine this possibility, we explore below in more detail 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 conduct a test that allows us to better understand the drivers of the variation in our and in the alternative measures.

5. Variance Decomposition

One of the challenges facing institutional investors, policy makers, and researchers alike is that measures of *firm-level* climate change exposure are thin on the ground. To bolster our claim that *CCExposure* and its topics-based components indeed quantify variation in exposure to climate change opportunities and events *at the firm level*, we conduct a simple analysis of variance. We then compare this analysis with a similar decomposition exercise for *Carbon Intensity* and *ISS Carbon Risk Ratings*.

Table 6, Panel A, reports the incremental explanatory power from conditioning each of our exposure measures on various sets of fixed effects that plausibly drive the variation. Some stylized facts emerge from the table. Time fixed effects, i.e., economy-wide changes in aggregate climate change exposure (as depicted in Figure 1) explain very little of the variation—yielding an incremental R^2 below 1% for all of our exposure measures. For industry fixed effects, the same observation holds true *only* with respect to the variation in $CCExposure^{Phy}$. Indeed, consistent with economic intuition, exposure to both opportunity and regulatory shocks have a sizeable industry component (18.6% and 10.3%, respectively), which might result from regulation that targets specific industries more than others or from technological developments that affect the entire sector. The interaction of industry and time fixed effects account for at most 2.4% of variation (in case of $CCExposure^{Opp}$). We also find relatively little additional explanatory power by including country fixed effects. Importantly, depending on the specific measure, between 70.4 and 96.8% of variation is not explained by these fixed effects, and therefore plays out at the firm level rather than at the level of the country, industry, or over-time.[26] The high unexplained variation for $CCExposure^{Phy}$ is unsurprising given that exposure to physical shocks is highly dependent on firm-specifics such as the exact location of a firm's headquarters and its production sites or the specific insurance policies against natural hazards. Adding firm fixed effect, we find that permanent differences across firms in an industry and countries account for 51.8, 56.3, 41.1, and 48.3% (for $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively). The remaining 48.3, 43.8, 58.9, and 51.7% is variation over time in the identity of firms in industries and countries most affected by the respective climate change variables.[27]

Table 6, Panel B, provides the same analysis for $Carbon\,Intensity$ and *ISS Carbon Risk Rating*. The results indicate that carbon intensities reflect substantially more industry-level variation compared to our measures. Regressing carbon intensities onto industry fixed effects yields an incremental R^2 of 38.4%. Including a full set of fixed effects reduces the variation at the "firm level" to 56.6%, of which about half reflects permanent differences across firms. The $ISS Carbon Risk Rating$ has somewhat higher firm-level variation remaining after accounting for the full set of fixed effects, but at 73%, this rating score too remains at a considerable distance from our topics-based measures. What's more, about two-thirds of the variation in the ISS ratings is persistent; much more compared to our measures. In other words, the $ISS\,Carbon\,Risk\,Rating$ reflects to a large extent persistent differences across firms and the industry assessments of climate change risk exposure, despite ISS's acknowledgment that "*some sectors exhibit a very heterogeneous exposure to climate change risks*" (ISS, 2020) and their attempt to adjust the measure to take this heterogeneity into account.[28]

[26]Following Hassan et al. (2019), we refer to this within-country and industry-time variation as "firm level".

[27]OA Table 17 reports the same variance decomposition for the sentiment and risk metrics.

[28]ISS also provides two subscores of the $ISS Carbon Risk Rating$, named $ISS Carbon Performance Score$ 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 the $ISS\,Carbon\,Performance\,Score$, the firm-level variation is only 69.2%.

6. Climate Change Exposure and Firm Characteristics

Having documented economically 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 as heterogeneity in climate change exposure within industries 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),

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

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

Table 7 presents Ordinary Least Squares estimates of Equation 4, reporting in brackets t-statistics based on standard errors that are clustered at the industry-year level. We find that larger firms, as measured by their total assets, tend to have fewer climate change opportunities as well as lower exposure to physical climate change events. At the same time, consistent with prior findings in political economy (Peltzman, 1976; Stigler, 1971), such firms are more exposed to climate change regulation. We also find a significant negative association between profitability ($Ebit/Assets$) and $CCExposure^{Opp}$ (t-stat of 4.65) as well as $CCExposure^{Reg}$ (t-stat of 4.41). A one-standard deviation increase in $EBIT/Assets$ is associated with a (1.065 x 0.052 =) 0.055 lower value for $CCExposure^{Reg}$ (21% of variable's standard deviation). Cash holdings are positively associated (at the 5% level or better) with $CCExposure^{Opp}$ and with $CCExposure^{Reg}$, but negatively, albeit marginally so, 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), we also find a somewhat puzzling negative association between R&D spending and climate opportunities. However, we do not over interpret this relation as overall R&D expenditure of firms may be a too noisy measure to capture innovation in climate-related technologies. Consistent with prior evidence that greater climate risk leads to lower firm leverage (Ginglinger and Moreau, 2019), we find that firms with higher regulatory exposure have lower leverage (*Debt/Assets*). The opposite relation seems to hold for climate opportunities and there is no relation between leverage and physical exposure. In OA Table 18, we extend these analyses to documenting correlations between firm characteristics and climate change *sentiment* and *risk*.

7. Climate Change Exposure and Alternative Firm-Level Exposure Measures

We next explore how well our measures of climate change exposure correlate with *Carbon Intensity* and *ISS Carbon Risk Rating*, the two alternative exposure measures available at the firm level. Carbon intensities play an important role as a measure for firm-level exposure to climate change (especially to regulatory shocks) and the measure is used by a wide range of papers (Bolton and Kacperczyk, 2020a,b; Ilhan et al., 2020; Shive and Forster, 2020; De Haas and Popov, 2020). The analysis of a firm's carbon footprint is also reported to be the single most frequently used climate risk management tool of institutional investors, according to the survey evidence in Krueger et al. (2020).

A benefit of using carbon intensities is that they are easy to understand and compute, readily available for subscribers to the CDP database, and genuinely related to changes in the global climate. However, important drawbacks of the measure include its lack of forward-looking scope and the voluntary nature of its disclosure, which introduces selection bias for researchers aiming to understand its effects.[29] Furthermore, carbon emissions are available only for a limited number of firms, which hinders their ability to act as a measure for a broad

[29] A notable exception in terms of using forward-looking emissions is Ramadorai and Zeni (2020), who use information in the CDP database on firms' plans for future carbon emissions abatement.

cross-section of companies.

The carbon risk rating by ISS have been employed mostly by investment professionals. One strength of the rating is that it considers factors beyond a firm's carbon footprint. For example, it includes scores that rate a firm's carbon reduction targets and actions or assess the management's perspective on climate change. That said, the measure also faces severe selection issues that make its analysis and usage nontrivial.[30] Moreover, the construction of the ISS metric is relatively complex and to some degree subjective, and, just as for carbon intensities, it is available only for a limited number of firms. OA Table 19 cross-tabulates the number of observations (frequencies) of $CCExposure$ and each of the two alternative measures. The figures show that in about 70% (66%) of the observations, our measure indicates positive (nonzero) climate change exposure, while data on carbon intensities (ISS ratings) is missing. In only 0.9% (2.3%) of cases does our measures suggest zero climate change exposure, while a firm's carbon intensity is nonzero (an ISS rating exists).

We first explore the relation of our exposure measures with carbon intensities. Higher levels of carbon emissions relative to a firm's asset base should be related to some of our exposure measures. Notably, high carbon intensities might attract the scrutiny of regulators aiming to reduce emissions in view of international agreements to keep global warming within certain limits (Ilhan et al., 2020). Such regulatory attention to firms is likely to emerge as a topic of conversation in earnings calls. But high carbon intensities may also spur technological innovations that provide firms with new opportunities in the market place. Utilities, for example, which have a large carbon footprint (see OA Table 14) may have strong incentives to develop new low-carbon alternatives (e.g., wind or solar farms), which provide opportunities in the future. To the contrary, carbon emissions should be unrelated to a firm's 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 basing its estimation on the intersection of the CDP sample and

[30] ISS decides on firm coverage based on factors such as investor interest or index membership.

our (much broader) sample for $CCExposure^T$. Our findings, presented 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, which originates from the positive correlation between $Carbon\ Intensity$ and $CCExposure^{Opp}$ in Column (2) as well as $CCExposure^{Reg}$ in Column (3) (t-stat of 3.87 and 5.69, respectively). A one-standard deviation increase in a firm's carbon intensity increases its exposure to regulatory shocks by (399.9 x 0.00026=) 0.10, which is about about twice the variable's mean or about 37% of its standard deviation. As expected, we find no association in Column (4) between carbon intensities and a firm's exposure to physical shocks. In OA Table 20, we further show that higher carbon emissions are associated with lower sentiment and higher risk regarding a firm's regulatory exposure to climate change.

We explore in Table 8, Panel B, the relation between our exposure measures and *ISS Carbon Risk Rating*. Again, note that the intersection of the ISS and $CCExposure^T$ data sets yields a smaller number of observations than we had available in our original estimation of Equation 4. In Column (1), a high value of $ISS\ Carbon\ Risk\ Rating$ (indicating lower assessed risk) is associated with higher overall exposure to climate change, which primarily originates from a higher exposure to climate opportunities, as shown in Column (2). This result is indicative of concordance between our and ISS's assessment of which firms are most (or least) strongly exposed to opportunities resulting from climate change. 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 with its rating. The lack of a relation with $CCExposure^{Reg}$ is worth pointing out, as it suggests that our measures capture different aspects when it comes to a firm's exposure to regulatory shocks.[31]

We conclude from this examination that our exposure measures do reflect some variation

[31] In OA Table 20, we find that the *ISS Carbon Risk Rating* is negatively associated with $CCSentiment^{Reg}$ and positively with $CCRisk^{Reg}$, suggesting that firms with high (good) ISS ratings have more negative exposures to regulatory impacts of climate change that are at the same time less risky.

in carbon intensities and ISS carbon risk ratings. At the same time, the overlap is partial at best, especially for the ISS rating, and appears to be limited mostly to climate change *opportunities* (and regulatory impacts for carbon intensities). The disagreement we document is consistent with our variance decomposition analysis, which revealed 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 accordingly vary less with industry-level shocks (as well as with the alternative measures). However, such disagreement is not unique to our climate setting, but it resembles related evidence from ESG ratings more broadly. For example, Berg et al. (2020) document only modest correlations among the ESG ratings of six prominent rating agencies. As in our setting, disagreement seems particularly high among firms with high risk (low ratings), not among firms with high opportunities (high ratings). Gibson et al. (2020) provide similar evidence on ESG rating disagreement, especially for environmental ratings ("E"), for which disagreement seems generally higher than for governance ("G") and social ("S") aspects.

