Firm-level Climate Change Exposure

Finance Working Paper N° 686/2020
September 2022

Zacharias Sautner
Frankfurt School of Finance and Management and ECGI

Laurence van Lent
Frankfurt School of Finance and Management

Grigory Vilkov
Frankfurt School of Finance and Management

Ruishen Zhang
Shanghai University of Finance and Economics

ECGI Working Paper Series in Finance

Firm-level Climate Change Exposure

Working Paper N° 686/2020
September 2022

Zacharias Sautner
Laurence van Lent
Grigory Vilkov
Ruishen Zhang

We thank Stefan Nagel, an anonymous associate editor, two referees, Artur Hugon, Marcin Kacperczyk, Bryan Kelly, Kelvin Law, Christian Leuz, Tim Loughran, Quentin Moreau, and Ane Tamayo for helpful comments. We are grateful to Aakash Kalyani for preparing the green jobs dataset and to Markus Schwedeler for sharing his code. Participants at AFA 2022 Meetings, NBER, NYU Stern (PhD Classes in Empirical Household Finance), University of Zurich, University of Dusseldorf, Stockholm Business School, SUFE, Bocconi University, Columbia University, CEIBS, LSE, Xiamen University, Duke Kunshan University, University of Miami, Tingshua University, Dongbei University of Finance and Economics, Chinese University of Hong Kong, and University of Hong Kong provided helpful feedback. Funding for this project was provided by DFG Project ID 403041268 - TRR 266 (Van Lent and Zhang); the Institute for New Economic Thinking (Van Lent); Shanghai Pujiang Program (Zhang); the 111 Project (B18033)(Zhang); and the MOE Project of Key Research Institute of Humanities and Social Science (Zhang). Parts of this project were conducted when Sautner was visiting NOVA School of Business and Economics and UCSD Rady School of Management (funded in part by the Norwegian Finance Initiative). We have read The Journal of Finance disclosure policy. Sautner is a Regular Research Visitor at the ECB. He has no other disclosure to make. Van Lent, Vilkov, and Zhang have no conflicts of interest to disclose

Abstract

We introduce a method that identifies the attention paid by earnings call participants to firms' climate change exposures. The method adapts a machine learning keyword discovery algorithm and captures exposures related to opportunity, physical, and regulatory shocks associated with climate change. The measures are available for more than 10,000 firms from 34 countries between 2002 and 2020. The measures are useful in predicting important real outcomes related to the net-zero transition, notably job creation in disruptive green technologies and green patenting, and they contain information that is priced in options and equity markets.

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

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

Zacharias Sautner*
Professor of Finance
Frankfurt School of Finance and Management, Finance Department
Adickesallee 32-34
60322 Frankfurt am Main, Germany
phone: +49 69 154008 755
e-mail: z.sautner@fs.de

Laurence van Lent
Professor of Accounting and Economics
Frankfurt School of Finance and Management
Adicksallee 32-34
Frankfurt am Main 60322, Germany
phone: +49 69 154008531
e-mail: L.vanLent@fs.de

Grigory Vilkov
Professor of Finance
Frankfurt School of Finance and Management
Adicksallee 32-34
Frankfurt am Main 60322, Germany
phone: +49 (069) 154008-842
e-mail: g.vilkov@fs.de

Ruishen Zhang
Assistant Professor of Accounting
Shanghai University of Finance and Economics, Institute of Accounting and Finance
Guoding Road 777, Yangpu District
Shanghai 200433, China
phone: +86 18637904884
e-mail: zhangruishen@sufe.edu.cn.

*Corresponding Author

Firm-level Climate Change Exposure

ZACHARIAS SAUTNER, LAURENCE VAN LENT, GRIGORY VILKOV,

and RUISHEN ZHANG*

Journal of Finance, forthcoming

ABSTRACT

We introduce a method that identifies the attention paid by earnings call participants to firms' climate change exposures. The method adapts a machine learning keyword discovery algorithm and captures exposures related to opportunity, physical, and regulatory shocks associated with climate change. The measures are available for more than 10,000 firms from 34 countries between 2002 and 2020. The measures are useful in predicting important real outcomes related to the net-zero transition, notably job creation in disruptive green technologies and green patenting, and they contain information that is priced in options and equity markets.

*Zacharias Sautner, Laurence van Lent, and Grigory Vilkov are at Frankfurt School of Finance & Management. Ruishen Zhang is at Shanghai University of Finance and Economics. The climate change exposure data is available at https://doi.org/10.17605/OSF.IO/FD6JQ. We thank Stefan Nagel, an anonymous associate editor, two referees, Artur Hugon, Marcin Kacperczyk, Bryan Kelly, Kelvin Law, Christian Leuz, Tim Loughran, Quentin Moreau, and Ane Tamayo for helpful comments. We are grateful to Aakash Kalyani for preparing the green jobs dataset and to Markus Schwedeler for sharing his code. Participants at AFA 2022 Meetings, NBER, NYU Stern (PhD Classes in Empirical Household Finance), University of Zurich, University of Dusseldorf, Stockholm Business School, SUFE, Bocconi University, Columbia University, CEIBS, LSE, Xiamen University, Duke Kunshan University, University of Miami, Tingshua University, Dongbei University of Finance and Economics, Chinese University of Hong Kong, and University of Hong Kong provided helpful feedback. Funding for this project was provided by DFG Project ID 403041268 - TRR 266 (Van Lent and Zhang); the Institute for New Economic Thinking (Van Lent); Shanghai Pujiang Program (Zhang); the 111 Project (B18033)(Zhang); and the MOE Project of Key Research Institute of Humanities and Social Science (Zhang). Parts of this project were conducted when Sautner was visiting NOVA School of Business and Economics and UCSD Rady School of Management (funded in part by the Norwegian Finance Initiative). We have read *The Journal of Finance* disclosure policy. Sautner is a Regular Research Visitor at the ECB. He has no other disclosure to make. Van Lent, Vilkov, and Zhang have no conflicts of interest to disclose.

Correspondence: Zacharias Sautner, Frankfurt School of Finance & Management, Adickesallee 32-34, 60322 Frankfurt am Main, Germany; e-mail: z.sautner@fs.de.

Climate change will profoundly affect the way business is conducted. Scientists have developed complex models that estimate the effect of greenhouse gas emissions on the global climate. At the same time, little evidence exists of the degree to which climate change impacts jobs, innovation, and risk-sharing in capital markets. One key challenge in estimating these impacts is that is difficult to measure how individual firms are affected by climate change (Giglio, Kelly, and Stroebel (2021)). Specifically, the effects of climate change are multifaceted, originating from multiple sources. While some firms face costs from physical climate changes, others are adversely affected by regulations implemented to combat global warming. At the same time, climate change provides opportunities for some firms (e.g., for those operating in renewable energy, electric cars, or energy storage). It is therefore important to develop disaggregated measures that capture this variation across firms. The measures should also reflect market participants' perceptions, judgments, and estimates about how climate change impacts individual firms. Such information is important to consider in a finance context given the critical role that different market participants play in the resource allocation and price discovery process.

In this paper, we make progress on this challenge by using transcripts of earnings conference calls to construct time-varying measures of how call participants across the globe perceive firms' exposures to different facets of climate change. Earnings calls are key corporate events in which financial analysts listen to management and ask firm officials about material current and future developments relevant to the firm (Hollander, Pronk, and Roelofsen (2010)). We interpret these measures as capturing the attention devoted to climate change topics by financial analysts and management at a given point in time. A benefit of the measures is that they reflect "soft" information originating from information exchanges between managers and analysts.[1]

[1]This feature allows us to provide economic insight beyond that generated by existing firm-level exposure measures based on "hard" information (e.g., carbon emissions, extreme local weather events). The exchanges are not limited to soft information but might also discuss specific quantitative data or

To construct the climate change exposure measures, we build upon recent work using quarterly earnings calls as a source for identifying firms' various risks and opportunities (Hassan et al. (2019, 2021a,b), Jamilov, Rey, and Tahoun (2021), Hassan et al. (2021c)). These studies use the proportion of the conversation during an earnings call that is centered on a particular topic to measure the firm's exposure to that topic. We follow these papers in defining "exposure" to an issue as the share of the conversation in a transcript devoted to that topic.[2] We modify the approach in these papers along two dimensions. Firstly, we address that climate change has multifaceted effects, spanning the issues of physical threats, regulatory interventions, and technological opportunities. Our measures, therefore, encapsulate the market's perception of a firm's exposure to the upside or downside aspects related to climate change. Secondly, studies in computational linguistics note the challenges of identifying "niche languages" that use specific wordings. For climate change, in particular, technical language is pervasive, and the language used varies among policymakers, journalists, and financial market participants (Webersinke et al. (2021)). Hence, using training libraries of authoritative texts to develop a vocabulary that is fine-tuned to the particular climate change language in earnings calls is unlikely to succeed.

Consequently, we introduce a new method that adapts the keyword discovery algorithm proposed in King, Lam, and Roberts (2017) to produce four related sets of climate change bigrams in earnings calls; the first captures broadly defined climate change as-

restate "hard" information in conversational terms. The prior literature provides important insights about the associations between "hard" information and firm-level real and financial outcomes (e.g., Bolton and Kacperczyk (2021b, 2022, 2021a), Ilhan, Sautner, and Vilkov (2021) or De Haas and Popov (2022) for carbon emissions, and Kruttli, Roth Tran, and Watugala (2021), Hong, Li, and Xu (2019), Addoum, Ng, and Ortiz-Bobea (2020), or Pankratz and Schiller (2021) for weather events).

[2] This definition of "exposure" is different from how risk exposure is defined in the asset pricing literature, and our measure is not intended to capture the covariance with aggregate fluctuations). Hassan et al. (2019) discuss the relationship between these two areas of literature.

pects, while the remaining three measures are disaggregated and cover specific climate change "topics:" specifically, opportunity, physical (e.g., sea level rises), and regulatory (e.g., carbon taxes, cap and trade markets) shocks. We employ these four sets of bigrams for each transcript to construct firm-level measures reflecting call participants' topical attention. The algorithm only requires human input to specify a shortlist of initial keywords associated with climate change. The measures have an intuitive interpretation: they count the frequency of specific climate change bigrams in a transcript, scaled by the number of bigrams.[3] Our sample covers data from over 10,000 firms in 34 countries between the years of 2002 and 2020.

A series of validation exercises verify our methodology. Firstly, we consider the face validity of the climate change bigrams. Secondly, we follow the practice set in Baker et al. (2016) and perform a structured human audit in which 18 graduate students independently coded over 2,000 transcript text fragments. Both exercises support the idea that our algorithm reliably captures bigrams identifying climate change discussions. Thirdly, our exposure measures are robust to excluding one keyword at a time from the initial keywords list. Fourthly, our keyword search-based measures substantially improve the identification of climate change discussions relative to an alternative approach using the initial keywords only. And fifthly, we find plausible industry patterns in the exposure measures. When we aggregate exposure to the industry level, the sector with the highest overall exposure is Electric, Gas, & Sanitary Services (utilities), followed by Construction (top-ranked firms build power generation systems or solar projects) and Transportation Equipment (top-ranked firms build fuel-cell or zero-emission vehicles). Utilities top the exposure ranking for opportunity and regulatory shocks, which signifies that this sector

[3]We also 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)), and "risk" measures, which count the relative frequency of climate change bigrams mentioned in the same sentence as the words "risk," "uncertainty," or their synonyms.

faces opportunities (e.g., renewable energy) *and* regulatory risks (e.g., carbon taxes).[4]

Our results reveal a sizeable within-industry variation for all measures; hence, firms benefit or suffer to various degrees from climate change. A case in point is the comparison between TotalEnergies and ExxonMobil. While TotalEnergies scores only slightly lower than ExxonMobil for its regulatory exposure, TotalEnergies scores a factor of four higher in terms of measured opportunities. This divergence in prospects is consistent with a broader perception about how differently these firms embrace renewable energy and the net-zero transition into their business models (Pickl (2019)).

In a final validity check, climate exposure positively correlates with carbon emissions and Engle et al. (2020)'s (EGKLS henceforth) index of public climate change attention. The association with emissions stems from regulatory and opportunity exposure (since physical exposure is unrelated to emissions).[5] The effect of public attention also originates from positive associations of EGKLS's index with opportunity and regulatory exposure.

We apply our measures to learn about the nature of climate change exposure for our sample of firms. Perhaps surprisingly, as climate change is often seen as an aggregate risk factor that emanates from global developments in the physical climate, its impact within a sector is far from uniform. Based on a variance analysis that separates the relative contributions of aggregate, sectoral, and firm-level exposure by including the corresponding sets of fixed effects, between 70 and 97% of the variation in the exposure

[4]That firms with heightened regulatory risks also exhibit climate-related opportunities is consistent with Cohen, Gurun, and Nguyen (2021), who document that several major electricity, oil, and gas firms are not only large CO_2 emitters, but also innovators in green technologies. This finding is consistent with how analysts view sectors with high regulatory risks (e.g., "Morgan Stanley: 'Second wave of renewables' to drive 70 GW of coal retirements," *S&P Global Market Intelligence*, December 20, 2019).

[5]This result may also reflect that some firms' emissions provides opportunities by supporting the transition to a greener economy (e.g., producers of building materials that make houses more energy-efficient). Such "enabling activities" are also explicitly included in the EU Taxonomy, which identifies activities that help reach the EU's climate targets.

measures plays out at the firm level. Only half of this firm-level variation is persistent, suggesting that firms within an industry are exposed to climate change over time to varying degrees. Thus, the effects of climate change on firms are heterogeneous even within an industry. This result is consistent with the idea that many factors that likely affect a firm's ability to adapt to a greener economy exhibit large firm-level components (e.g., managerial skill, financing constraints).