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 level that plausibly relate to climate change exposure. This analysis helps us in establishing that our measures capture meaningful variation. Again, 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. Such attention, which tends to increase after natural disasters or climate summits, has been shown to also affect financial market participants. Choi et al. (2020) show that retail investors sell carbon-intensive firms when attention to climate change spikes, leading to the under performance of carbon-intense stocks. In their paper, there seems to be a much weaker positive performance effect of "clean" stocks at times when attention to climate change is low. This indicates that climate attention has asymmetric effects on firms; firms with exposure to regulatory shocks suffer, while firms with opportunities do not benefit to the same degree. Ilhan et al. (2020) document that high public attention to climate change increases the cost of option protection against carbon tail risk. Based on this prior evidence, we predict that discussions in conference calls also reacts to the salience of climate change topics in the public discussion. Specifically, we expect that times of higher climate attention are associated with an increase in firm-level climate change exposure, especially when it comes to exposure 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 estimation results in Table 9, Panel A, are in line with our prediction. Notably, we find in Columns (3) and (4) a strong positive association between time-series variation in media attention to climate change and firm-level exposure to regulatory and physical shocks. When the media index increases by one-standard deviation, this is associated with an increase in $CCExposure^{Opp}$ by (0.001 x 4.441 =) 0.004 or 9% of the variable's mean. There is a lack of a 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 et al. (2020). In our context, an explanation of the asymmetry in the results may be that the (business) media is paying more attention to environmental rules and physical threats to economic activity than to the opportunities climate change might offer to businesses. Participants in conference calls that follow the business media may therefore have a higher inclination to address "downside" topics.

Second, we explore the relation between firm-level institutional ownership and climate change exposure. As documented in Krueger et al. (2020), institutional investors are increasingly concerned about the effects that climate change has on their portfolio firms, causing more and more investors to divest (or underweight) holdings in firms with high climate change exposure. In fact, some institutions even started to impose ex-ante investment restrictions towards firms with particularly high risks. A case in point is Norges Bank Investment Management (NBIM), managing the investments of the Norwegian Sovereign Wealth Fund, which has excluded from its investment universe firms that produce coal or coal-based energy.[32] This process of exclusionary screening has accelerated over the recent years and it is likely to increase further. Based on these developments, we predict a negative association between climate change exposure and institutional ownership, especially during the recent years.

To test this prediction, we augment Equation 4 by adding $Institutional\,Investors$. The estimation results in Table 9, Panel B, document in Column (1) that institutional ownership is negatively associated with our broad measure of exposure ($CCExposure$). Interestingly, this overall effect originates from a negative correlation with both $CCExposure^{Opp}$ (Column (2)) and $CCExposure^{Reg}$ (Column (3)). While the negative correlation with regulatory exposure is unsurprising, the existence of a negative effect for opportunities is indicative of institutions not differentiating where the source of the climate exposure originates from. Further, in unreported regressions, we find that these associations are particularly strong in the more recent years. Overall, these findings indicate that institutional investors increasingly avoid firms with high climate change exposure, apparently without distinguishing much between upside and downside exposures. Yet, as we are unable to establish any causation regarding this relationship, it may also be that low institutional ownership may lead to an increase in climate change exposure.

Third, we investigate whether climate change exposure is higher in country years when firms are required by law to disclosure more environmental information. Such disclosed information could make climate change exposure more salient and trigger analysts to ask additional questions. We find in Table 9, Panel C, some evidence of a positive association, but limited to $CCExposure^{Phy}$ and then only at the 10% level. These estimates are, how-

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

ever, somewhat comforting inasmuch they speak against the idea that our $CCExposure^D$ measures, which are based on *voluntary* information exchanges between management and financial analysts during earnings calls, are unduly affected by variation across countries in disclosure standards.

9. Climate Change Exposure and Firm Valuations

In a last step, we explore whether our measures are associated with financial outcomes that matter to firms and investors. To this end, we test whether the exposure to opportunity, regulatory, and physical climate shocks are reflected in firm valuations. Our tests exploit that the cross-sectional average of climate change exposure has shown two distinct phases over time, a phase of steady increase till 2011 and a relatively high level since then (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 $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are the measures of climate change exposure, which we include both individually and jointly. The vector 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.

The estimation results are reported in Table 10. For the years after 2011, reported in Columns (1) through (4), we do not find that changes in firm valuations statistically significantly reflect the opportunities of climate change. However, it appears that exposure to regulatory events negatively correlates with valuations changes (t-stat of 1.98). In economic magnitudes, a one-standard deviation shock in $CCExposure^{Reg}$ is associated with a (0.254 x - 0.302 =) 0.076 change in $\Delta Tobin'sQ$, which is roughly equal to the variable's mean. Exposure to physical events is also negatively associated with valuation changes, but the effect is statistically insignificant. In Columns (5) through (8), for the period prior to 2011, neither of the climate change exposure measures seems to be related to firm valuation changes. This evidence is consistent with Delis et al. (2019), who document that banks only started to price exposure to regulatory climate risks in the recent past.

The regression estimates in OA Table 22 provide the results for the sentiment and risk measures. A few observations from these regressions stand out. When conditioning on sentiment, we find that post-2011 market valuations do reflect opportunities related to climate change, though the effect is significant only at the 10% level. When combined with positive tones, there is also a positive effect of a firm's exposure to physical shocks (physical changes in the climate benefit some firms, e.g., producers of certain agricultural products or those of genetically modified seeds). For our risk measures, we find a strong negative relation between regulatory climate risk and firm valuation changes in the second half of the sample. Interestingly, for physical climate risk, there appears to be such a negative effect in the first half of the sample.

10. Conclusions

A key challenge for investors, regulators, and policy makers is the difficulty to quantify firm-level exposure to climate change, with respect to both the associated risks and opportunities. We introduce a new method that identifies firm-level climate change exposure from word combinations that signal climate change conversation in earnings conference calls. As these earnings calls reflect both the demand side (i.e., analysts) and supply side (senior management) on a "market for information", our measures reflect the combined views of key stakeholders on the climate change exposure of the firm. What's more, earnings calls are to a large extent forward-looking; while they review past results, analysts spend much of their time probing management about their future plans (Huang et al., 2018). Our analysis is based on a global sample of more than 10,000 firms from 34 countries and covers the years 2002 to 2019.

To construct our measures, we build on recent work that has identified such conference call transcripts 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 these prior papers in several important dimensions, allowing us to capture aspects related to the opportunities as well as (physical and regulatory) risks associated with climate change. For this purpose, we adapt the machine learning keyword discovery algorithm proposed by King et al. (2017) to produce several sets of climate change bigrams. Doing so, we further limit the susceptibility of our method to researcher-dependent biases. Rather than having to choose a training library (which often are extensive collections of texts), we simply 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 conference call that is centered on climate change topics. The measures that we construct exhibit cross-sectional and time-series variation which aligns with reasonable priors. They are better able to capture firm-level variation in climate change exposure than alternatives, notably 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. Specifically, it appears that measurement agreement is limited mostly to climate change *opportunities* (and regulatory shocks for carbon intensities). Firm-level variation in our exposure measures relate to economic factors that prior work has identified as important correlates of climate change exposure (e.g., public climate attention and institutional ownership). Further, firm exposure to regulatory shocks is negatively associated with firm valuations changes. We find such an effect only for the second half of the sample, that is, the years after 2011.

Together, our findings provide a nuanced take on the recent IMF statement, quoted in the introduction, that investors do not pay sufficient attention to climate change. For one, analysts (frequently) raise the topic in conference calls, especially during the last years. What's more, equity market valuations appear to reflect firm exposure to climate change, albeit only partially so. An avenue for future research would be to better understand which frictions cause market valuations to associate higher regulatory exposure with lower firm value, while no corresponding effect seem to exist for opportunities or physical threats.

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 regulation 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 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.
$CCSentiment^{Phy}$	2002-2019	Relative frequency with which bigrams that capture regulation 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 regulation 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	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. (2020) that takes the value one if a country has mandatory ESG disclosure; and zero otherwise. Source: Krueger et al. (2020).

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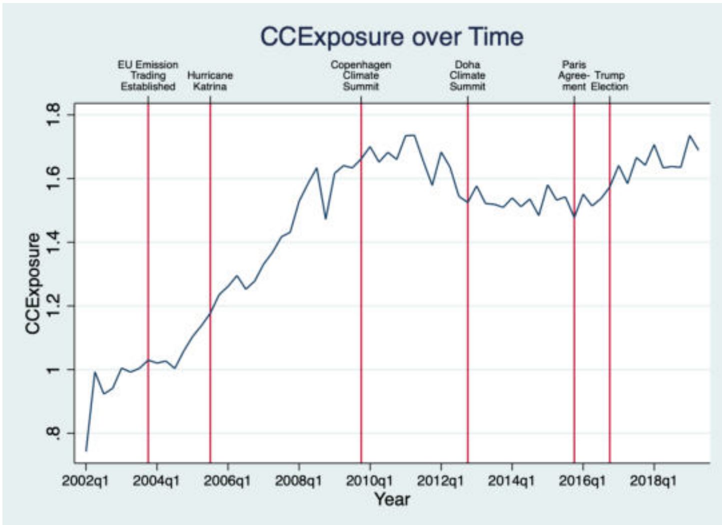
Figure 1: Climate Change Exposure over Time



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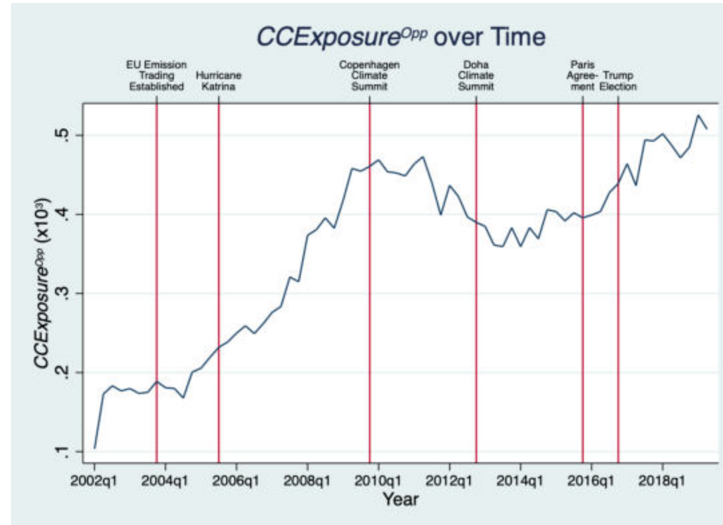

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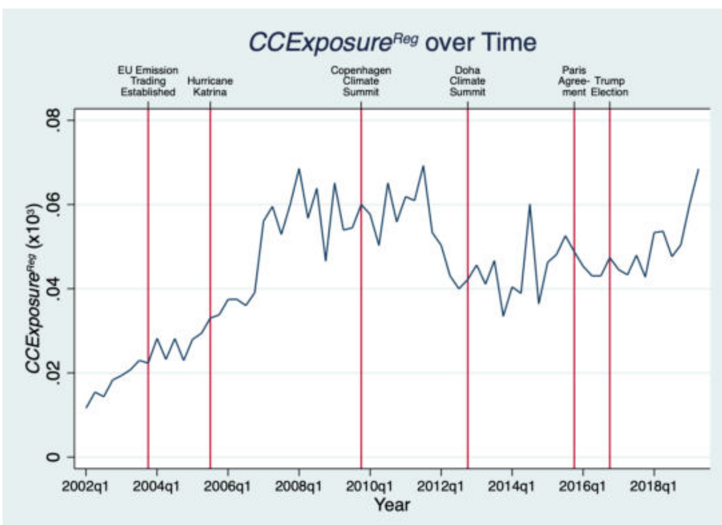

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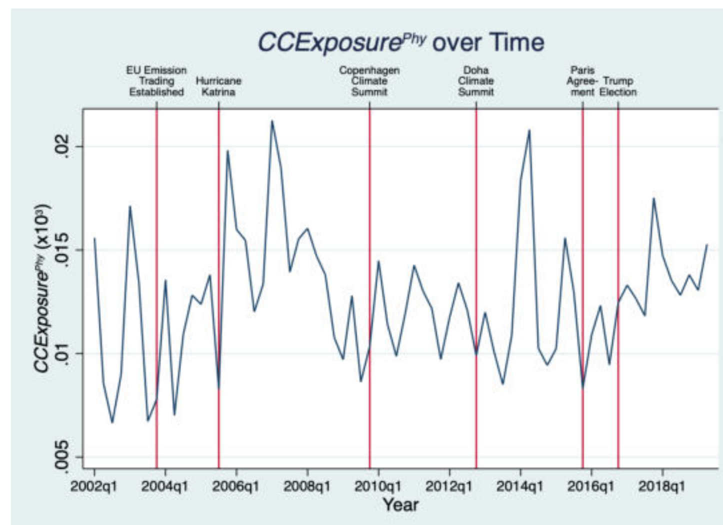
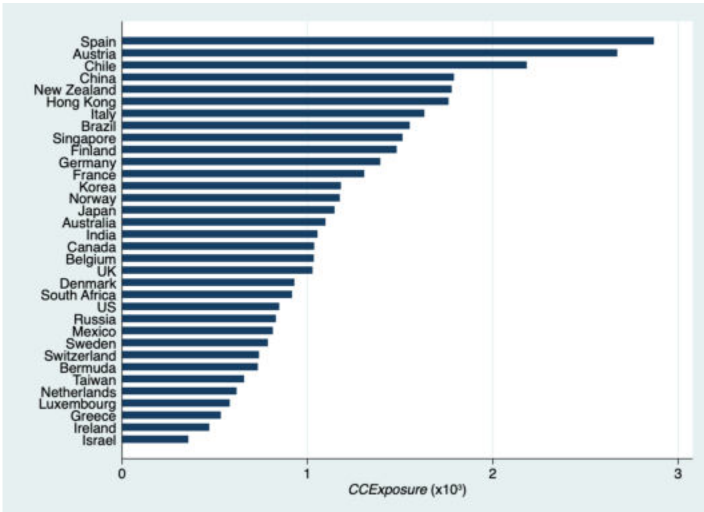


(d)

Figure 1 continued

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. Appendix A defines all variables in detail.

Figure 2: Climate Change Exposure across Countries



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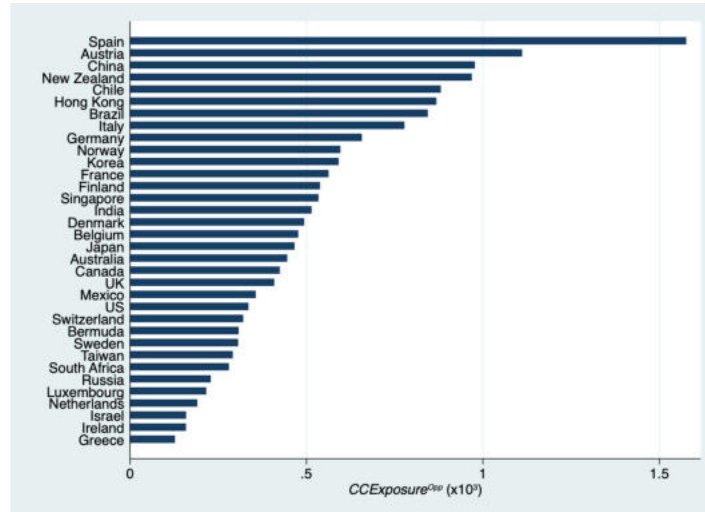

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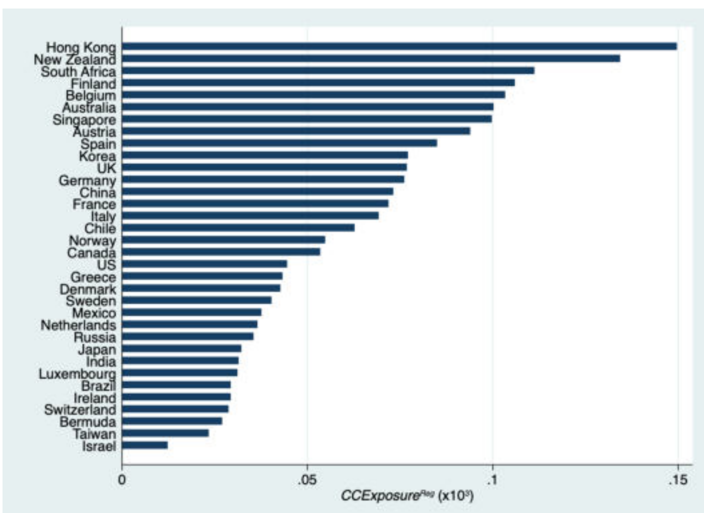

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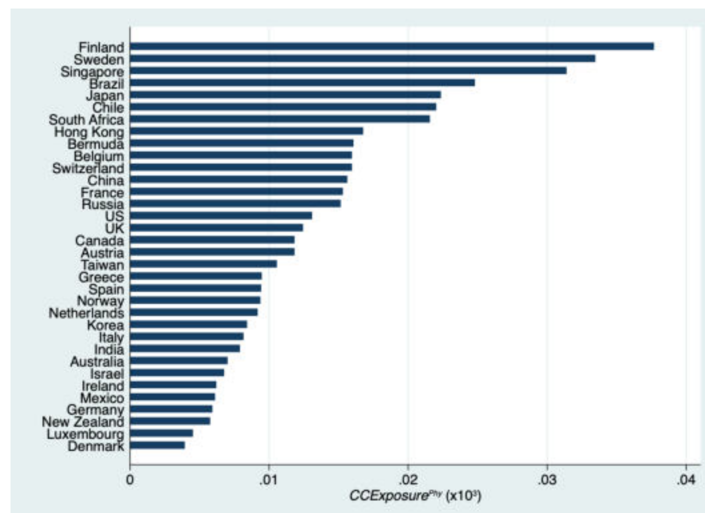


(d)

Figure 2 continued

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.