We interpret the large share of firm-level variance as capturing economically meaningful heterogeneity and argue that a firm's idiosyncratic climate change exposure is the key driver of it. That being said, a plausible alternative is that part of the variation reflects idiosyncratic measurement error. A set of tests dispel this alternative for several reasons. Firstly, as discussed below, we report robust associations between our measures and green job creation, green innovation, and risk-related outcomes. Secondly, following Hassan et al. (2019), we directly quantify the amount of measurement error contained in the firm-level variation. Approximately 5 to 10% of the variation in measured exposure is attributable to measurement error. The implied measurement error at the firm level is about two percentage points higher than that in the overall variation. Although we interpret these results with due caution, they suggest that measurement error in the firm-level dimension is higher than in the overall panel, but only modestly so.

Having bolstered the confidence that the firm-level variation in measured climate change exposure is meaningful, we apply it to four real and financial market outcomes. In the first two applications, we demonstrate that climate change exposure predicts green technology hiring and green patents, two key drivers of the low-carbon transition. Using data compiled from Burning Glass by Bloom et al. (2021), we establish that firms with higher measured climate exposures create more jobs in disruptive green technologies over the subsequent year.[6] A one-standard-deviation increase in climate change exposure is

[6]Our data do not encapsulate all jobs potentially related to climate change, but they identify job

associated with a 109% increase in green jobs in the following year. This overall effect originates from more job creation at firms exhibiting higher measured opportunity and regulatory exposures.

The results for green tech job creation extend to green patenting. A one-standard-deviation increase in climate change exposure is associated with a 72% rise in the number of green patents in the following year. Once more, this finding stems from firms with higher opportunity and regulatory exposure. High-exposure firms are not simply recruiting more across fields. They are also not more innovative, in general. In fact, firms with higher exposure hire less in non-green tech areas and generate fewer non-green patents.

The remaining two applications relate climate change exposure to financial market outcomes. Firstly, measured exposure is related to risks and risk premiums in the options market. Such relationships are plausible, as policy uncertainty surrounding regulation, including climate policy uncertainty, is priced in options (Kelly, Pastor, and Veronesi (2016), Ilhan, Sautner, and Vilkov (2021)). Likewise, there is plenty of uncertainty surrounding green technologies or renewable energy investments. Realizing these opportunities leads to significant gains, if successful, or large losses, if unsuccessful. Therefore, it is plausible that measured exposure relates to investors' propensity to hedge extreme climate risks and/or gamble on climate outcomes. Indeed, for options written on stocks with high overall exposure, the tail regions are relatively more expensive. Effects are magnified at firms with high opportunity exposure, for which investors are willing to pay a (variance risk) premium. In comparison, effects are smaller, but still statistically significant, for firms with high regulatory exposure. This finding corroborates that some firms with high regulatory exposure face downside risks and upside potential (due to their innovation activity).

postings with the potential to make a lasting and meaningful real impact, as Bloom et al. (2021) only consider job creation in "disruptive" technologies (e.g., solar or battery technology).

Secondly, we document the conditional pricing of a factor that reflects innovations to the aggregate level of climate change exposure. Firms with higher betas to this factor face higher uncertainty related to future developments in climate-related areas and, as a result, earn higher returns.[7] Our estimation applies the approach of Gagliardini, Ossola, and Scaillet (2016), which performs well when—as in our case—the cross-section is large relative to the time-series. We obtain a positive average conditional risk premium on the factor, and, more importantly, find large time-series variability in the risk premium.[8]

Our keyword discovery approach of extracting climate-related information from text offers an alternative approach to contemporaneous papers that try to accomplish the same task by relying on other advances in natural language processing (NLP). All of this work, including ours, centers on the understanding that standard NLP methods cannot deal well with "niche languages," more specifically, specialized, highly technical vocabulary that varies substantially by textual source (Webersinke et al. (2021),Varini et al. (2020)). These frictions are exacerbated when the wordings associated with a topic are complex, ambiguous, and fast moving. A promising approach among these alternatives is to use pre-trained language models to learn word patterns in the language. When this pre-training is implemented in the specific domain of interest (e.g., climate change), rather than using large generic corpora, some promising results have been obtained (Kölbel et al. (2022), Bingler et al. (2022)). Work is ongoing on these problems, and ultimately, which approach works best in the climate finance context is an empirical matter.

[7] Our primary objective is to show that climate attention in earnings calls is linked to systematic risk, with shocks to such attention being priced in the cross-section. We do not want to propose a new factor to be added to the factor zoo, and do not try to use a conditional model framework to explain asset pricing anomalies (Lewellen and Nagel (2006)).

[8] A caveat of all four applications is that any evidence of our measures' ability to predict real and financial outcomes is a form of success only if the true relationship exists in the data. Hence, we face the usual joint-hypothesis problem between the quality of our measures and the true economic model generating the data.

A valid question is whether or not our approach delivers meaningful gains over an alternative, off-the-shelves approach. Our main argument is that keyword discovery is useful when the language of interest is not common. We illustrate this claim by constructing, for comparison purposes, alternative exposure measures using a list of pre-specified keywords from EGKLS. These keywords appear more frequently in earnings calls than the bigrams we identify, probably because EGKLS's set also contains unigrams and more general terms. However, several of EGKLS's unigrams are part of our top-100 list of bigrams, and exposure measures based on the pre-specified keywords correlate positively with our measures. Beyond these correlations, a question is why the approaches differ. As mentioned above, our measures have the benefit of capturing the context-specific jargon used in specialized economic environments (earnings calls), while an approach using pre-specified keywords better captures broader discussions (e.g., in news media in case of EGKLS's keywords). In addition, our approach adjusts the vocabulary over time while using pre-specified keywords fixes this vocabulary ex ante.[9] Finally, especially for the topics-based measures, it is easier to identify initial seed bigrams than develop keywords from authoritative texts.

Most closely related to our paper is the contemporaneous work by Li et al. (2021) (LSTY henceforth), who also use earnings calls to identify climate risks. We diverge from their work in terms of our method, focus, and sample. More specifically, LSTY use a pre-specified training library to identify climate risk words, which, we argue, is unlikely to uncover the exact language used in earnings calls to discuss climate change (see also Varini et al. (2020)). In addition, while LSTY focus on physical and regulatory risks among U.S. firms, we provide a more comprehensive analysis based on a global sample and include the opportunity impacts of climate change. Based on a textual analysis of

[9]Time-series variation in true (unobservable) climate change exposure, especially over long horizons, is more likely to be picked up by such an "evolutionary" approach. Indeed, the selection of pre-specified keywords may become obsolete over time with changing technologies or climate change concerns.

10K reports, Baz et al. (2022) document that firms with more *regulatory* climate change exposure experience positive stock return effects after the 2016 Trump election.

Since making our data available, our measures have been related to a series of real and financial outcomes. This "out-of-sample evidence" is reassuring, as it indicates that the measures capture meaningful variation across firms and do not reflect mostly noise. On the real side, as in our paper, von Schickfus (2021) illustrates more green patenting when the overall and opportunity measure are higher, and Li, Lin, and Lin (2022) show that the overall measure predicts depressed *overall* innovation. Furthermore, our overall measure positively relates to cash holdings (Heo (2021)) and explains how strongly U.S. firms' emissions declined in response to the EPA's 2010 Greenhouse Gas Reporting Program (Tomar (2021)). Our physical measure is related to physical risk disclosure in 8K filings (Gostlow (2021)), and the opportunity measure relates to firms' carbon risk management (Duong et al. (2021)). On the financial side, our physical measure is associated with lower leverage after the Paris Agreement (Ginglinger and Moreau (2022)). Mueller and Sfrappini (2022) show that after regulatory climate risks become salient, bank lending is skewed towards firms with high regulatory exposure in the U.S., but away from such firms in the EU. We provide additional evidence in Sautner et al. (2022) that our measures are priced in equity markets, and Kölbel et al. (2022) show that the overall measure is negatively associated with CDS spreads after the Paris Agreement. Di Giuli et al. (2022) find that investors' propensity to vote for climate proposals after experiencing hot temperatures is higher at firms with more overall climate change exposure. Heath et al. (2022) find that SRI funds invest less in firms with higher overall climate change exposure. Our keyword dictionary is used by Hail, Kim, and Zhang (2021).

The rest of the paper proceeds as follows. Section I describes the data. Section II presents the method to quantify firm-level climate change exposure. Section III validates the exposure measures. Section IV presents a variance decomposition of the exposure measures and addresses measurement error. Section V presents four applications of the exposure measures. Section VI concludes.

I. Data

A. Data on Earnings Conference Calls

We use transcripts of quarterly earnings calls held by publicly listed firms to construct time-varying measures of the attention paid by call participants to firm-level climate change exposure. The measures are constructed using the entire earnings call, including both the management presentation and the Q&A session with analysts.[10] The transcripts are collected from the Refinitiv Eikon database. We use the complete set of English-language transcripts from the year 2002 to 2020. Unless indicated otherwise, as most of our other data vary at the year level, we average quarterly transcript-based measures for each firm. We exclude countries with 150 or less firm-year observations and drop SIC codes 9900-9999 ("Non-classifiable"). Our final sample includes 86,152 firm-year observations from 10,673 firms headquartered in 34 countries. Variable definitions are presented in Appendix A.[11]

B. Data on Carbon Emissions

Some tests use data on carbon emissions (*Total Emissions*), calculated as the sum of Scope 1 and Scope 2 emissions, from S&P Global Trucost. It includes emissions reported

[10] We also provide tests based on the measured exposure constructed from only the Q&A session. The Q&A part is less scripted and may be less subject to strategic disclosure incentives than the presentation part. In some calls, analysts ask no questions (and we would calculate a zero climate change exposure score). However, zero question calls are a non-random event, and treating these calls as if the firm is unexposed to climate change likely introduces bias (Chen et al. (2014).)

[11] Table IA.I in the Internet Appendix provides the distribution of firm-years across countries. The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

by the firms and emissions estimated by Trucost. We use emission levels, rather than intensities, as emission levels are associated with a risk premium (Bolton and Kacperczyk (2021b, 2022)), the prime target of policy and investor initiatives aiming to achieve net-zero emissions, and directly linked to carbon budgets (Bolton, Kacperczyk, and Samama (2021)). Further, many firms have witnessed strong investor opposition on reporting emission intensities. To link the emissions data with our sample firms, we apply a series of matching variables based on the following order: (i) GVKEYs, (ii) ISINs, (iii) exact names, (iv) fuzzy names, and (v) tickers plus the first two ISIN digits. We can match 33,789 firm-years with the emissions data (4,999 unique firms from 34 countries between 2004 and 2020).[12]

C. Data on Public Attention to Climate Change

We borrow an index developed by EGKLS to capture how public climate change attention varies in the time-series. *WSJ CC News Index* is constructed by measuring news about climate change in the *Wall Street Journal* (*WSJ*). To quantify the intensity of climate news coverage, EGKLS compare the *WSJ*'s news content to a corpus of authoritative texts on climate change. The resultant measure reflects the fraction of the *WSJ* dedicated to the topic of climate change each day (we use average annual values). For our sample, *WSJ CC News Index* is available from 2002 to 2017.

D. Data on Green Technology Jobs

Job data related to important green technologies is from Bloom et al. (2021). These authors use a textual analysis to identify 29 disruptive technologies over the past decades,

[12] Table IA.II illustrates that Trucost data coverage is higher for firm-years with higher climate change exposure, larger, more profitable, and less-R&D intense firms, and non-U.S. firms. The higher climate change exposure scores are expected given that Trucost caters to clients in need of climate risk data (especially risks related to emissions).

of which four are broadly related to climate change ("hybrid vehicle electric car," "lithium battery," "solar power," and "fracking"). Our data from Bloom et al. (2021) contain online job postings by firms related to these four technologies, and we label the jobs related to these technologies as "green tech jobs."[13] The data do not encapsulate all jobs potentially related to climate change, but do identify those green jobs that have, by Bloom et al. (2021)'s construction, a lasting and meaningful ("disruptive") real impact. Bloom et al. (2021) obtained these data from Burning Glass (BG), which aggregates online job postings using "spider bots" from job boards or employer websites.[14] We match these data by GVKEY and year. Jobs data are available for U.S. firms for 2007 and 2010 to 2020.

#Green Tech Jobs is the number of postings for disruptive green tech jobs in a firm-year. We assume no green tech job was posted if a firm-year does not indicate disruptive green tech job creation in the BG database. (The results are robust to only considering firm-years within the BG database; many firm-years in BG also show zero green tech postings). Some tests use *#Non-Green Tech Jobs*, the number of job postings related to non-green disruptive technologies in a firm-year. We observe disruptive green job postings in 5.4% of firm-years and conditional on *#Green Tech Jobs* being non-zero, the average (median) number of green tech jobs is 38 (3). The top-5 firms in the cumulative count of new green tech jobs include Tesla, Sunrun, First Solar, Sunpower Corp, and Viviant Solar.

[13] It is unclear ex ante whether fracking has positive or adverse environmental effects. More specifically, Acemoglu et al. (2019) argue that shale gas has the short-term benefit of lower emissions, when compared to conventional fossil fuels. However, the shale gas boom may lead to less innovation in other emission-reducing technologies in the long-run. Furthermore, fracking has negative climate effects, due to emission leakage. Our results are robust when we exclude fracking jobs.

[14] BG data have recently also been used by Darendeli, Law, and Shen (2021) to measure green hiring. Campello, Gao, and Xu (2021) also use BG data, though not in a climate context.

E. Data on Green Patents

To identify green patents, we collect patent data from the Google Patents (GP) database. This database is also used by Kogan et al. (2017) and Kelly et al. (2021). To identify "green" patents, we follow Cohen, Gurun, and Nguyen (2021) and apply an OECD classification that identifies patents with the potential to address environmental problems. A description of how the OECD classifies patents into technology groups is provided by Haščič and Migotto (2015). Green patents include patents on emission abatement technologies, renewable energy, and energy storage. As in Kogan et al. (2017), we use name matching to match patent assignee names to our firms.[15] Patent data is available for U.S. firms from 2002 to 2019 (GP coverage for 2020 was still limited at the time of writing).