Table 1: Summary Statistics

	Mean	Std.Dev.	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
$Mandatory\ ESG\ Disclosure$	0.117	0.322	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	Bigrams	Top Snippet
China Ming Yang Wind Power Group Ltd	China	3511	2014Q4	development distribute; distribute renewable; energy goal; renewable energy; wind power	therefore we believe that with large wind power base, large power transmission channels, large offshore 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	US	3621	2008Q2	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	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	US	4911	2008Q2	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	US	3511	2008Q4	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.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	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)					Panel D. $CCExposure^{Phy}$ (x10ˆ3)				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	Median	Obs.
Top-10 Industries					Top-10 Industries				
49 Electric, Gas, & Sanitary Services	0.405	0.727	0.122	2675	26 Paper & Allied Products	0.097	0.329	0.000	705
12 Coal Mining	0.162	0.270	0.000	285	16 Heavy Construction, Except Building	0.059	0.261	0.000	450
29 Petroleum Refining	0.128	0.286	0.000	685	64 Insurance Agents, Brokers, & Service	0.047	0.184	0.000	204
32 Stone, Clay, & Glass Products	0.105	0.332	0.000	577	14 Nonmetallic Minerals, Except Fuels	0.047	0.133	0.000	182
10 Metal Mining	0.088	0.313	0.000	1245	49 Electric, Gas, & Sanitary Services	0.040	0.151	0.000	2675
33 Primary Metal	0.085	0.271	0.000	748	12 Coal Mining	0.039	0.209	0.000	285
34 Fabricated Metal Products	0.080	0.337	0.000	925	35 Industrial Machinery & Equipment	0.034	0.301	0.000	2305
37 Transportation Equipment	0.076	0.209	0.000	1401	10 Metal Mining	0.029	0.125	0.000	1245
87 Engineering & Management Services	0.075	0.257	0.000	1216	15 General Building Contractors	0.029	0.104	0.000	690
16 Heavy Construction, Except Building	0.070	0.236	0.000	450	24 Lumber & Wood	0.029	0.136	0.000	708
Bottom-10 Industries					Bottom-10 Industries				
70 Hotels	0.007	0.048	0.000	542	61 Non-Depository Institutions	0.003	0.030	0.000	667
78 Motion Pictures	0.006	0.040	0.000	417	48 Communication	0.003	0.024	0.000	2274
82 Educational Services	0.006	0.032	0.000	415	83 Social Services	0.003	0.019	0.000	96
23 Apparel & Other Textile Products	0.006	0.027	0.000	194	82 Educational Services	0.003	0.022	0.000	415
60 Depository Institutions	0.005	0.040	0.000	3585	21 Tobacco	0.002	0.023	0.000	85
57 Home Furniture	0.005	0.042	0.000	136	57 Home Furniture	0.002	0.020	0.000	136
56 Apparel & Accessory Stores	0.005	0.043	0.000	347	62 Security & Commodity Brokers	0.002	0.035	0.000	1280
21 Tobacco Produts	0.002	0.019	0.000	85	78 Motion Picturs	0.002	0.015	0.000	417
59 Miscellaneous Retail	0.002	0.014	0.000	342	67 Holding & Other Investment Offices	0.002	0.021	0.000	101
83 Social Services	0.002	0.011	0.000	96	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 Effect	0.6%	0.6%	0.2%	0.0%
Sector Fixed Effect	26.3%	18.6%	10.3%	1.6%
Sector x Time Fixed Effect	1.9%	2.4%	2.0%	1.4%
Country Fixed Effect	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 Effect)	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 Effect	0.3%	1.0%
Sector Fixed Effect	38.4%	17.3%
Sector x Year Fixed Effect	1.2%	1.7%
Country Fixed Effect	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 Effect)	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. $ISS\,Carbon\,Risk\,Ratings$ 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

	$CCExposure$ (1)	$CCExposure^{Opp}$ (2)	$CCExposure^{Reg}$ (3)	$CCExposure^{Phy}$ (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 Ratings* 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 country-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	0.082	0.032	0.004	0.006*
	(1.16)	(0.59)	(0.46)	(1.83)
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 Index developed in Engle et al. (2020) that captures climate change news in the *Wall Street Journal*. $Institutional\,Ownership$ is the ownership by institutional investors. $Mandatory\,ESG\,Disclosure$ is a dummy variable constructed in Krueger et al. (2020) 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Table 10: Climate Change Exposure Measures and Firm Valuations

	$\Delta\, Tobin's\,Q$ After 2011 (1)	$\Delta\, Tobin's\,Q$ After 2011 (2)	$\Delta\, Tobin's\,Q$ After 2011 (3)	$\Delta\, Tobin's\,Q$ After 2011 (4)	$\Delta\, Tobin's\,Q$ Before 2011 (5)	$\Delta\, Tobin's\,Q$ Before 2011 (6)	$\Delta\, Tobin's\,Q$ Before 2011 (7)	$\Delta\, Tobin's\,Q$ 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

Online Appendix

to

"Firm-level Climate Change Exposure"

by

Zacharias Sautner, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang

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 $\mathbb{C}^0$.

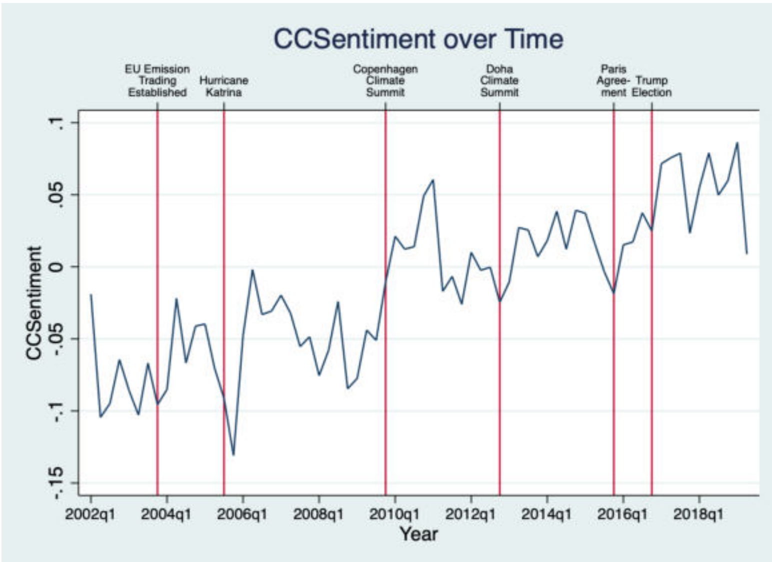
Finding climate change bigrams. In a last step, we identify bigrams that best discriminate the target set $\mathbb{T}$ from the nontarget set $\mathbb{S} \setminus \mathbb{T}$. We first mine all bigrams $\mathbb{T}$ and $\mathbb{S} \setminus \mathbb{T}$. We find that about 3,800 bigrams appears only 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 et al. (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. Additional Tables and Figures

OA Figure 1: Climate Change Sentiment/Risk over Time



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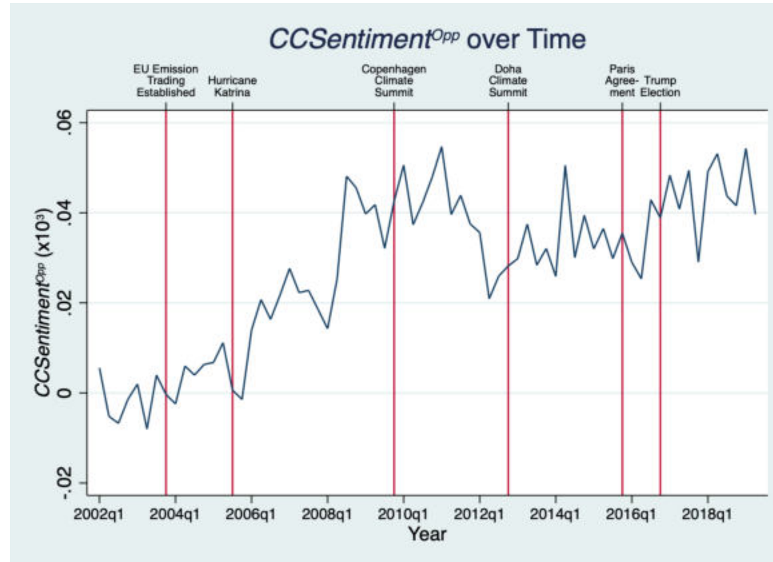

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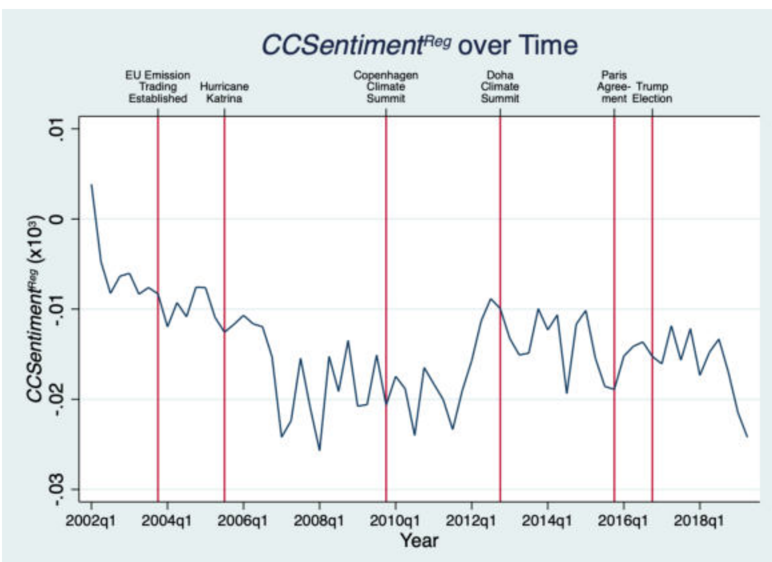

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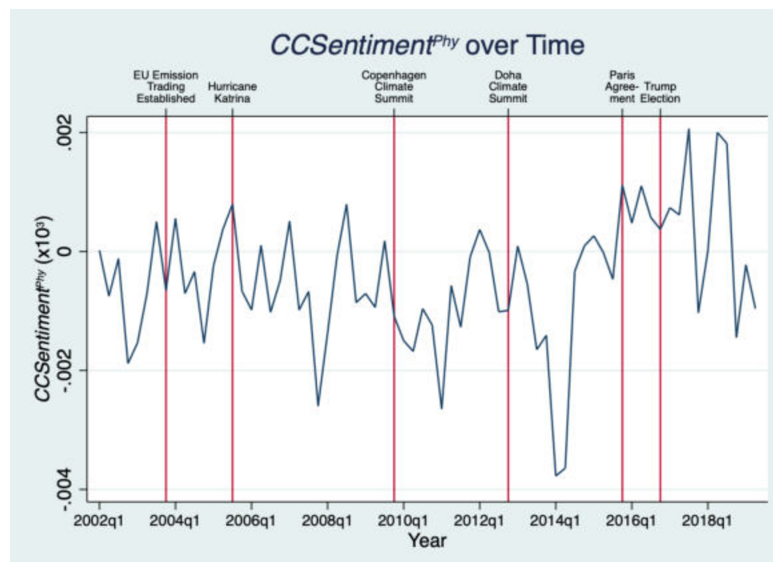