#Green Patents is the number of green patents filed in a firm-year. We assume that no green patenting occurred if we are unable to identify a green patent in GP for a firm-year (results are robust to relaxing this assumption). Consistent with Acemoglu et al. (2019), new green patents are relatively rare—consequently, we only observe green patenting in 1.4% of firm-years. However, the distribution is highly skewed. If we consider observations within GP, then green patenting is observed in 15% of firm-years. Conditional on green patenting being non-zero, the average (median) number of green patents equals 8.5 (2). The top green patent producer is Caterpillar, with 1,364 green patents over the sample period.[16] We also use the total number of non-green patents filed (*#Non-Green Patents*).

[15]We track the timing of an invention by matching patents using the priority year, that is, the effective date of a patent filing (De Haas and Popov (2022)). While the "filing date" is when a patent application is filed at the patent office, the "priority date" is when the novelty of an invention is established.

[16]Caterpillar traditionally manufactured diesel engines and mining equipment, but moved into selling photovoltaic or energy storage technology. The firm also ranks in the top-10 in Cohen, Gurun, and Nguyen (2021)'s sample; the slight ranking divergence is due to different sample periods.

F. *Data on Risks and Risk Premiums in the Options Market*

Data on option-implied variables are from the Volatility Surface File of Ivy DB OptionMetrics. We focus these tests on S&P500 firms, for which data on liquid options is available. We match options data through the historical CUSIP link of OptionMetrics. We construct six measures: implied variance ($IVar$), implied skewness ($ISkew$), implied kurtosis ($IKurt$), implied volatility slopes ($SlopeD$ and $SlopeU$), and variance risk premium (VRP). The variable construction process is detailed in Internet Appendix B. The high frequency of the option-implied measures allows us to use quarterly values of $CCExposure$.[17]

G. *Data on Risk Premiums in the Equity Market*

Our tests examining the climate change exposure factor use monthly data on the standard factors from Ken French's data library. Term and default spread data are from the St. Louis Fed's FRED library. The term spread is the difference between the ten-year and three-month Treasury constant maturity data series (variable *T10Y3MM*). The default spread is the difference between the Baa and Aaa corporate bond yield (*BAA10YM* and *AAA10YM*). Book-to-market ratio data (defined in log terms as in Fama and French (2008)) is from Compustat North America.Term and default spreads and book-to-market ratio for each firm are centered and standardized in the time-series, and then used as instruments for conditional risk premium estimation. We restrict the risk premium tests to S&P500 firms with more than 28 monthly returns (out of 228) during our sample period.

[17] To avoid look-ahead bias, we match quarterly exposure values covering earnings calls in quarter t (typically discusses quarter $t-1$) with option-implied measures from the last day of quarter t.

H. Financial Statement Data

Data on firm financial variables (e.g., total assets, debt, capex, R&D or cash holdings) are from Compustat North America and Compustat Global.

II. Quantifying Firm-level Exposure to Climate Change

A. Discovery of Climate Change Bigrams

To quantify exposure to climate change, we build on Hassan et al. (2019, 2021a,b). Extracting climate-related information from text sources is challenging (Webersinke et al. (2021)). Methods using training libraries or pre-specified word lists do not cope well with the niche language employed to discuss climate change.[18] In addition, earnings calls discuss climate change in conjunction with topics including regulation, tax credits, technological breakthroughs, and performance. This results in substantial ambiguity about when the discussion is genuinely about climate change. Finally, the vocabulary used to discuss climate change is fast moving, changing to reflect shifting opinions about how climate change matters, what regulations are proposed, or what innovations are developed.

To address these challenges, we adapt the keyword discovery algorithm proposed in King, Lam, and Roberts (2017).[19] This algorithm does not need a comprehensive "climate change" training library; instead, it only requires a small set of "initial" bigrams (listed in Table IA.III). These initial bigrams are chosen because they unambiguously relate to climate change. The algorithm then uses these initial bigrams to search for new bigrams that also likely indicate climate change conversation and it searches di-

[18] That said, researchers have used the SEC Climate Disclosure Search tool, which looks for pre-specified keywords in SEC filings, to develop a measure for climate risk (Berkman, Jona, and Soderstrom (2019)).

[19] Details, including how we define the set of initial bigrams, are presented in Internet Appendix A.

rectly in the transcripts. Because each initial bigram is connected to a specific group of new bigrams discovered through the search algorithm, one can easily decompose the measure of climate change exposure into its constituent parts based on the presence of these bigrams. The initial bigrams allow the algorithm to identify sentences of interest that unambiguously talk about climate change. It then extracts features by relying on supervised learning methods. Features are bigrams beyond the initial set predicting climate change from the identified sentences of interest. Finally, the algorithm constructs a model predicting whether or not a sentence is related to climate change. We apply this prediction model to sentences that do not include any initial bigrams and then assess whether or not the predicted sentences are climate-related. To discover new climate change bigrams, we reverse-engineer the ML process and trace back the bigrams that best discriminate climate-change-related sentences from other sentences. The resultant set of climate change bigrams $\mathbb{C}$ includes the initial bigrams and the newly identified bigrams.

That our approach generates meaningful climate change bigrams based on the initial bigrams is helpful for several reasons. Firstly, it extends the rather broadly specified initial bigrams into more specialized word combinations.[20] Secondly, $\mathbb{C}$ includes the names of several power stations and wind farms (e.g., "kibby wind" or "coughlin power"), which are of interest to call participants that discuss the climate change exposure of these facilities' operators. These bigrams illustrate the challenge of using training libraries or pre-specified word lists to identify climate change talk; few researchers have the detailed field knowledge to recognize the relationship between these words and climate change.

Our approach allows us to adapt the bigram-searching algorithm to discover three unique sets of bigrams from $\mathbb{C}$ that capture opportunity, regulatory, and physical climate "shocks." To this end, we feed a set of initial bigrams reflecting these three topics to

[20]For example, "rooftop solar" and "photovoltaic panel" come from the initial bigram "solar energy," while "nuclear power" or "event fukushima" come from "renewable energy;" and "tesla battery" and "hybrid plug" originate from "electric vehicle."

the searching algorithm. We then allow the algorithm to discover bigrams related to the topic of interest. Table IA.IV lists the initial bigrams used for the topic search. We construct new initial bigrams for these topics by hand-picking appropriate bigrams from the top-500 bigrams discovered after the first generic, non-topic specific, bigram search. We then re-perform the searching algorithm to find a broader set of bigrams for each topic. As the topics-based algorithm yields some general climate change bigrams, we drop bigrams appearing in more than one topic to guarantee that we do not have overlapping topic measures. Lastly, we take the intersection between $\mathbb{C}$ and each set of topic bigrams to obtain the sets of opportunity, regulatory, and physical climate change bigrams (i.e., $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$), respectively.

B. Construction of Climate Change Exposure Measures

Using the bigram sets, we construct measures of climate change exposure for each transcript. We interpret these measures as capturing the attention devoted to climate change topics by call participants at a point in time, rather than as measures of fundamental exposure. We use the broad set of climate change bigrams $\mathbb{C}$ to illustrate how we construct these measures. The topic measures are constructed analogously; we simply replace $\mathbb{C}$ with the bigrams that relate to the corresponding topic.

We construct an overall exposure measure, $CCExposure$, based on how frequently the specified bigrams appear in a transcript. This involves taking the set of climate bigrams $\mathbb{C}$ to the transcript of firm i in quarter t and counting the frequency of these bigrams. To account for the call length, we scale the count by the number of bigrams in the transcript:

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

where $b = 0, 1, ..., B_{i,t}$ are the bigrams in the earnings call transcripts of firm i in quarter

t and where $1[\cdot]$ is the indicator function. We create an annual measure for each firm by averaging the quarterly measures. We produce exposure measures from $\mathbb{C}^{Opp}$, $\mathbb{C}^{Reg}$, and $\mathbb{C}^{Phy}$, respectively, by scoring each transcript using the same method. We label the topics-based measures as $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$.

Some of our tests use two refinements. In the first refinement, we create two sentiment measures by counting the number of climate change bigrams after conditioning on the presence of the positive or negative tone words in Loughran and McDonald (2011):

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

where S represents the sentence containing bigrams $b = 0, 1, ..., B_{i,t}$ and where $\mathcal{T}^{Pos/Neg}(b)$ assigns sentiment to each bigram b:[21]

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

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

In the second refinement, we construct a measure of risk by counting the relative frequency of the climate change bigrams mentioned in the same sentence with the words

[21] Though not used in this paper, we also combine both sentiment measures into an overall measure by counting the climate change bigrams after conditioning on the presence of positive and negative tone words:

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

where $\mathcal{T}(b) = 1$ (-1) if b has a positive (negative) tone; and 0 if otherwise.

"risk," "uncertainty," or their synonyms:

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

where r contains the words "risk," "uncertainty," or a synonym.

The exposure measures do not adjust for the differences in the importance or typical frequencies of individual bigrams. For robustness, we account for such differences by constructing measures that weigh each bigram with a score reflecting the bigram's representativeness for climate discussions. We do this so that common terms that appear in most transcripts receive low scores (they are less informative about a call's content), as do rare terms in a given transcript (they have low text frequency). This approach follows Hassan et al. (2019), Gentzkow, Kelly, and Taddy (2019) or Engle et al. (2020) and is commonly referred as "term frequency–inverse document frequency" (TFIDF). Formally:

$$CCExposure_{i,t}^{TFIDF} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} \left(1[b \in \mathbb{C}] \times log(\frac{N_{\mathbb{T}}}{f_{b,\mathbb{T}}})\right), \tag{4}$$

where $N_{\mathbb{T}}$ refers to the number of transcripts and $f_{b,\mathbb{T}}$ to the number of transcripts where bigram b appears. Therefore, a bigram appearing in many transcripts has a low weight when calculating the TFIDF score, and—in the extreme case—if one bigram appears in every transcript, it receives a zero weight ($log(\frac{N_{\mathbb{T}}}{f_{b,\mathbb{T}}}) = 0$).

Table I reports summary statistics of the exposure measures (for purposes of exposition, the measures are multiplied by 10^3).[22] Table IA.V illustrates the correlations across the exposure measures. A few correlations deserve further comment. The correlation between $CCExposure^{Reg}$ and $CCExposure^{Opp}$ is positive at 33%, and $CCExposure^{Phy}$ is

[22]The magnitudes of $CCExposure^{TFIDF}$ are larger than those of $CCExposure$ as the inverse document frequency of the climate change bigrams can be much larger than one (the document frequencies of the climate change bigrams are much smaller than the total number of transcripts).

largely unrelated to $CCExposure^{Reg}$ and $CCExposure^{Opp}$. In addition, the correlations between $CCExposure$ and $CCExposure^{TFIDF}$ is 99.7%.

Insert Table I about here.

Tables IA.VI to IA.VIII report the sample distribution at the earnings-call (transcript) level across countries, years, and industries. We report the distributions for all sampled earnings calls and for those calls with non-zero climate change exposure. The tables show meaningful proportions of calls with non-zero climate change exposure across all three sample cuts; transcripts with $CCExposure > 0$ are not concentrated in certain countries, years or industries. Our analysis does not make use of a binary indicator for whether or not $CCExposure$ is non-zero, but instead uses a continuous measure.

III. Validation

A. *Validation at the Bigram Level*

A.1. Face Validity of Climate Change Bigrams

We validate our exposure measures using a multi-pronged approach. First, we consider the bigrams' face validity. Table II lists the 100 highest-frequency bigrams in $\mathbb{C}$. The top bigrams associated with $CCExposure$ capture aspects of the opportunities and risks associated with climate change. Top bigrams include opportunity-related word-pairs (e.g., "battery power," "new energy") but also include risk-related terms (e.g., "environmental concern," "extreme weather").

Insert Table II about here.

Table IA.IX considers the three topics-based measures. When we use for the construction of $CCExposure^{Opp}$ initial bigrams such as "wind power," or "solar energy," we find several new bigrams that refer to new (green) technologies (e.g., "solar pv," "carbon free") (Panel A). Several word combinations are linked to developments in "electric vehicles," including "charge infrastructure" and "battery electric." With respect to $CCExposure^{Reg}$ (Panel B), when we use initial bigrams "carbon tax," "air pollution," or "air quality", terms reminiscent of climate-related regulatory interventions, we discover bigrams that explicitly include the word "regulation" or its synonyms (e.g., "control regulation," "energy regulatory," "environmental standard"). Turning to the top bigrams for $CCExposure^{Phy}$ (Panel C), we use initial bigrams such as "natural hazard" or "sea level" to identify word pairs intuitively linked to physical climate aspects (e.g., "area florida," "ice control," "large desalination").

For the ten highest scoring firms on $CCExposure$, Table IA.X provides "snippets." These snippets are text fragments taken from the point in the transcript that the algorithm identifies as the moment when the participants discuss climate issues. Consider Ocean Power Technologies, a U.S. firm that turns ocean wave power into electricity for offshore applications. In its 2008Q4 call, bigrams such as "energy requirement," "powerbuoy wave," "wave condition," and "wave power" were heavily featured. In the top snippet, participants discuss the increased demand for the firm's trademark technology (the PowerBuoy®) due to heightened attention to renewable energy. Not surprisingly, high scoring firms are involved in energy production or the broader energy infrastructure. Indeed, when the call participants of ECOtality use climate change bigrams, they discuss how charging infrastructures are central to advancing zero-emissions transportation.