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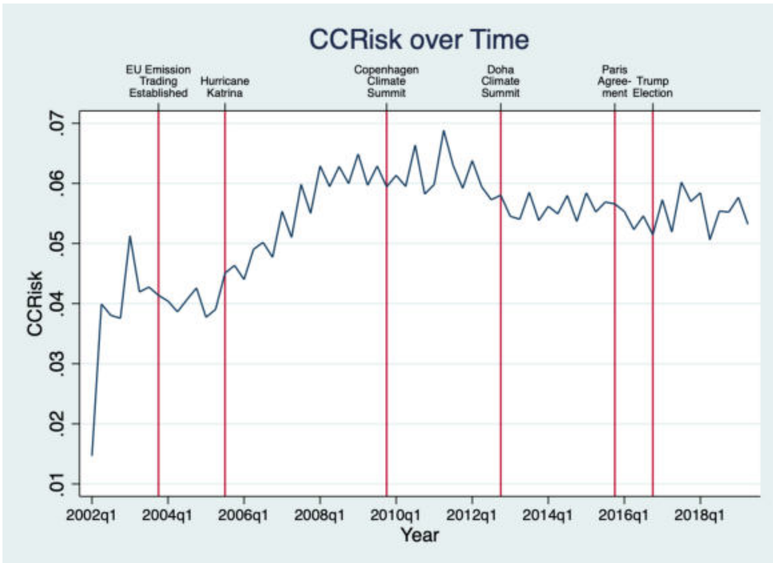
OA Figure 1 continued



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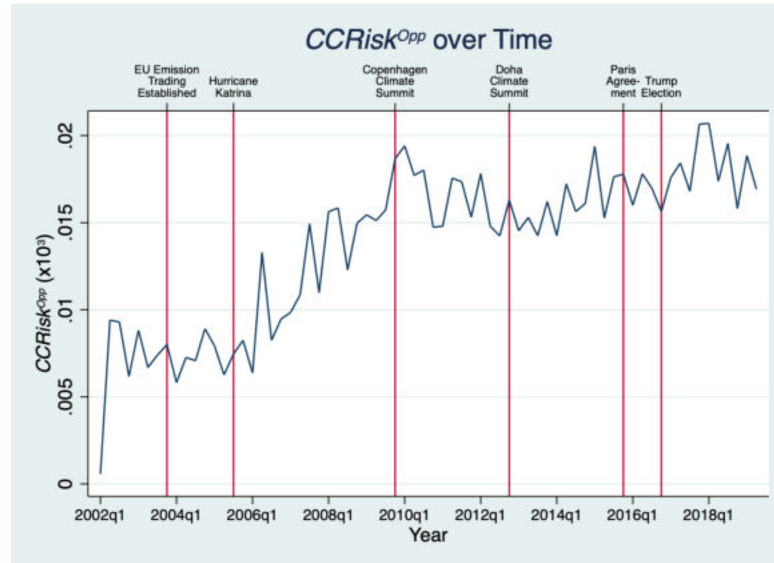

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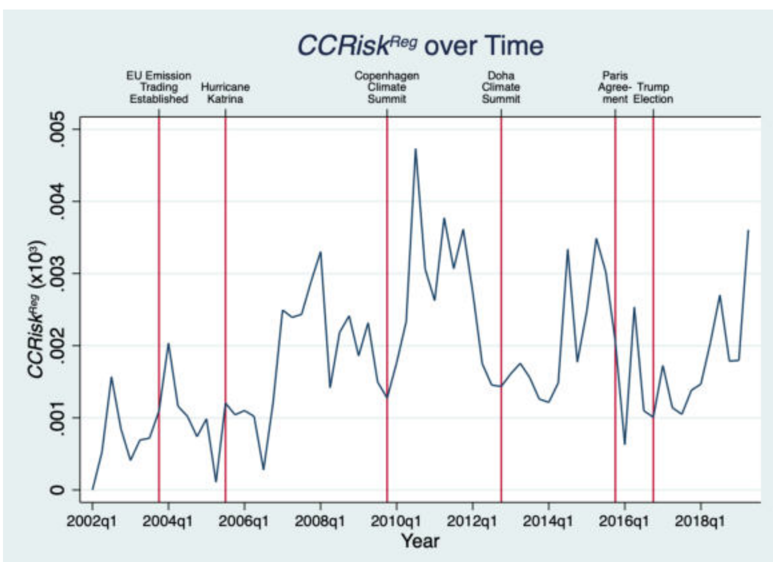

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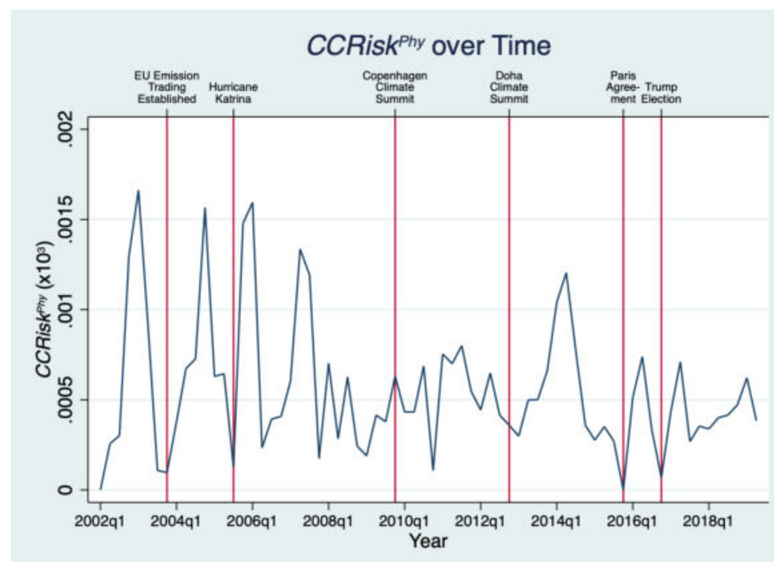
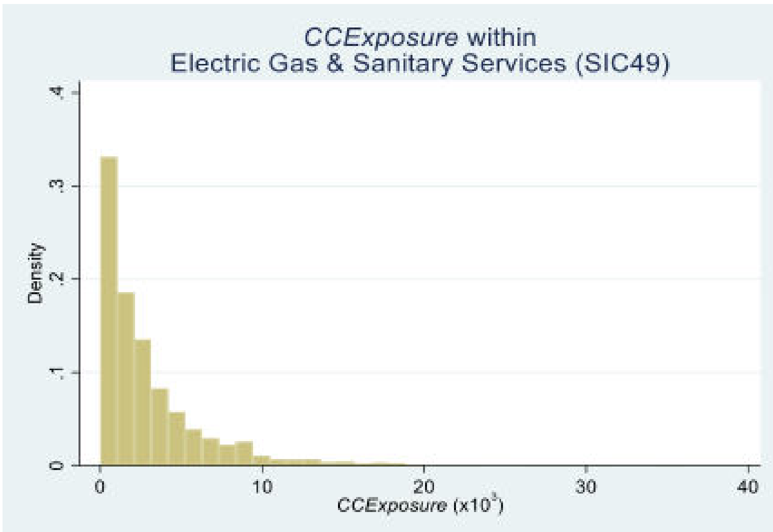


(h)

OA 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). Appendix A defines all variables in detail.

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



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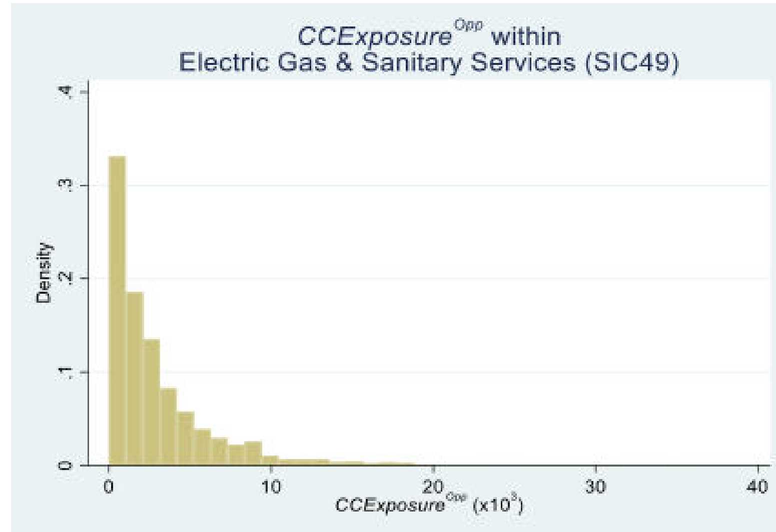

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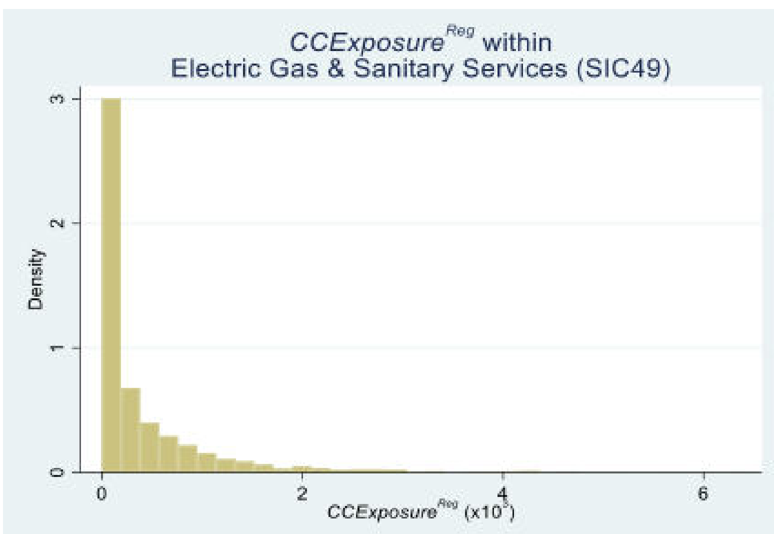