A.2. Audit Study Based on Human Reading

We developed a two-stage snippet-based audit to evaluate the scoring of our algorithm (Baker, Bloom, and Davis (2016), Hassan et al. (2019)). While our algorithm should be judged in the context of the entire transcript, rather than assessing a single snippet (albeit the highest scoring), a snippet-based audit, instead of using the full transcripts, improves our ability to sample across a large number of transcripts. In the first stage, we define a snippet as the ten sentences around the climate change bigram with the highest text frequency in a transcript. For transcripts with $CCExposure$=0, we randomly choose a snippet of ten consecutive sentences for the audit. In our pilot study, each of the authors independently coded 250 identical and randomly selected snippets using a binary coding scheme. The coding used the variable $CCAudit$, which equals one if the rater classifies the text as providing evidence of climate change exposure, and 0 otherwise. In addition, we recorded for each snippet a *Coding Confidence*, ranging from 3 (the rater is highly confident that their coding is correct) to 1 ("hard calls"). We identified some slight coding differences between the authors and resolved discrepancies. Based on this iterative procedure, we developed a detailed guide with definitions of what text should be coded as climate change exposure and which snippets should not qualify as such. The audit guide describes examples of snippets and offers interpretations and suggested coding to help the raters solve complex cases in the audit process. We then instructed two graduate students based on the audit guide and asked them to audit the same 250 snippets the author team coded to assess any remaining inconsistencies.

In the second stage, we recruited 19 graduate students to each independently code 250 new snippets from the audit universe. Together they assessed 2,090 unique snippets.[23] Auditors received training based on the audit guide. The snippets were partially overlapping to allow us to conduct some inter-rater correspondence tests. Our goal is to verify the information content of $CCExposure$ at various points of its distribution. Following Hassan et al. (2019), we create portfolios with the same number of transcripts based on their percentile of the $CCExposure$ distribution. We then count the number of transcripts at that percentile that the auditors rated as $CCAudit$=1 (i.e., the snippet is

[23]We first sorted all transcripts with non-zero $CCExposure$ into deciles. Then, we randomly selected ten snippets from each decile and another ten from $CCExposure$=0 transcripts for each sample year.

classified as containing a clear discussion of a firm's climate change exposure). We count 310 true positives out of 339 snippets (91% correct positives) in the top-decile portfolio (transcripts with the highest value of $CCExposure$). The rate of correct positives declines almost linearly as we move to the median and bottom portfolios. This is displayed in Figure 1, which plots the relationship between (the predicted probability of) true positives (as judged by the human reading) at each decile and the median percentile score of $CCExposure$ at that percentile. The association is positive and nearly linear, as would be expected if our algorithm reliably identifies climate change discussions.[24]

Insert Figure 1 about here.

A.3. Comparison with Approach Using Pre-Specified Keywords

We construct alternative exposure measures from a list of pre-specified climate change keywords to compare these measures with those produced by our algorithm. To obtain such a list, we use the set of unique stemmed unigrams and bigrams $\mathbb{C}^{EGKLS}$ used by EGKLS to build their time-varying, news-based index of climate change attention. These keywords originate from 74 authoritative texts . To create $CCExposure^{EGKLS}$, we replace $\mathbb{C}$ with $\mathbb{C}^{EGKLS}$ and recompute the relative frequency with which the alternative terms appear in the transcripts. We construct a frequency-unweighted and a TFIDF version, denoted as $CCExposure^{EGKLS-EW}$ or $CCExposure^{EGKLS-TFIDF}$, respectively.

Table IA.XI illustrates that the unigrams and bigrams in $\mathbb{C}^{EGKLS}$ appear more frequently in earnings calls than the bigrams in $\mathbb{C}$. This finding is unsurprising as $\mathbb{C}^{EGKLS}$

[24]These findings suggest that our algorithm correctly identifies climate change text, even at relatively low $CCExposure$ scores. A benchmark is provided in Hassan et al. (2019), where the number of correct positives reduces to below five out of 20 at the 90th percentile of their text-based political risk score. Weighting observations by *Coding Confidence* does not materially change our findings.

includes more unigrams and more general terms (the top-3 bigrams are "market," "increase," and "time"). Using unigrams, rather than bigrams, trades off the higher likelihood of a given term occurring in a text, with the higher probability of a false positive; that is, wrongly classifying a fragment as climate-change text (van Zaanen and Kanters (2010)). Several of the unigrams in $\mathbb{C}^{EGKLS}$ are part of the top-100 bigrams in $\mathbb{C}$ (e.g., "carbon," "energy," or "water"). As would be expected from Table IA.XI, the mean values of both alternative exposure measures (Table IA.XII, Panel A) are larger than those of $CCExposure$. Hence, larger parts of the earnings calls are classified as discussing climate topics if we use $\mathbb{C}^{EGKLS}$ instead of $\mathbb{C}$. At the same time, Table XII, Panel B, indicates that the measures correlate positively with $CCExposure$. The correlation table illustrates that our and the alternative measures yield more similar assessments when the public pays close attention to climate change (*WSJ CC News Index* is in the top quartile). A reason could be that at times when the *WSJ* devotes a lot of space to climate topics, terms from a more general climate library (on which the index and pre-specified keywords measures build) become more commonly used in earnings calls. Intuitively, media attention might homogenize the language used to talk about climate change. When the media pivots to other events, the vocabulary likely used to discuss climate change in earnings calls becomes more idiosyncratic again. Such instances are plausibly better reflected in our keyword-search-based approach.

The question remains how our measure and a measure using pre-defined keywords differ economically. Our measure is well suited to capture context-specific jargon used in specialized environments with experts and allows us to construct topics-based measures. The pre-specified keyword approach better captures broader discussions by the public, as reflected in articles published in the *WSJ*. A corollary of this statement is that identifying specific or emerging topics with a pre-specified keyword approach is more challenging. A further difference is that our approach is "evolutionary," as it will reflect changes in the vocabulary used in transcripts over time, while an approach using pre-specified keywords fixes this vocabulary ex ante. Time-series variation in true (unobservable) climate change exposure, especially over long time horizons, is more likely to be picked up by such an "evolutionary" approach. Any selection of pre-specified keywords is due to become obsolete the further one moves out in time.

A.4. Perturbation Tests for Individual Initial Bigrams

We evaluate how strongly our overall exposure measure depends on *individual* bigrams in the initial bigram list (Table IA.III) by performing a perturbation test. We successively exclude one initial bigram at a time, and then each time recompute the modified set of bigrams $\mathbb{C}^{Pert}$ as well as the modified measure $CCExposure^{Pert}$. As our initial short list contains 50 bigrams, we construct 50 new versions of $CCExposure^{Pert}$. After aggregating the measure to the firm-year level, we calculate the correlation of each of these exposure measures with $CCExposure$. These correlations are above 85%, which means that $CCExposure$ does not depend much on specific initial seed bigrams.

A.5. Comparison with Approach Using Initial Bigrams Only

Table II shows that the initial keywords dominate the top-100 bigrams used in the construction of $CCExposure$. This raises the question of how big the performance gain of the keyword discovery approach is relative to the alternative that only uses the initial seed bigrams. To evaluate this question, we construct the new exposure measure $CCExposure^{Initial}$ from the initial bigrams only. Figure 2, Panel A, evaluates how frequently the new measure signals zero exposure, while $CCExposure$ instead reveals that climate topics are discussed. Results are reported by $CCExposure$ decile. In the top decile, $CCExposure^{Initial}$ indicates no exposure in 27% of transcripts. Hence, even among the most exposed firms, there is a performance gain when applying our approach. These gains increase once we consider other deciles—already in the second decile, $CCExposure^{Initial}$ deviates from $CCExposure$, indicating the absence of exposure in more than 62% of transcripts. The effects increase monotonically as we move to lower exposure deciles.

Panel B reports the results of the topics-based exposure measures, with the alternative measures using only the topics-based initial bigrams (Table IA.IV). For all three measures and deciles, significant fractions of the transcripts are incorrectly classified as having zero exposure. Even in the three respective top deciles, the alternative approach misses positive exposure in 10 to 30% of the transcripts. Across all deciles, the gain from the keyword discovery approach is largest for $CCExposure^{Opp}$ (especially in the lower deciles).

Beyond these statistics, identifying exposure using bigrams beyond the initial seed words is economically important. We show below that, within the set of firms where $CCExposure^{Initial}$=0, our exposure measures keep predicting green outcomes. These effects are purely identified from the bigrams obtained through the keyword-search algorithm.

B. Validation at the Climate Change Exposure Level

B.1. Climate Change Exposure: Industry Variation

We now move away from the bigram level to examine the properties of the exposure measures. This involves several steps. In the first step, we compute averages by industry sector (two-digit SIC code level) and present a ranking of these means in Table III. In Panel A, using $CCExposure$, the sectors with the highest overall exposure include Electric, Gas, & Sanitary (SIC49). Top-ranked firms within this sector include China Longyuan Power Group, China's largest producer of wind power, and the U.S. utility Allete. This sector is followed by Heavy Construction (SIC16) and Construction (SIC17). High-ranking firms in these sectors include A-Power Energy Generation Systems, a Chinese firm providing on-site power generation systems, ReneSola, a U.S. firm developing and operating solar projects, and Quanta Services, an U.S. infrastructure solutions provider for firms in the energy and pipeline business. Top-ranked firms in the Transportation Equipment sector (SIC37), ranked next, include alternative fuel and zero-emission vehicle firms.

Insert Table III about here.

A few sectors are worth commenting on in Panels B to D, which report the topics-based measures. Utilities top the list for $CCExposure^{Opp}$ (Panel B) and $CCExposure^{Reg}$ (Panel C). While the latter ranking position is expected, given the sector's exposure to carbon taxes or related regulations, the earlier position is more surprising. Yet, it is consistent with Cohen, Gurun, and Nguyen (2021), who find that this sector is a key innovator in the energy-transition space. Coal Mining (SIC12) displays high exposure to regulatory and physical shocks (Panels C and D). While the high regulatory exposure is expected given the large emissions associated with burning coal, the high physical exposure is less obvious. This may reflect mining firms' exposure to heavy precipitation, or heat, which pose physical challenges to their operations. Stone, Clay & Glass Products (SIC32), in the top-5 for $CCExposure^{Reg}$, includes mostly cement producers among its top-ranked firms (they belong to the largest CO_2 emitters). A sector in the top-10 of $CCExposure^{Phy}$ (Panel D) is the insurance industry, which, unsurprisingly, is highly exposed to the costs of storms or flooding.

The large variation in exposure *between* sectors masks important heterogeneity *within* each sector (apparent from the large within-sector standard deviations). A case to illustrate this heterogeneity is the comparison of TotalEnergies and ExxonMobil. Both firms operate in Petroleum Refining (SIC29), a sector ranking among the top-10 for $CCExposure^{Opp}$ and $CCExposure^{Reg}$. In terms of the average regulatory exposure since

2010, TotalEnergies scores only modestly lower than ExxonMobil ($CCExposure^{Reg}_{TotalEnergies}$=0.25 vs. $CCExposure^{Reg}_{ExxonMobil}$=0.27), but the French oil major exhibits much higher average opportunity exposure ($CCExposure^{Opp}_{TotalEnergies}$=1.21 vs. $CCExposure^{Opp}_{ExxonMobil}$=0.27). This divergence reflects a broader perception in the market about how these firms embraced renewable energy and the net-zero transition into their business models (see the evidence in Pickl (2019)). More generally, the large within-industry variation illustrates that sectors have "winners" and "losers." Investors may, in turn, be able to address climate risks and opportunities by keeping a broad industry diversification (rather than banning some industries) and by then performing a negative screening of climate change "losers." This observation echoes arguments by academics (Andersson, Bolton, and Samama (2016)) and by providers of low-carbon index solutions.

B.2. Climate Change Exposure: Times-Series Variation

In Figure 3, Panels A to D, we compute the cross-sectional means for $CCExposure$ and the topics-based measures and plot them over time (for each measure, we focus on top-10 sectors). The figures also highlight some key moments in the public awareness of climate change, covering climate policy events relevant to regulatory and opportunity shocks (in Panels B and C), selected physical shocks (in Panel D), or both (in Panel A). In Panel A, $CCExposure$ generally increases over the sample period, especially since the mid-2000s. The rise in the early years indicates that earnings calls discussed climate issues earlier than we might have expected. A plateau is reached around 2009 (the year of the unsuccessful Copenhagen Climate Summit). Afterwards, there is a slight decline in the years leading up to the 2012 Doha Climate Summit. We note a renewed increase in $CCExposure$ since around 2013. At the end of the sample, $CCExposure$ peaks with earnings calls exhibiting about four climate change bigrams per 1,000 bigrams; this compares to about 0.1 political bigrams per 1,000 bigrams in Hassan et al. (2019).

Insert Figure 3 about here.

In Panel B, the time-series for $CCExposure^{Opp}$ resembles that of the overall measure; $CCExposure^{Opp}$ trends upward, especially at the beginning of the sample. In Panel C, $CCExposure^{Reg}$ increases between 2002 and 2008, but varies around a markedly lower level between 2011 and 2013. There is a spike in $CCExposure^{Reg}$ in 2015 (Paris Agreement), and a substantial increase since 2017. This is consistent with intensified policy discussions about how to achieve the Paris goals. In Panel D, $CCExposure^{Phy}$ displays more swings than the other measures, albeit also around an upwards trend. It appears that $CCExposure^{Phy}$ does not strongly reflect major, highly salient climate events. For example, while there is a jump after major U.S. hurricanes (i.e., Katrina, Sandy, and Harvey), the jumps occur with a considerable time lag. This pattern indicates that $CCExposure^{Phy}$ primarily reflects firm-specific exposures to physical climate events, (e.g., local heat waves or droughts).

B.3. Climate Change Exposure and Carbon Emissions

We explore how well the exposure measures correlate with firms' carbon emissions. Carbon emissions constitute an essential variable to measure firm-level exposure to climate change, especially for regulatory shocks (Bolton and Kacperczyk (2021b, 2022)). The analysis of carbon emissions is also the most frequently used climate risk management tool of institutional investors (Krueger, Sautner, and Starks (2020)). A benefit of using carbon emissions is that they are easy to understand and compute, readily available for subscribers of ESG databases, and genuinely related to changes in the global climate.

We expect that regulatory climate topics emerge more frequently in earnings calls of large carbon emitters, as they are more strongly affected by carbon taxes or related regulations. At the same time, regulatory threats related to emissions may also spur technological innovation that provides firms with opportunities in the marketplace.[25] Furthermore, some firms' emissions may be "good" in supporting the transition to a greener economy; these firms, called "climate enablers," include, for example, manufacturers of building materials that help houses to become more energy-efficient. Finally, carbon emissions should be unrelated to the exposure to physical shocks at the firm level.

We examine these possibilities by regressing the exposure measures on lagged emission values (we use lagged values as emissions covering year $t-1$ are reported in year t). Table IV, Panel A, illustrates the results. In Column 1, there is a strong positive association between $Total\ Emissions$ and $CCExposure$. As predicted, this association originates from positive correlations between emissions and both $CCExposure^{Opp}$ (Column 2) and $CCExposure^{Reg}$ (Column 3). A one-standard-deviation increase in the emissions variable is associated with an increase in $CCExposure^{Reg}$ that equals 24% of its standard deviation (using values for the regression sample). In Column 4, we find no association between emissions and physical exposure.

Insert Table IV about here.

B.4. Climate Change Exposure and Public Attention to Climate Change

Time-series variation in public attention to climate change, as proxied by *WSJ CC News Index*, has been shown to affect financial market participants (e.g., Choi, Gao, and Jiang (2020) or Ilhan, Sautner, and Vilkov (2021)). Therefore, we expect earnings call discussions to react to the salience of climate topics in the public arena. Indeed, Table IV, Panel B, shows that measured climate change exposure is higher at times when

[25] For example, utilities with a large carbon footprint may have strong incentives to develop low-carbon alternatives (e.g., wind farms, solar farms), which provide future opportunities. Indeed, as mentioned above, Cohen, Gurun, and Nguyen (2021) demonstrate that some of the largest carbon emitters produce more and better green innovation than other firms.

public climate attention rises. In Column 1, a one-standard-deviation increase in *WSJ CC News Index* is associated with an increase in $CCExposure$ of 0.05 (5% of the mean within the regression sample). This overall effect reflects a positive association of *WSJ CC News Index* and $CCExposure^{Opp}$, as well as $CCExposure^{Reg}$. Hence, when public climate attention is high, these are times when earnings calls discuss regulatory shocks and climate opportunities more extensively. Higher values of *WSJ CC News Index* do not translate into more discussions of physical shocks. This suggests that $CCExposure^{Phy}$ mostly captures firm-specific physical shocks, rather than economy-wide shocks that make it to the *WSJ* (this conclusion is consistent with the time-series evidence in Figure 3).

IV. Variance Decomposition and Role of Measurement Error

A. Variance Decomposition

We conduct a variance analysis to examine the extent to which $CCExposure$ and its components quantify firm-level variation in climate change exposure. Table V reports the incremental explanatory power from conditioning the exposure measures on fixed effects that plausibly drive the variation. Time fixed effects (i.e., economy-wide changes in aggregate exposure) explain little variation, yielding an incremental R^2 below 1% for each measure. For industry fixed effects, the same observation holds true *only* for $CCExposure^{Phy}$. On the contrary, exposures to opportunity or regulatory shocks have a sizeable industry component (20% and 8%, respectively), which might stem from regulation targeting specific industries or technological developments affecting entire sectors. The interaction of industry and time fixed effects accounts for, at most, an additional 2.5% of the variation (in the case of $CCExposure^{Opp}$). Country-fixed effects provide little additional explanatory power, which mitigates concerns that our measures are strongly affected by the native language in a country or how distant this language is from English. Depending on the measure, between 70 and 97% of the variation is *unexplained* by these sets of fixed effects. Thus, variation plays out at the firm level, rather than at the level of the country, industry, or over-time. (The high unexplained variation for $CCExposure^{Phy}$ is unsurprising given that exposure to physical shocks highly depends on the location of a firm's production sites or insurance policies.) Adding firm fixed effects, permanent differences across firms in an industry and country account for 52, 55, 46, and 47% of the variation of $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$, respectively. The remaining 48, 45, 54, and 53%, respectively, come from variation over time in the identity of firms in industries and countries most affected by the respective climate change variables.

Insert Table V about here.

B. *Assessing Measurement Error*

We interpret the large share of variance within the firm-year as capturing economically meaningful heterogeneity. In this view, a firm's idiosyncratic exposure to climate change is the key driver of the measured variation. A plausible alternative explanation is that part of the firm-level variation reflects idiosyncratic measurement error. We conduct a set of tests to dispel this alternative. Firstly, we note that we report robust associations between $CCExposure$ and important real and financial outcomes (as do other papers). These findings suggest that the variation reflected in firm-level $CCExposure$ is not simply noise.

Secondly, following Hassan et al. (2019), we quantify the amount of measurement error contained in the firm-level variation by assuming that a firm's "true" exposure follows a first-order auto-regressive (AR) process. We then assume that $CCExposure$ measures this true exposure with classical (i.i.d.) measurement error.[26] Suppose a valid instrument

[26] Under these assumptions, if the correlation between two different lags of the firm-year data is known, the AR(1) parameter and the estimated measurement error can be backed out. For example, if the first

for (lagged) $CCExposure_{i,t-1}$ were available. In this case, one could back out the share of its variation consisting of measurement error by comparing the OLS and IV coefficients. Intuitively, the idea is that candidate IVs measure true climate change exposure with error. Under the i.i.d. assumption, the measurement error in the IV is uncorrelated with that in $CCExposure_{i,t}$ and can thus be used to "purge" the latter's. For this procedure to work, we do *not* assume that the IV has lower measurement error, in fact it is likely to have higher measurement error. We only assume that the measurement error in the IV and in measured climate change exposure are statistically independent.

Table VI shows three implementations of this idea. One implementation uses an alternative exposure measure constructed by applying our algorithm to the "Management Discussion and Analysis" (MD&A) section in firms' annual 10K filings. The other two implementations use lags of this alternative measure and $CCExposure$ itself as instruments. While the estimates of the share of measurement error in $CCExposure$ vary somewhat across the three approaches, approximately 5 to 10% of the variation in measured $CCExposure$ is attributable to measurement error.[27] The implied measurement error at the firm level (in Panel B) is about 2pps higher than in the overall variation (Panel A). Although we interpret these results with due caution, they suggest that measurement error in the firm-level dimension is higher than in the overall panel, but only modestly. Concerns that the variation displayed at the firm level is subject to more measurement error than the overall climate change exposure measure (before any fixed effects) are not substantiated.

lag has a correlation of 0.45 (=0.5*0.9) and the second lag of 0.41 (=0.5*0.9*0.9) that would imply a measurement error of 50% of the variation and an AR coefficient of 0.9. If the first lag has a correlation of 0.9 and the second equals 0.8, this implies no measurement error and an AR coefficient of 0.9.

[27] These estimates compare favorably to the amount of measurement error found using similar assumptions in firm-level variables measured using accounting data (e.g., measures of total factor productivity constructed by Bloom et al. (2018) and Collard-Wexler (2011)).

Insert Table VI about here.

V. Economic Applications

A. Real Outcomes: Green Technology Jobs and Green Patents

Significant climate-related innovation is required to reach net-zero emissions by 2050 (Stern and Valero (2021)), implying huge investments by firms in human capital and R&D. According to some estimates, incremental investments of $50 trillion are needed by 2050 in solar technology, decarbonization, energy efficiency, or carbon capture (World Economic Forum (2021)). To illustrate that our exposure measures help predict real outcomes related to the net-zero transition, we relate next year's creation of disruptive green tech jobs and green patents to this year's values of climate change exposure. Among the sampled U.S. firms, we estimate for firm i and year t:

$$Green\,Outcome_{i,t+1} = exp(\alpha_i + \beta \log(1 + CCExposure_{i,t}) + \gamma \mathbf{X}_{i,t} + \delta_j \times \delta_t + \epsilon_{i,t+1}) \tag{5}$$

where $Green\,Outcome_{i,t+1}$ is $\#Green\,Tech\,Jobs_{i,t+1}$ or $\#Green\,Patents_{i,t+1}$ in year $t+1$ and $CCExposure$ is the climate change exposure measure in t (we include the overall and topics-based measures). The vector $\mathbf{X}_{i,t}$ includes *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets*, *Capex/Assets*, and *R&D/Assets*. The variables $\delta_j \times \delta_t$ represent industry-by-year fixed effects. We account for industry shocks that vary over time as firm-level innovation-related activity contains a large time-varying industry component (Aghion et al. (2005)). As demonstrated in Table V, such variation is also an important driver of climate change exposure, making it important to identify effects *within* industry-by-year pairs. We cluster standard errors at the industry-by-year group level.

We estimate Equation 5 using Poisson regressions, which provide us with two distinct benefits (Cohn, Liu, and Wardlaw (2022)). First, Poisson regressions account for the distributional characteristics of our count-based outcomes (they provide unbiased estimates for dependent variables with a large mass of values at 0 combined with severe skewness). Second, Poisson regressions allow the inclusion of industry-by-year fixed effects without biasing the estimation. They thereby address the issue of separable group fixed effects (in our case at the industry-by-year level) by only basing the estimation on observations with at least one non-zero value within a group. This is desirable, as it restricts the usable sample to those groups that are informative about the effects of $CCExposure$.[28] For robustness, we also estimate linear and log1plus-linear models (with and without industry-by-year fixed effects) on the unrestricted sample (we interpret these models' estimates with caution).

The estimation results for $\#GreenTechJobs$ are reported in Table VII. In Column 1, the estimates show that firms with higher overall exposure post more vacancies for jobs in disruptive green technologies over the subsequent year. A one-standard-deviation increase in $CCExposure$ is associated with a 109% increase in the number of green tech jobs over the next year.[29] Columns 2 to 4 consider the topics-based measures. As would be expected, the overall exposure effect originates in large part from high-opportunity firms (Column 2). Firms with higher regulatory exposure also plan to hire more green tech workers than firms with lower exposure (Column 3). We cannot detect that firms with larger physical exposure post more green tech jobs (Column 4). In Column 5, we

[28]Cohn, Liu, and Wardlaw (2022) show that log1plus-linear models may be biased in our context. The admission of separable group fixed effect in Poisson regressions differs from that in other non-linear count-data models. These alternative models are subject to the incidental parameter problem, which leads to biased and inconsistent estimates (Lancaster (2000)).

[29]In a Poisson model, for a regression coefficient β, the magnitude of a one-standard-deviation change in the independent variable is calculated as $e^{\beta \times STD} - 1$. This effect size (when multiplied by 100%) represents the percentage change in the dependent variable. We use the within-fixed effects (rather than the overall panel) standard deviation to capture plausible variation. The large magnitude of the effect also reflects that the average number of disruptive green tech jobs is relatively low.

continue to find that $CCExposure$ positively predicts green tech hiring if we replace $\#Green Tech Jobs$ with $I(Green Tech Jobs)$, an indicator for whether or not a firm posts a green tech job (we estimate a linear model with the same observations as in Columns 1 to 4). Similarly, in Column 6 estimates are robust to using the ratio of green tech jobs to all tech jobs (*Green Tech Ratio*). Column 7 addresses the potential concern that high-exposure firms may simply recruit more personnel in disruptive technologies across the board, without a specific focus on *green* jobs (for example, because these firms happen to be more innovative). To this end, we replace $\#Green Tech Jobs$ with *#Non-Green Tech Jobs* and re-estimate the regression in Column 1. We do not find positive predictive effects of the exposure measure, which mitigates concerns of spurious relationships. In fact, firms with higher climate change exposure hire less, not more, non-green tech jobs. Overall, the data is more consistent with a recruiting shift from non-green tech jobs to green tech jobs, rather than a general expansion of tech-related hiring at high-exposure firms.

Insert Table VII about here.

The results for green tech jobs broadly extend to green patents in Table VIII. In Columns 1 to 4, firms with greater climate change exposure show more green patenting in the next year; the effects originate from all three topics-based measures. A one-standard-deviation increase in $CCExposure$ is associated with a 72% increase in the number of green patents generated over the next year. The effect for $CCExposure^{Opp}$ is intuitive, as green innovation provides business opportunities during the net-zero transition. To illustrate the intuition behind the effects for $CCExposure^{Reg}$, the case study of Caterpillar is insightful. This firm is not only the top green patent producer in our sample (see Section I.E), but it also exhibits high measured regulatory exposure. This latter feature stems from its legacy business related to mining and diesel engines (sample mean of $CCExposure^{Reg}_{Caterpillar}$=0.16, situated in the top decile of $CCExposure^{Reg}$). The effect for $CCExposure^{Phy}$ is consistent with prior evidence that extreme weather events can act as drivers of climate adaptation innovation (Berkhout, Hertin, and Gann (2006)). In Columns 5 and 6, we continue to find that $CCExposure$ predicts green patenting if we replace *#Green Patents* with an indicator for whether or not a firm created a green patents (Column 5) or with the green patents ratio as in Cohen, Gurun, and Nguyen (2021) (Column 6). Column 7 shows that high-exposure firms are not simply more innovative in general; the estimates indicate fewer, not more, non-green patents by firms with high values of $CCExposure$.

Insert Table VIII about here.

Table IA.XIII shows that the results in Tables VII and VIII are robust to controlling for carbon emissions. This demonstrates that our measures contain additional information beyond what is reflected in emissions (the sample size is reduced in the panel due to the lower number of observations on carbon emissions).