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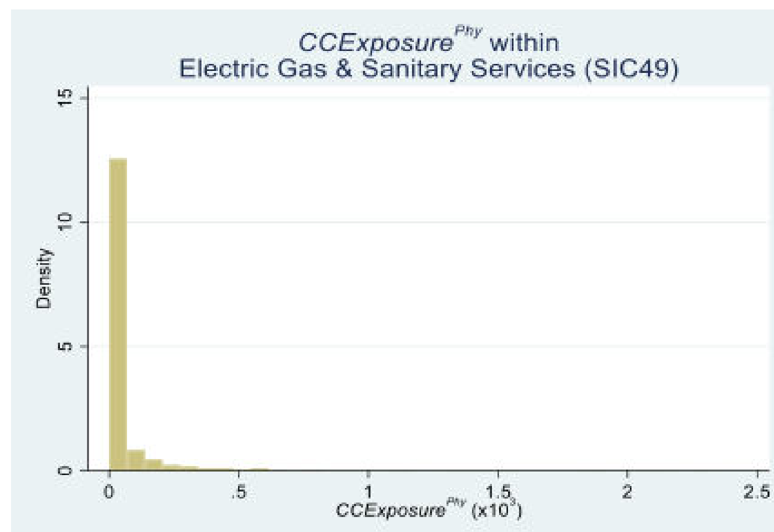
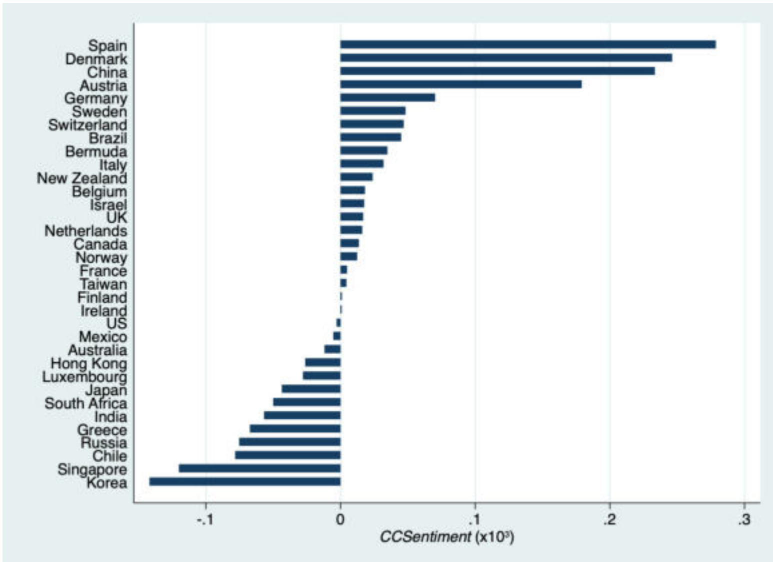


(d)

OA 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.

OA Figure 3: Climate Change Sentiment/Risk across Countries



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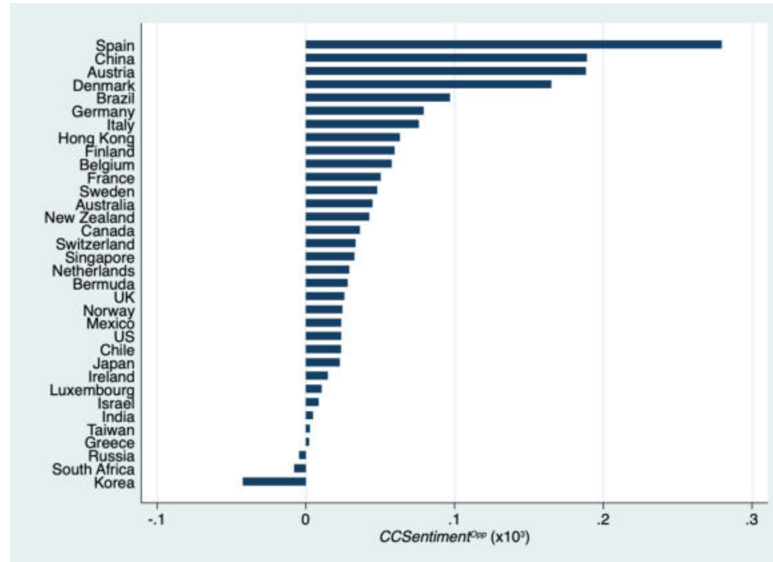

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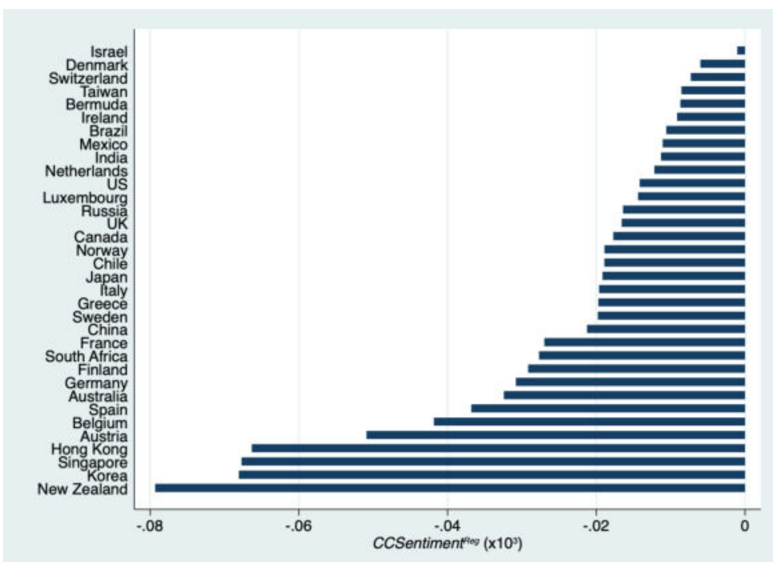

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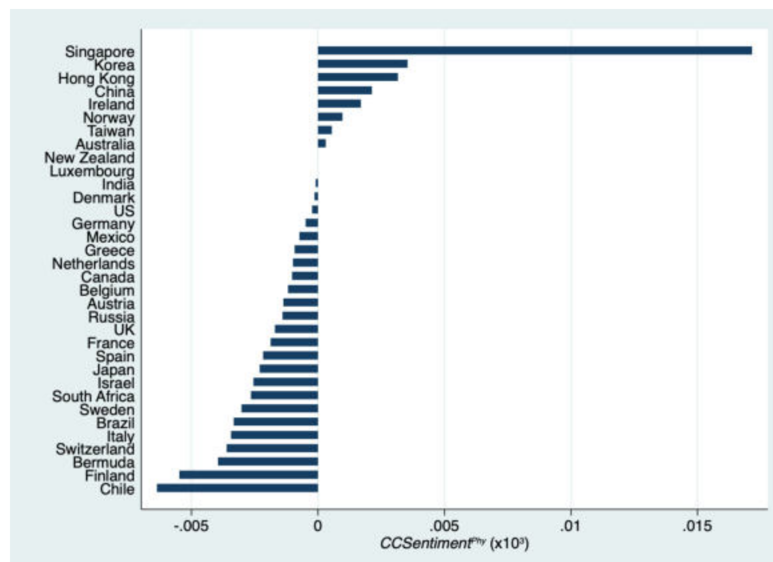

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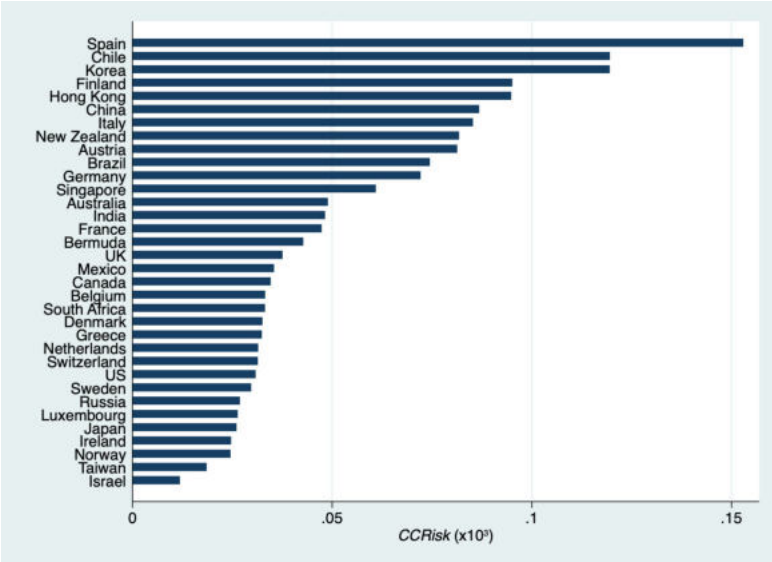
OA Figure 3 continued