In Table IA.XIV, a series of alternative specifications continue to document that $CCExposure$ predicts green tech job creation. In Column 1, we dispel concerns related to strategic disclosure in earnings calls (Mayew (2008), Hassan et al. (2019)). One specific potential concern is that managers may want to distract attention from poor performance and strategically "cheap talk" about climate change (Hail, Kim, and Zhang (2021)). Following Hassan et al. (2019), we test for this possibility by adding a control for the firm's overall sentiment (share of positive and negative tone words across the earnings call transcript) and two proxies for recent performance.[30] The estimates show that our results

[30]We measure performance as the pre-call stock returns accumulated over the seven days prior to the earnings call, and the earnings surprise. Earnings surprise is defined as earnings per share before extraordinary items minus earnings per share in the same quarter of the prior year, divided by the price per share at the beginning of the quarter (Ball and Bartov (1996)). We average the two variables across the earnings calls of a firm-year to obtain an annual measure.

are robust to adding these controls. In Column 2, we restrict the sample to firm-years within the BG database to ensure that the results are unaffected by how we classify the firms missing in BG; recall that we assume no green tech job creation for them (BG may systematically miss scraping some firms' postings). In Column 3, exposure is based on a count of bigrams in the Q&A session, that is, the part of the call that is less under management control and, in turn, less subject to concerns of strategic (non-)disclosure and greenwashing. In Column 4, $CCSentiment^{Pos}$ strongly predicts next-year green tech job creation, while $CCSentiment^{Neg}$ is insignificant (albeit marginally). In Column 5, $CCRisk$ is positively associated with green tech job creation. In Column 6 to 9, we show that results are robust if we estimate OLS specifications to address potential concerns with the Poisson specification. We estimate models with and without industry-by-year fixed effects, and with $\#Green\ Tech\ Jobs$ or $Log(1 + \#Green\ Tech\ Jobs)$. We also provide estimates that replace the log1plus version of $CCExposure$ with an unlogged version. Table IA.XV applies the same alternative specifications to green patenting. The estimates show that these results are also robust.

Table IA.XVI reports regressions within the subsamples where the exposure measures that rely exclusively on the initial bigrams indicate zero exposure. In these estimations, our exposure measures keep predicting green outcomes. This finding corroborates the performance gain from using more subtle and less visible climate change bigrams, as the estimation is identified from the bigrams obtained through the keyword-search algorithm.

Finally, Table IA.XVII documents the covariate balance of observations that are either included or excluded from the estimations in Tables VII and VIII. Excluded firm-years exhibit lower climate change exposure, implying that our estimates are obtained within the set of firms for which climate change issues are most pressing.

B. Financial Market Outcomes

B.1. Options Market Risks and Risk Premiums

Firms with higher regulatory exposure are more strongly affected by future regulations to combat global warming, and uncertainty over such regulations should be priced in the options market (Kelly, Pastor, and Veronesi (2016)). Likewise, climate opportunities are risky, with plenty of uncertainty surrounding investments in green technologies or renewable energy. Hence, we proceed with testing whether climate change exposure is related to option-implied risks and risk premiums. We consider three sets of risk variables. First, to quantify general risks, we use three implied central moments, namely variance ($IVar$), skewness ($ISkew$), and kurtosis ($IKurt$). Second, we calculate two heuristic measures quantifying the relative expensiveness of protection against left ($SlopeD$) and right ($SlopeU$) tail risks.[31] Third, we use the variance risk premium (VRP) to measure the premiums that investors are willing to pay to hedge against general climate-related variance risk (or uncertainty, as suggested in Bali and Zhou (2016)). Using each of these variables, we perform the following regressions:

$$OI\ Outcome_{i,t+1} = \alpha_i + \beta\ Log(1 + CCExposure)_{i,t} + \gamma \mathbf{X}_{i,t} + \delta_j \times \delta_t + \epsilon_{i,t+1} \quad (6)$$

where $OI\ Outcome_{i,t+1}$ is an option-implied measure for firm i measured at the end of quarter t (i.e., a conditional expectation of some quantity over the period $t+1$), and $CCExposure$ is firm i's climate change exposure in quarter t. The vector $\mathbf{X}_{i,t}$ includes the same controls as before (delayed to be available in the third quarter after the annual close of the fiscal period). The variables δ_j and δ_t represent industry and year fixed

[31] $SlopeD$ increases when the cost of left tail protection goes up (relative to the cost of ATM options), and $SlopeU$ decreases (becomes more negative) when the relative cost of obtaining upside growth increases. Note that Sautner et al. (2022) define their measure of $SlopeU$ as minus one times $SlopeU$.

effects, respectively. We cluster standard error at the industry-by-year group level.

Table IX, Panel A, documents that $CCExposure$ is strongly linked to forward-looking risks and risk premiums. In Columns 2 and 3, $CCExposure$ predicts a more negatively skewed return distribution ($ISkew$) and fatter tails ($IKurt$). Furthermore, tail exposure is found to be more costly for firms with higher climate change exposure. More specifically, downside protection in Column 4 (positive and significant coefficient on $SlopeD$) and upside potential in Column 5 (negative and significant coefficient of $SlopeU$) become more expensive when $CCExposure$ is higher. In terms of magnitudes, the effects are strongest in Column 3 for $IKurt$. A one-standard-deviation change in $CCExposure$ is associated with a change in $IKurt$ equivalent to 4.3% of its standard deviation. The effects for $SlopeD$ and $SlopeU$ are 2.3% and 2.2%, respectively.

Insert Table IX about here.

The remaining three panels consider the topics-based measures. Earnings calls should contain more discussions of climate-related opportunities if a firm is well positioned for the growth potential arising from climate change. The realization of these opportunities could lead to large gains, if successful, and to large losses, if unsuccessful. Investors may, in turn, trade in the options market to reflect the two-sided effects of climate opportunities. Panel B confirms this intuition: the tail effects for $CCExposure^{Opp}$ in Columns 4 and 5 are slightly stronger compared to the corresponding estimates in Panel A. The magnitude of a one-standard-deviation increase in $CCExposure^{Opp}$ is 2.6% for $SlopeD$ and 2.8% for $SlopeU$, respectively. Thus, it is not only the case that options are more expensive on both tails if climate opportunities are higher, but also that the cost of upside potential grows faster than the cost of downside crash protection. The link between $CCExposure^{Opp}$ and VRP in Column 6 demonstrates that the wedge between the implied and "historically fair" price of OTM calls increases with opportunity exposure. Thus, investors are ready to pay an extra (volatility) premium when buying options on stocks with climate-related upside potential. However, the effect is small in magnitude and only marginally significant.

In Panel C, the pattern for $CCExposure^{Reg}$ is similar to the one for $CCExposure^{Opp}$, though the magnitudes are smaller. While the right-tail option expensiveness increases by 1.6% of its standard deviation (i.e., *SlopeU* diminishes) for a one-standard-deviation change in $CCExposure^{Reg}$, the crash protection grows by 1.2%. This confirms our earlier evidence that some firms with high regulatory exposure face downside risks *and* upside potential due to their green innovation activity. In Panel D, the effects for $CCExposure^{Phy}$ are less conclusive. On the one hand, firms with higher $CCExposure^{Phy}$ are perceived as less risky in general when we consider $IVar$ or VRP (possibly because these firms use insurance policies to hedge out physical climate events more than others). On the other hand, however, upside tail exposure (*SlopeU*) is also more costly. That said, all effects are relatively small in magnitude.[32]

Overall, climate change exposure is priced in the options market. Considering all the evidence, stocks with higher exposure have probability mass shifted to the tails of the distribution, making crash protection and upside potential relatively more expensive. Obtaining protection and upside growth potential comes at a premium, which increases more strongly for firms facing higher opportunities. We acknowledge that the effect magnitudes are modest and hardly tradeable after transaction costs.

[32]Our inference for the pricing of physical exposure is different from the link between hurricane uncertainty and variance pricing in Kruttli, Roth Tran, and Watugala (2021). For example, while we concentrate on the unconditional pricing using the expected variance risk premium, Kruttli, Roth Tran, and Watugala (2021) study dynamics of the realized variance risk premium. However, these authors also conclude that (especially in the early sample years) investors underprice variance in options of firms strongly exposed to extreme weather events.

B.2. Cross-Section of Stock Returns

Climate change exposure is related to risks and risk premiums in the options market. Consequently, systematic risk related to *CCExposure* may be associated with a risk premium in the cross-section of returns. That said, testing for the pricing effects of a climate change exposure factor, labelled *CCEXPOSURE*, is challenging for several reasons. A conceptual challenge arises because return effects are theoretically more ambiguous to predict compared to the risk measures. On the one hand, firms with high betas for *CCEXPOSURE* should be more risky and—in expectation—earn a risk premium[33] On the other hand, the relations may actually be the opposite, with risks gradually getting priced in during the sample period; as risks emerge, stock prices decline, implying lower realized returns. Pastor, Stambaugh, and Taylor (2021) illustrate this difference between ex-ante and ex-post returns. An estimation challenge arises because *CCExposure* reflects the attention devoted to climate topics at a point in time. This implies that the pricing of *CCEXPOSURE* should vary over time, requiring the estimation of conditional risk premiums. Another challenge arises because the number of assets for such tests is large relative to the time points available for the estimation (less than 20 years of data).

With these challenges in mind, we investigate the conditional pricing of *CCEXPOSURE* in the cross-section of stocks. We follow Jamilov, Rey, and Tahoun (2021) and construct the factor as an unexpected shock to the aggregate value of *CCExposure*. This involves three primary steps. Firstly, we convert quarterly transcript-level values of $CCExposure_{i,t}$ for U.S-traded firms to a monthly frequency by propagating the last exposure values for up to three months forward (i.e., we match the month-year of each climate change exposure to the month-year of the respective quarterly transcript). Sec-

[33]For example, such firms face higher uncertainty related to future developments in climate-related areas; that is, their valuation should include real option value depending on the path of climate-related technologies, regulations or physical climate shifts.

ondly, we compute cross-sectional monthly averages of $CCExposure_m$. Thirdly, we take the first differences in these monthly averages as proxy for unexpected monthly shocks to the aggregate exposure level, and use them as the *CCEXPOSURE* factor.[34]

To examine the conditional pricing of *CCEXPOSURE* among S&P500 firms, we follow Gagliardini, Ossola, and Scaillet (2016) (GOS henceforth), who provide a conditional extension of the two-pass regression approach (Fama and MacBeth (1973)). We use this approach as it delivers good small-sample performance when—as in our case—the cross-section is large relative to the time-series. GOS assume a linear conditional factor model for excess returns with time-varying factor exposures and risk premiums. They model the parameters as linear functions of lagged instruments. The factor loadings $\beta_{i,m}$ depend on stock-specific instruments ($Z_{i,m-1}$) as well as common instruments (Z_{m-1}), and the factor expectations only on common instruments. Under this framework, the conditional expected return on stock i in month m is

$$E[R_{i,m}|Z_{i,m-1}, Z_{m-1}] = \beta_{i,m}^{\intercal}\lambda_m, \tag{7}$$

where the risk premium λ_m is the sum of the conditional factor expectation $E[F_m|Z_{m-1}]$ and the process ν_m, estimated from the cross-section of stocks. The process ν_m allows the estimated risk premium to deviate from the conditional expectation of a factor due to market imperfections for tradeable factors (Cremers, Petajisto, and Zitzewitz (2013), GOS) and it also reveals an "implicit cost" of projecting a non-tradeable factor (like ours) on returns. A similar framework is used, for example, in Barras and Malkhozov (2016). As in GOS, we use as common instruments the term spread and the default spread and

[34]The factor is standardized to have zero mean and annual volatility of 10%. Results are robust to using the residuals from an AR(1) process fitted to the monthly exposure series, as implemented in Jamilov, Rey, and Tahoun (2021) (the resulting factors are almost perfectly correlated). However, fitting an AR(1) process may introduce a look-ahead bias.

as the stock-specific instrument the log of the book-to-market ratio (see Section I.G for definitions). We estimate the time-varying components of the risk premiums with the 4-factor model by Carhart (1997) that is augmented with the *CCEXPOSURE* factor.[35]

When performing the estimation, we obtain average conditional risk premiums in line with expectations (risk premiums for the market, size, value, and momentum factors are 11.4%, 5.0%, -5.8%, and 8.5% p.a., respectively). The *CCEXPOSURE* premium is positive, on average (3.7% p.a.), and we obtain positive point estimates for most months. More importantly, the risk premium is not constant over time, and we reject the hypotheses that its two components are constant (p-values of 0.0137 and 0.0001, respectively).

In Table X, we report the estimated annualized components of the risk premium λ_m, that is, the estimates of F and ν. Similar to the results in GOS, most of the action for the risk premiums comes through the cross-sectional component ν. For *CCEXPOSURE* ν has a positive unconditional mean (Constant of 3.73%) and a positive link to the default spread (3.13%)—both are highly significant. This indicates that stocks with high exposure to the *CCEXPOSURE* factor are expected to earn higher returns, especially when market-wide default risk increases.

Insert Table X about here.

The time-series of the estimated risk premium on *CCEXPOSURE* is depicted in Figure 4. The series illustrates significant variability over time, with a large spike around the financial crisis. Further tentative interpretations indicate a temporary spike around the time of Hurricane Sandy (October 2012) and the Doha Climate Summit (November 2012). Another temporary spike occurs just after the Paris Agreement (December 2015). Considering the most recent five years, the risk premium was lowest around the time

[35]The factor is essentially orthogonal to the other factors, with all unconditional correlations being smaller than 0.05. The results are robust to using 3- and 5-factor models.

President Trump took office (January 2017); it gradually increased since then with a drop around the onset of the Covid-pandemic.[36]

Insert Figure 4 about here.

We emphasize that our objective is not to create an ultimate climate factor to be added to the factor zoo (Feng et al. (2020)), but instead to show that attention to climate topics in earnings calls is linked to systematic risk, with shocks to such attention potentially being priced in the cross-section (following a narrative as in Shiller (2017)).

VI. Conclusion

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

Our measures build on recent work that has identified earnings calls as a source for identifying the various risks and opportunities that firms face over time. We adjust the approach of this prior work along several critical dimensions, allowing us to capture aspects of the opportunities and the (physical and regulatory) risks associated with climate change. For this purpose, we adapt the machine learning keyword discovery algorithm

[36]As in the previous applications, we estimate the risk premiums separately by topic. The topics-based premiums are on average positive, but demonstrate distinct time-series patterns; for example, at times when the physical risk premium goes up, the opportunity risk premium tends to go down. We do not want to overemphasize the topics-based differences here, for example, as our framework uses the same set of instruments for all topics-based factors.

proposed by King, Lam, and Roberts (2017) to produce several sets of climate change bigrams. Rather than choosing a training library, we start with a short list of initial bigrams that most experts would agree are related to climate change. Our exposure measures capture the proportion of the earnings call centered on climate change topics. They are available for a global sample of more than 10,000 firms covering the years of 2002 to 2020. We demonstrate that our measures are helpful in predicting important real outcomes related to the net-zero transition, notably green tech growth and green patenting. We also document that the measures contain information that is priced in the options and equity market.

Appendix A. Variable Definitions

Variable	Years	Definition
CCExposure	2002-2020	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCExposure^{Opp}$	2002-2020	Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCExposure^{Reg}$	2002-2020	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCExposure^{Phy}$	2002-2020	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCExposure^{Q\&A}$	2002-2020	Relative frequency with which bigrams related to climate change occur in the Q&A session part of transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the Q&A session. Source: Self-constructed.
$CCSentiment^{Pos}$	2002-2020	Relative frequency with which bigrams related to climate change are mentioned together with positive tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCSentiment^{Neg}$	2002-2020	Relative frequency with which bigrams related to climate change are mentioned together with the negative tone words that are summarized by Loughran and McDonald (2011) in one sentence in the transcripts of earnings conference calls. Source: Self-constructed.
CCRisk	2002-2020	Relative frequency with which bigrams related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Self-constructed.
$CCExposure^{10K}$	2002-2020	Climate change exposure constructed by applying our algorithm to the "Management Discussion and Analysis" (MD&A) section in firms' annual 10K filings. Source: Self-constructed.
Total Emissions	2004-2020	Sum of annual Scope 1 and Scope 2 carbon emissions (metric tons of CO2) at the end of the year. Scope 1 emissions are caused by the combustion of fossil fuels or from the releases during manufacturing. Scope 2 emissions originate from the purchase of electricity, heating, or cooling. Source: Trucost.
WSJ CC News Index	2002-2017	Time-series index of the fraction of the *Wall Street Journal* dedicated to the topic of climate change. Source: Engle et al. (2020).

Variable	Years	Definition
#Green Tech Jobs	2007, 2010-2020	Number of job postings for disruptive green tech jobs in a year according to the Burning Glass (BG) database. Disruptive green tech job postings relate to jobs in one of four climate-related technology areas that were identified by Bloom et al. (2021) as having been disruptive ("hybrid vehicle electric car," "lithium battery," "solar power," and "fracking"). We assume that no disruptive green tech job has been posted if a firm-year is not included in the BG database. Source: Bloom et al. (2021) and Burning Glass.
I(Green Tech Jobs)	2007, 2010-2020	Indicator that equals one if *#Green Tech Jobs* is positive, and zero otherwise. Source: Bloom et al. (2021) and Burning Glass.
Green Tech Ratio	2007, 2010-2020	Number of job postings for disruptive green jobs relative to the total number of all disruptive job postings. Set to zero if the number of disruptive job postings is zero. Source: Bloom et al. (2021) and Burning Glass.
#Non-Green Tech Jobs	2007, 2010-2020	Number of job postings for non-green disruptive tech jobs in a year according to the Burning Glass (BG) database. Non-green disruptive tech job postings relate to jobs in one of 25 climate-related technology areas that were identified by Bloom et al. (2021) as having been disruptive and are unrelated to climate change. We assume that no non-green disruptive tech job has been posted if a firm-year is not included in the BG database. Source: Bloom et al. (2021) and Burning Glass.
#Green Patents	2002-2019	Number of green patents obtained in a year according to the Google Patents (GP) database. To identify "green" patents, we follow the approach in Cohen, Gurun, and Nguyen (2021) and apply the OECD classification to identify what constitutes a patent with the potential to address environmental problems. We assume that no green patenting has occurred if we are unable to identify a green patent in the GP database for a firm-year. Source: Google Patents.
I(Green Patents)	2002-2019	Indicator that equals one if *#Green Patents* is positive, and zero otherwise. Source: Google Patents.
Green Patents Ratio	2002-2019	Number of green patents (*#Green Patents*) relative to the total number of patents. Set to zero if the number of total patents is zero. Source: Google Patents.
#Non-Green Patents	2002-2019	Number of non-green patents obtained in a year according to the Google Patents (GP) database. We assume that no patenting has occurred if we are unable to identify a non-green patent in the GP database for a firm-year. Source: Google Patents.
Assets	2002-2020	Total assets (in $ millions) at the end of the year (Compustat item AT). Winsorized at the 1% level. Source: Compustat NA/Global
Debt/Assets	2002-2020	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) divided by total assets (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
Cash/Assets	2002-2020	Cash and short-term investments (Compustat data item CHE) divided by total assets (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
PPE/Assets	2002-2020	Property, plant, and equipment (Compustat data item PPENT) divided by total assets (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.

Variable	Years	Definition
$EBIT/Assets$	2002-2020	Earnings before interest and taxes (Compustat data item EBIT) divided by total assets (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global
$R\&D/Assets$	2002-2019	R&D expenditures (Compustat data item XRD) divided by total assets (Compustat data item AT). Missing values set to zero. Winsorized at the 1% level. Source: Compustat NA/Global.
$Capex/Assets$	2002-2020	Capital expenditures (Compustat data item CAPX) divided by total assets (Compustat data item AT). Winsorized at the 1% level. Source: Compustat NA/Global.
$IVar$	2002-2020	Implied variance of log returns computed from 30-day out-the-money options following Bakshi et al. (2003). Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File.
$ISkew$	2002-2020	Implied skewness of log returns computed from 30-day out-the-money options following Bakshi et al. (2003). Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File.
$IKurt$	2002-2020	Implied kurtosis of log returns computed from 30-day out-the-money options following Bakshi et al. (2003). Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File.
$SlopeD$	2002-2020	Slope of the implied volatility smile on the left side from the at-the-money level (i.e., for negative returns relative to ATM), computed as the slope coefficient from regressing implied volatilities of out-the-money puts on the respective option deltas (and a constant). The variable is computed from 30-day options. Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File.
$SlopeU$	2002-2020	Slope of the implied volatility smile on the right side from the at-the-money level (i.e., for positive returns relative to ATM), computed as the slope coefficient from regressing implied volatilities of out-the-money calls on the respective option deltas (and a constant). The variable is computed from 30-day options. Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File.
VRP	2002-2020	Variance risk premium computed as the difference between the implied variance of log returns ($IVar$) and the realized variance of daily log returns over a historical monthly window. Winsorized at the 1% level. Source: Ivy DB OptionMetrics Volatility Surface File for options data and CRSP for daily returns.

References

Acemoglu, Daron, Philippe Aghion, Lint Barrage, and David Hemous, 2019, Climate change, directed innovation, and energy transition: The long-run consequences of the shale gas revolution, Working paper, MIT.

Addoum, Jawad, David Ng, and Ariel Ortiz-Bobea, 2020, Temperature shocks and establishment sales, *The Review of Financial Studies* 33, 1331–1366.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, 2005, Competition and innovation: an inverted-u relationship, *The Quarterly Journal of Economics* 120, 701–728.

Andersson, Mats, Patric Bolton, and Frédéric Samama, 2016, Hedging climate risk, *Financial Analysts Journal* 72, 13–32.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Bakshi, Gurdip S., Nikunj Kapadia, and Dilip B. Madan, 2003, Stock return characteristics, skew laws, and the differential pricing of individual equity options, *The Review of Financial Studies* 16, 101–143.

Bali, Turan G., and Hao Zhou, 2016, Risk, uncertainty, and expected returns, *Journal of Financial and Quantitative Analysis* 51, 707–735.

Ball, Ray, and Eli Bartov, 1996, How naive is the stock market's use of earnings information?, *Journal of Accounting and Economics* 21, 319–337.

Barras, Laurent, and Aytek Malkhozov, 2016, Does variance risk have two prices? Evidence from the equity and option markets, *Journal of Financial Economics* 121, 79–92.

Baz, Salim, Lara Cathcart, Alexander Michaelides, and Yi Zhang, 2022, Firm-level climate regulatory exposure, Working paper, Imperial College London.

Berkhout, Frans, Julia Hertin, and David M. Gann, 2006, Learning to adapt: Organisational adaptation to climate change impacts, *Climatic Change* 1, 135–156.

Berkman, Henk, Jonathan Jona, and Naomi S Soderstrom, 2019, Firm-specific climate risk and market valuation, Working paper, University of Auckland Business School.

Bingler, Julia Anna, Mathias Kraus, and Markus Leippold, 2022, Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures, *Finance Research Letters* 47, 102776.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen Terry, 2018, Really uncertain business cycles, *Econometrica* 86, 1031–1065.

Bloom, Nicholas, Tarek A. Hassan, Aakash Kalyani, Josh Lerner, and Ahmed Tahoun, 2021, The diffusion of disruptive technologies, Working paper, Stanford University.

Bolton, Patrick, and Marcin Kacperczyk, 2021a, Carbon disclosure and the cost of capital, Working paper, Imperial College London.

Bolton, Patrick, and Marcin Kacperczyk, 2021b, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2022, Global pricing of carbon-transition risk, *The Journal of Finance* forthcoming.

Bolton, Patrick, Marcin Kacperczyk, and Frédéric Samama, 2021, Carbon disclosure and the cost of capital, Working paper, Imperial College London.

Campello, Murillo, Janet Gao, and Qiping Xu, 2021, Personal income taxes and labor downskilling: Evidence from 27 million job postings, Working paper, Kelley School of Business.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Chang, Bo-Young, Peter Christoffersen, Kris Jacobs, and Gregory Vainberg, 2012, Option-implied measures of equity risk, *Review of Finance* 16, 385–428.

Chen, Shuping, Stephan Hollander, and Kelvin Law, 2014, The price of silence: When no one asks questions during conference calls, Working paper, University of Texas at Austin.

Choi, Garwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *The Review of Financial Studies* 33, 1112–1145.

Cohen, Lauren, Umit Gurun, and Quoc Nguyen, 2021, The ESG-innovation disconnect: Evidence from green patenting, Working paper, Harvard Business School.

Cohn, Jonathan B, Zack Liu, and Malcolm Wardlaw, 2022, Count (and count-like) data in finance, Working paper, University of Texas Austin.

Collard-Wexler, Allan, 2011, Productivity dispersion and plant selection in the ready-mix concrete industry, Working paper, NYU Stern.

Cremers, K. J. Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate jump and volatility risk in the cross-section of stock returns, *The Journal of Finance* 70, 577–614.

Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz, 2013, Should benchmark indices have alpha? Revisiting performance evaluation, *Critical Finance Review* 2, 1–48.

Darendeli, Alper, Kelvin Law, and Michael Shen, 2021, Green new hiring, *Review of Accounting Studies* forthcoming.

De Haas, Ralph, and Alexander Popov, 2022, Finance and carbon emissions, *The Economic Journal* forthcoming.

DeMiguel, Victor, Yuliya Plyakha, Raman Uppal, and Grigory Vilkov, 2013, Improving portfiolio selection using option-implied volatility and skewness, *Journal of Financial and Quantitative Analysis* 48, 1813–1845.

Di Giuli, Alberta, Alexandre Garel, Roni Michaely, and Arthur Petit-Romec, 2022, Climate change and mutual fund voting on environmental proposals, Working paper, European Corporate Governance Institute.

Duong, Huu Nhan, Petko S. Kalev, Madhu Kalimipalli, and Saurabh Trivedi, 2021, Do firms benefit from carbon risk management? Evidence from the credit default swaps market, Working paper, Monash University.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *The Review of Financial Studies* 33, 1184–1216.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *The Journal of Finance* 63, 1653–1678.

Fama, Eugene F., and James D. MacBeth, 1973, Risk return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu, 2020, Taming the factor zoo: a test of new factors, *The Journal of Finance* 75, 1327–1370.

Gagliardini, Patrick, Elisa Ossola, and Olivier Scaillet, 2016, Time-varying risk premium in large cross-sectional equity data sets, *Econometrica* 84, 985–1046.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy, 2019, Text as data, *Journal of Economic Literature* 57, 535–74.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel, 2021, Climate finance, *Annual Review of Financial Economics* 13, 15–36.

Ginglinger, Edith, and Quentin Moreau, 2022, Climate risk and capital structure Working paper, Université Paris–Dauphine.

Gostlow, Glen, 2021, The materiality and measurement of physical climate risk: evidence from Form 8-K, Working paper, London School of Economics.

Hail, Luzi, Shawn Kim, and Rachel Xi Zhang, 2021, How do managers greenwash? Evidence from earnings conference calls, Working paper, University of Pennsylvania Wharton School.

Haščič, Ivan, and Mauro Migotto, 2015, Measuring environmental innovation using patent data, Working paper, OECD.

Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2019, Firm-level political risk: Measurement and effects, *The Quarterly Journal of Economics* 134, 2135–2202.

Hassan, Tarek Alexander, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2021a, Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1, NBER Working paper 26971.

Hassan, Tarek Alexander, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2021b, The global impact of brexit uncertainty, NBER Working paper 26609.

Hassan, Tarek Alexander, Jesse Schreger, Markus Schwedeler, and Ahmed Tahoun, 2021c, Sources and transmission of country risk, NBER Working paper 29526.

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2022, Does socially responsible investing change firm behavior?, Working paper, University of Utah.

Heo, Yuna, 2021, Climate change exposure and firm cash holdings, Working paper, Rutgers Business School.

Hollander, Stephan, Maarten Pronk, and Erik Roelofsen, 2010, Does silence speak? An empirical analysis of disclosure choices during conference calls, *Journal of Accounting Research* 48, 531–563.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2019, Climate Risks and Market Efficiency, *Journal of Econometrics* 208, 265–281.

Huang, Allen H, Reuven Lehavy, Amy Y Zang, and Rong Zheng, 2018, Analyst information discovery and interpretation roles: A topic modeling approach, *Management Science* 64, 2833–2855.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, Carbon tail risk, *The Review of Financial Studies* 34, 1540–1571.