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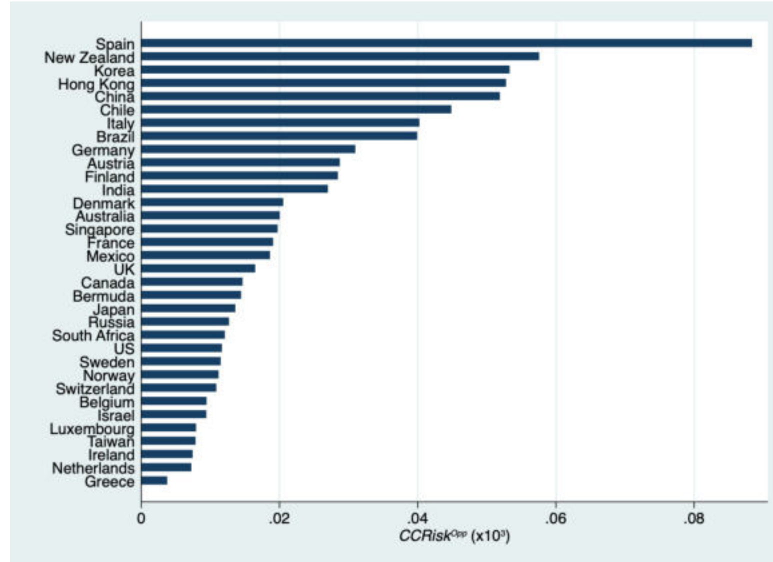

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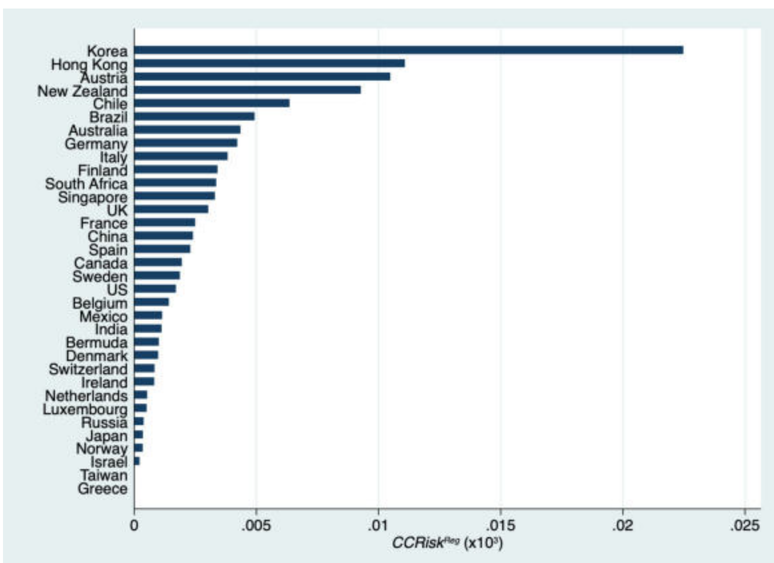

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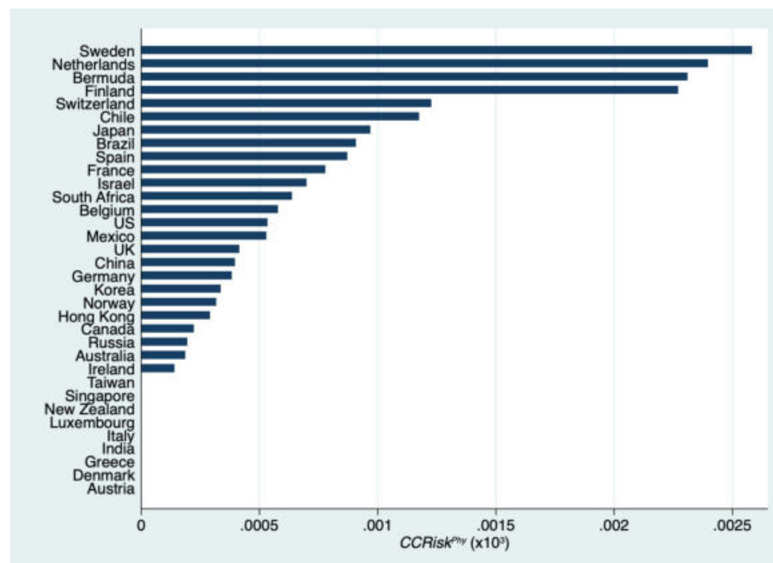

(h)

OA 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.

OA 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.

OA Table 2: Initial Bigrams for Searching Climate Change Bigrams

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

OA Table 3: Top-200 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	energy program	499	industry energy	412
renewable resource	800	unit megawatt	498	environmental upgrade	411
carbon tax	792	environmental standard	496	deliver energy	409
carbon price	760	exist power	496	social environmental	405
power generator	756	new clean	493	new battery	401
indoor outdoor	755	increase renewable	492	dioxide emission	396
solar farm	753	help state	490	use coal	396

OA Table 3 continued

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
green technology	395	diesel vehicle	366	generate energy	347
recovery reinvestment	395	energy category	366	mercury control	346
thermal energy	395	environmental quality	365	portfolio energy	346
solar generation	394	sea level	365	flue gas	345
lot clean	390	provide water	364	power component	345
market wind	390	come wind	362	ontario power	344
utility state	389	home energy	362	control power	344
state land	387	nickel metal	362	example energy	342
come renewable	386	inner mongolia	361	hybrid car	341
efficient light	385	guangdong province	360	issue request	341
thing energy	385	joaquin valley	358	report china	341
energy standard	384	energy world	358	improve environmental	340
energy intensive	384	compliance plan	357	market air	339
power cool	382	president elect	356	term renewable	339
vehicle company	379	electricity grid	353	carbon reduction	338
vehicle commercial	377	regional transmission	353	lng fuel	335
sustainable energy	376	resource board	351	step advance	333
vehicle charge	374	facilitate development	351	increase gigawatt	333
energy requirement	373	water pipeline	351	bush administration	329
nearly megawatt	373	efficiency power	351	energy opportunity	329
generation resource	372	variable speed	351	wind wind	329
water recycle	371	quality monitor	351	clean burn	327
lng truck	371	use state	350	build wind	325
epa regulation	370	burn fuel	350	loy yang	324
state power	370	energy independence	350	charge infrastructure	323
coal capacity	369	carbon intensity	348	energy legislation	322
area florida	367	vehicle europe	348		

Notes: This table reports the top-200 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. Appendix A defines all variables in detail.

OA Table 4: 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. Appendix A defines all variables in detail.

OA Table 5: 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. Appendix A defines all variables in detail.

OA Table 6: 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 "uncertainty" (or synonyms thereof). Appendix A defines all variables in detail.

OA Table 7: 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		
Regulatory Initial 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	

OA Table 8: 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

OA Table 8 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.

OA Table 9: 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

OA Table 9 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.

OA Table 10: 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.

OA Table 11: Top-5 Firms by Opportunity Climate Change Exposure

Firm	HQ	SIC	Time	Bigrams	Top Snippet
China Ming Yang Wind Power Group Ltd	China	3511	2014Q4	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	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	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	US	3621	2008Q4	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	US	4911	2018Q4	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.

OA Table 12: Top-5 Firms by Regulatory Climate Change Exposure

Firm	HQ	SIC	Time	Bigrams	Top Snippet
Korea Electric Power Corp	South Korea	4911	2016Q2	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	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	US	3499	2011Q3	epa regulation	but our business is diversifying enough that we are going to do well without the epa regulations kicking-in.
Rentech Inc	US	851	2007Q4	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	US	3564	2010Q3	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.

OA Table 13: Top-5 Firms by Physical Climate Change Exposure

Firm	HQ	SIC	Time	Bigrams	Top Snippet
Cincinnati Financial Corp	US	6331	2005Q4	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	US	3822	2015Q2	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	US	2653	2007Q1	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	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	security engergy	looking at the end market development, all markets except security & energy markets increased in q3.

OA Table 14: Industry Distribution of Carbon Intensity and ISS Carbon Risk Rating

Carbon Intensity					*ISS Carbon Risk Rating*				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	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 Ratings* 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 Ratings* is constructed by ISS and provides an assessment of the carbon-related performance of companies. Appendix A defines all variables in detail.

OA Table 15: Industry Distribution of Climate Change Sentiment & Risk

Panel A. $CCSentiment$ ($\times 10^3$)					Panel B. $CCSentiment^{Opp}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	Median	Obs.
Top-10 Industries					Top-10 Industries				
16 Heavy Construction, Except Building	0.281	1.639	0.000	450	16 Heavy Construction, Except Building	0.248	1.186	0.000	450
35 Industrial Machinery & Equipment	0.247	1.719	0.000	2305	35 Industrial Machinery & Equipment	0.207	1.278	0.000	2305
36 Electronic & Other Electric Equip.	0.201	0.867	0.000	5896	49 Electric, Gas, & Sanitary Services	0.174	1.254	0.000	2675
40 Railroad Transportation	0.117	0.665	0.001	182	36 Electronic & Other Electric Equip.	0.110	0.591	0.000	5896
52 Building Material	0.105	0.447	0.000	38	08 Forestry	0.067	0.333	0.000	27
75 Auto Repair Services	0.061	0.372	0.000	121	29 Petroleum Refining	0.051	0.390	0.000	685
15 General Building Contractors	0.051	0.399	0.000	690	87 Engineering & Management Services	0.049	0.441	0.000	1216
54 Food Stores	0.048	0.255	0.000	215	34 Fabricated Metal Products	0.048	0.385	0.000	925
57 Home Furniture	0.039	0.167	0.000	136	37 Transportation Equipment	0.045	0.384	0.000	1401
34 General Building Contractors	0.039	0.622	0.000	925	40 Railroad Transportation	0.039	0.299	0.000	182
Bottom-10 Industries					Bottom-10 Industries				
44 Water Transport	-0.047	0.461	0.000	784	62 Security & Commodity Brokers	-0.003	0.109	0.000	1280
14 Nonmetallic Minerals, Except Fuels	-0.060	0.386	0.000	182	10 Metal Mining	-0.013	0.214	0.000	1245
26 Paper & Allied Products	-0.069	0.419	0.000	705	46 Pipelines, Except Natural Gas	-0.015	0.242	0.000	309
07 Agricultural Services	-0.096	0.472	0.000	164	26 Paper & Allied Products	-0.017	0.237	0.000	705
46 Pipelines, Except Natural Gas	-0.101	0.484	0.000	309	17 Construction	-0.018	0.314	0.000	167
10 Metal Mining	-0.116	0.474	0.000	1245	41 Local & Interurban Passenger Transit	-0.025	0.235	0.000	82
67 Holding & Other Investment Offices	-0.118	0.492	0.000	101	07 Agricultural Services	-0.028	0.245	0.000	164
17 Construction	-0.122	1.251	0.000	167	01 Agricultural Production – Crops	-0.030	0.207	0.000	107
49 Electric, Gas, & Sanitary Services	-0.258	1.952	-0.263	2675	12 Coal Mining	-0.030	0.214	0.000	285
12 Coal Mining	-0.310	0.625	-0.202	285	67 Holding & Other Investment Offices	-0.049	0.253	0.000	101

OA Table 15 continued

Panel C. $CCSentiment^{Reg}$ ($\times 10^3$)					Panel D. $CCSentiment^{Phy}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	Median	Obs.
Top-10 Industries					Top-10 Industries				
57 Home Furniture	0.004	0.032	0.000	136	40 Railroad Transport	0.008	0.072	0.000	182
54 Food Stores	0.004	0.049	0.000	215	35 Industrial Machinery & Equipment	0.006	0.095	0.000	2305
59 Miscellaneous	0.001	0.006	0.000	342	30 Rubber & Miscellaneous Plastics Products	0.004	0.033	0.000	568
58 Eating & Drinking Places	0.000	0.060	0.000	196	53 General Merchandise Stores	0.003	0.027	0.000	291
21 Tobacco	0.000	0.000	0.000	85	31 Leather & Leather Products	0.002	0.025	0.000	112
82 Educational Services	-0.001	0.013	0.000	415	37 Transportation Equipment	0.002	0.044	0.000	1401
83 Social Services	-0.001	0.008	0.000	96	25 Furniture & Fixtures	0.002	0.041	0.000	310
56 Apparel & Accessory Stores	-0.001	0.017	0.000	347	15 General Building Contractors	0.001	0.043	0.000	690
60 Depository Institutions	-0.001	0.021	0.000	3585	47 Transportation by Air	0.001	0.021	0.000	574
27 Printing & Publishing	-0.002	0.029	0.000	1309	51 Wholesale Trade – Nondurable Goods	0.001	0.032	0.000	2031
Bottom-10 Industries					Bottom-10 Industries				
34 Fabricated Me	-0.028	0.191	0.000	925	22 Textile Mill Products	-0.004	0.063	0.000	99
76 Miscellaneous Repair Services	-0.031	0.160	0.000	34	55 Automative Dealers & Service Stations	-0.004	0.067	0.000	283
55 Automative Dealers & Service	-0.032	0.186	0.000	283	75 Auto Repair S	-0.005	0.040	0.000	121
33 Primary Metal	-0.033	0.168	0.000	748	29 Petroleum Refining	-0.006	0.042	0.000	685
29 Petroleum Refining	-0.035	0.144	0.000	685	49 Electric, Gas, & Sanitary Services	-0.007	0.060	0.000	2675
17 Construction	-0.044	0.171	0.000	167	10 Metal Mining	-0.007	0.072	0.000	1245
32 Stone, Clay, & Glass Products	-0.052	0.262	0.000	577	26 Paper & Allied Products	-0.010	0.096	0.000	705
12 Coal Mining	-0.056	0.141	0.000	285	01 Agricultural Production – Crops	-0.010	0.058	0.000	107
49 Electric, Gas, & Sanitary Services	-0.164	0.409	0.000	2675	12 Coal Mining	-0.010	0.084	0.000	285
08 Forestry	-0.202	0.394	0.000	27	08 Forestry	-0.021	0.069	0.000	27

OA Table 15 continued

Panel E. $CCRisk$ ($\times 10^3$)					Panel F. $CCRisk^{Opp}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	Median	Obs.
Top-10 Industries					Top-10 Industries				
49 Electric, Gas, & Sanitary Services	0.289	0.558	0.115	2675	49 Electric, Gas, & Sanitary Services	0.130	0.357	0.000	2675
16 Heavy Construction, Except Building	0.118	0.317	0.000	450	75 Auto Repair, Services, & Parking	0.123	0.290	0.000	121
12 Coal Mining	0.115	0.274	0.000	285	16 Heavy Construction, Except Building	0.047	0.180	0.000	450
29 Petroleum Refining	0.069	0.160	0.000	685	37 Transportation Equipment	0.037	0.126	0.000	1401
37 Transportation Equipment	0.067	0.200	0.000	1401	55 Automative Dealers & Service Stations	0.036	0.113	0.000	283
35 Industrial Machinery & Equipment	0.066	0.240	0.000	2305	35 Industrial Machinery & Equipment	0.034	0.145	0.000	2305
87 Engineering & Management Services	0.060	0.190	0.000	1216	34 Fabricated Metal Products	0.033	0.380	0.000	925
36 Electronic & Other Electric Equipment	0.053	0.206	0.000	5896	36 Electronic & Other Electric Equipment	0.029	0.144	0.000	5896
61 Non-Depository Institutions	0.052	0.492	0.000	667	08 Forestry	0.025	0.097	0.000	27
34 Fabricated Metal Products	0.052	0.190	0.000	925	29 Petroleum Refining	0.022	0.083	0.000	685
Bottom-10 Industries					Bottom-10 Industries				
23 Apparel & Oth	0.007	0.045	0.000	194	39 Miscellaneous Manufacturing Industries	0.002	0.022	0.000	121
56 Apparel & Accessory Stores	0.006	0.031	0.000	347	70 Hotels	0.002	0.017	0.000	542
59 Miscellaneous	0.005	0.027	0.000	342	83 Social Services	0.002	0.011	0.000	96
57 Home Furniture	0.005	0.032	0.000	136	78 Motion Pictures	0.002	0.013	0.000	417
78 Motion Pictures	0.003	0.021	0.000	417	21 Tobacco	0.001	0.010	0.000	85
22 Textile Mill Products	0.003	0.021	0.000	99	56 Apparel & Accessory Stores	0.001	0.009	0.000	347
31 Leather & Leather Products	0.003	0.020	0.000	112	59 Miscellaneous	0.001	0.010	0.000	342
53 General Merchandise Stores	0.002	0.017	0.000	291	53 General Merchandise Stores	0.001	0.009	0.000	291
58 Eating & Drinking Places	0.002	0.016	0.000	196	58 Eating & Drinking Places	0.000	0.000	0.000	196
76 Miscellaneous Repair Services	0.000	0.000	0.000	34	76 Miscellaneous Repair Services	0.000	0.000	0.000	34

OA Table 15 continued

Panel G. $CCRisk^{Reg}$ ($\times 10^3$)					Panel H. $CCRisk^{Phy}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	Obs.	Industry (SIC2)	Mean	Std.Dev.	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.

OA Table 16: 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

OA Table 16 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.

OA Table 17: Variance Decomposition of Climate Change Sentiment and Risk

Panel A. Variance Decomposition of Climate Change Sentiment Measures

Variable	$CCSentiment$	$CC\ Sentiment^{Opp}$	$CCSentiment^{Reg}$	$CCSentiment^{Phy}$
	Incremental R-sq.			
Time Fixed Effect	0.1%	0.1%	0.1%	0.0%
Sector Fixed Effect	2.2%	1.7%	5.8%	0.4%
Sector x Time Fixed Effect	1.6%	1.4%	1.3%	1.7%
Country Fixed Effect	0.6%	0.6%	0.5%	0.2%
"Firm Level"	94.5%	92.6%	96.1%	98.1%
Sum	100.0%	100.0%	100.0%	100.0%
	Fraction of variation			
Permanent differences across firms within sectors and countries (Firm Fixed Effect)	51.4%	56.6%	30.0%	44.8%
Variation over time in the identity of firms within sectors and countries most affected by climate change variable (residual)	48.6%	43.4%	70.0%	55.2%
Sum	100.0%	100.0%	100.0%	100.0%

Panel B. Variance Decomposition of Climate Change Risk Measures

Variable	$CCRisk$	$CCRisk^{Opp}$	$CCRisk^{Reg}$	$CCRisk^{Phy}$
	Incremental R-sq.			
Time Fixed Effect	0.2%	0.1%	0.1%	0.0%
Sector Fixed Effect	9.3%	5.3%	2.1%	0.5%
Sector x Time Fixed Effect	1.4%	1.3%	1.3%	1.3%
Country Fixed Effect	0.7%	0.7%	0.4%	0.1%
"Firm Level"	88.5%	92.6%	96.1%	98.1%
Sum	100.0%	100.0%	100.0%	100.0%
	Fraction of variation			
Permanent differences across firms within sectors and countries (Firm Fixed Effect)	34.2%	30.1%	45.1%	17.2%
Variation over time in the identity of firms within sectors and countries most affected by climate change variable (Residual)	65.8%	86.0%	54.9%	82.8%
Sum	100.0%	100.0%	100.0%	100.0%

OA Table 17 continued

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. $CCSentiment$ 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.

OA 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

OA 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

OA 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 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.

OA 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

OA 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. $ISS\ Carbon\ Risk\ Ratings$ 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

OA 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	-0.006	0.003	0.001	-0.007	-0.003	-0.002	-0.000
	(0.45)	(-0.34)	(0.49)	(0.75)	(-0.87)	(-0.66)	(-1.33)	(-1.05)
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

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OA 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 Index developed in Engle et al. (2020) that captures climate change news in the *Wall Street Journal*. $Institutional\,Ownership$ is the ownership by institutional investors. $Mandatory\,ESG\,Disclosure$ is a dummy variable constructed in Krueger et al. (2020) 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

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

	$\Delta\, Tobin's\, Q$ After 2011 (1)	$\Delta\, Tobin's\, Q$ Before 2011 (2)	$\Delta\, Tobin's\, Q$ After 2011 (3)	$\Delta\, Tobin's\, Q$ 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

OA Table 22 continued

Notes: Regressions are estimated at the firm-year level. $\Delta Tobin's Q$ 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 country-year, are in parentheses. *p< .1; **p< .05; ***p< .01.

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