Jamilov, Rustam, Hélène Rey, and Ahmed Tahoun, 2021, The anatomy of cyber risk, NBER Working paper 28906.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2021, Measuring technological innovation over the long run, *American Economic Review: Insights* 3, 303–320.

Kelly, Bryan, Lubos Pastor, and Pietro Veronesi, 2016, The price of political uncertainty: Theory and evidence from the option market, *The Journal of Finance* 71, 2417–2480.

King, Gary, Patrick Lam, and Margaret E Roberts, 2017, Computer-assisted keyword and document set discovery from unstructured text, *American Journal of Political Science* 61, 971–988.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics* 132, 665–712.

Kölbel, Julian F., Markus Leippold, Jordy Rillaerts, and Qian Wang, 2022, Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure, *Journal of Financial Econometrics* forthcoming.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, 2020, The importance of climate risks for institutional investors, *The Review of Financial Studies* 33, 1067–1111.

Kruttli, Mathias S, Brigitte Roth Tran, and Sumudu W Watugala, 2021, Pricing Poseidon: Extreme weather uncertainty and firm return dynamics, Working paper, Federal Reserve Bank of San Francisco.

Lancaster, Tony, 2000, The incidental parameter problem since 1948, *Journal of Econometrics* 95, 391–413.

Lewellen, Jonathan, and Stefan Nagel, 2006, The conditional CAPM does not explain asset pricing anomalies, *Journal of Financial Economics* 82, 289–314.

Li, Fengfei, Chen Lin, and Tse-Chun Lin, 2022, A one-two punch to the economy: Climate vulnerability and corporate innovation strategies, Working paper, The University of Hong Kong.

Li, Qing, Hongyu Shan, Yuehua Tang, and Vincent Yao, 2021, Corporate climate risk: Measurement and response, Working paper, University of Florida.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *The Journal of Finance* 66, 35–65.

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

Mueller, Isabella, and Eleonora Sfrappini, 2022, Climate change-related regulatory risks and bank lending, Working paper, IWH-Halle.

Pankratz, Nora, and Christoph Schiller, 2021, Climate change and adaptation in global supply-chain networks, Working paper, Board of Governors of the Federal Reserve System.

Pastor, Lubos, Robert Stambaugh, and Lucian Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pickl, Matthias, 2019, The renewable energy strategies of oil majors – From oil to energy?, *Energy Strategy Reviews* 29, 1–7.

Poon, Ser-Huang, and Clive W.J. Granger, 2003, Forecasting volatility in financial markets: A review, *Journal of Economic Literature* 41, 478–539.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, 2022, Pricing climate change exposure, *Management Science* forthcoming.

Shiller, Robert J., 2017, Narrative economics, *American Economic Review* 107, 967–1004.

Stern, Nicholas, and Anna Valero, 2021, Innovation, growth and the transition to net-zero emissions, *Research Policy* 50, 104293.

Tomar, Sorabh, 2021, Greenhouse gas disclosure and emissions benchmarking, Working paper, Southern Methodist University, Cox School of Business.

van Zaanen, Menno, and Pieter Kanters, 2010, Automatic mood classification using tf*idf based on lyrics, *Proceedings of the 11th International Society for Music Information Retrieval Conference* 75–80.

Vanden, Joel M., 2008, Information quality and options, *The Review of Financial Studies* 21, 2635–2676.

Varini, Francesco S, Jordan Boyd-Graber, Massimiliano Ciaramita, and Markus Leippold, 2020, Climatext: A dataset for climate change topic detection, Working paper, ETH Zurich.

von Schickfus, Marie-Theres, 2021, Institutional investors, climate policy risk, and directed innovation, Working paper, ifo Institute Munich.

Webersinke, Nicolas, Mathias Kraus, Julia Anna Bingler, and Markus Leippold, 2021, ClimateBert: A pretrained language model for climate-related text, Working paper, University of Zurich.

World Economic Forum, 2021, Financing the transition to a net-zero future, Report.

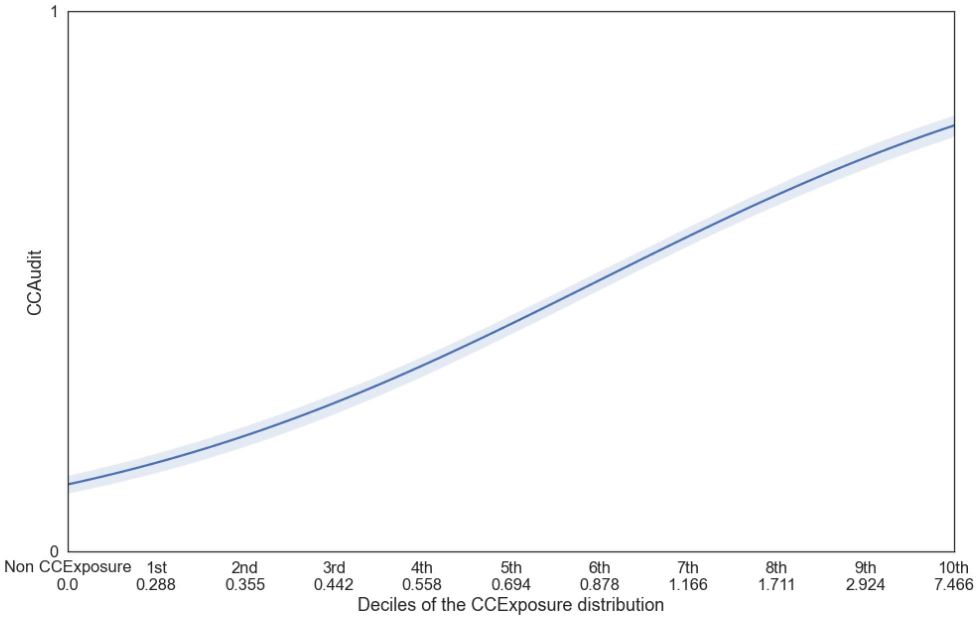
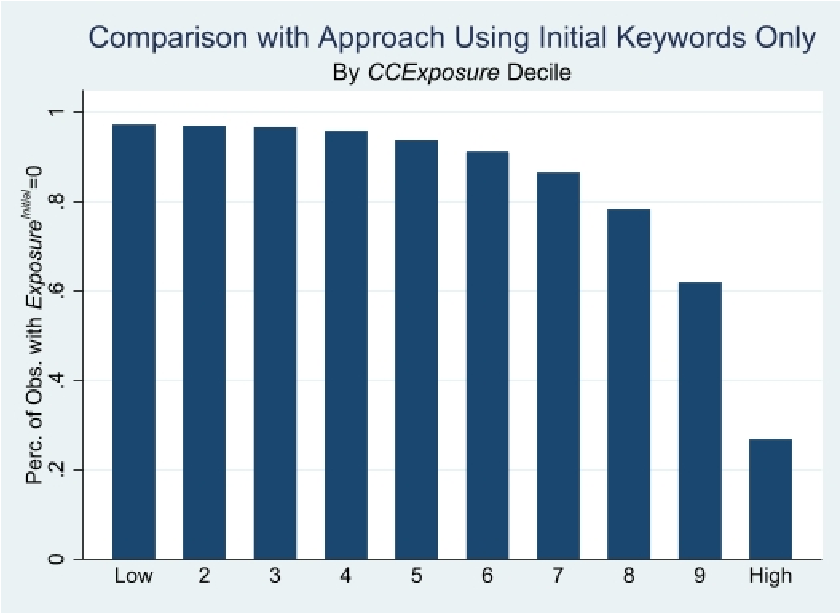
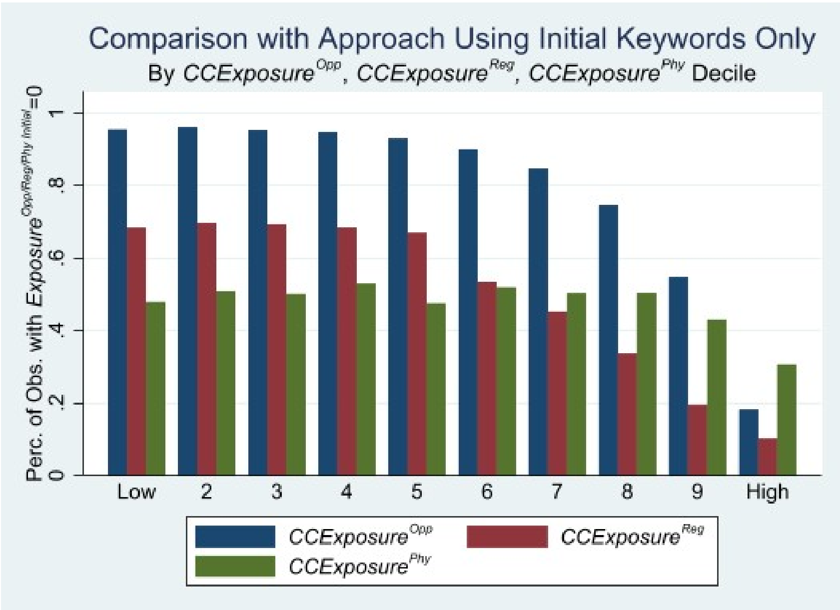


Figure 1. Probability of Correctly Identified Positives by Decile

This figure plots on the vertical axis the predicted probability of having a correctly identified positive (i.e., the audit study of the snippet confirms climate change related text) against on the horizontal axis deciles of the $CCExposure$ distribution. The median score of $CCExposure$ in a given decile is shown on the axis. Predicted probabilities are computed by estimating a logit model on the sample of 2,090 audited snippets.



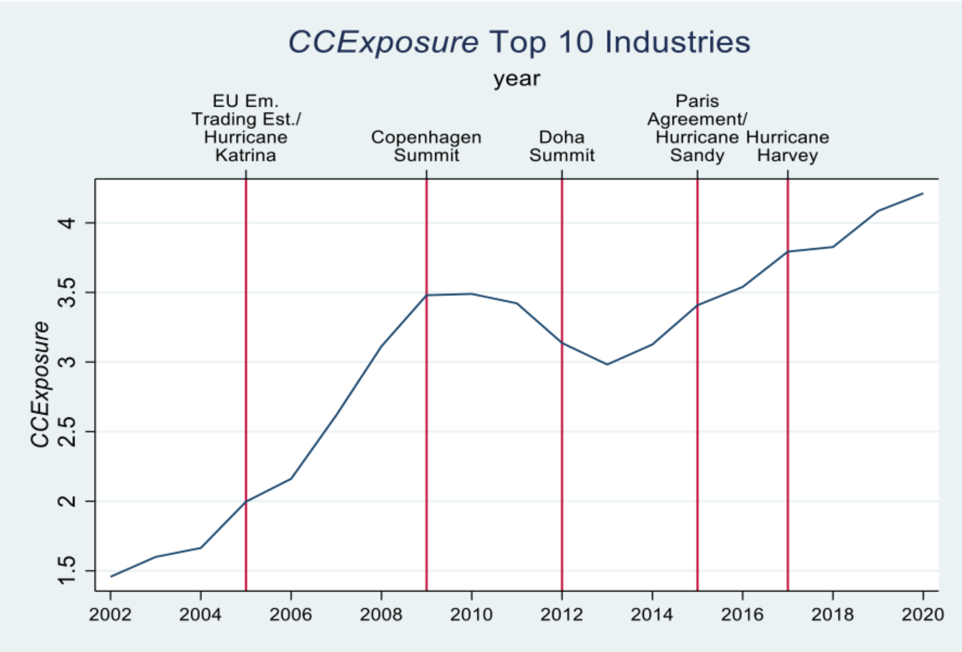
(a)



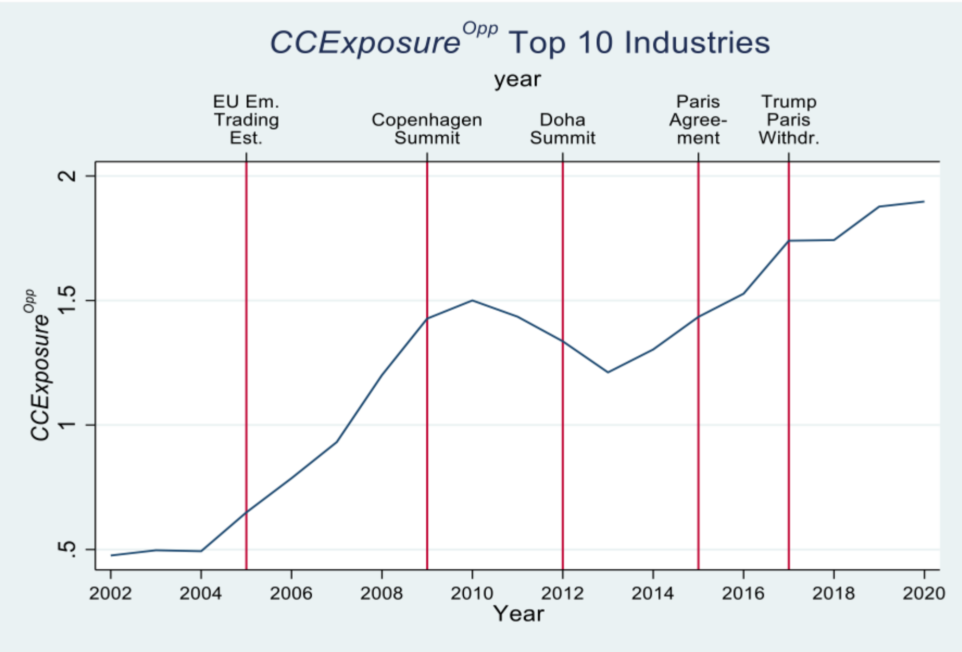
(b)

Figure 2. Climate Change Exposure Calculated with Initial Bigrams

These figures evaluate how frequently $CCExposure^{Initial}$ signals zero climate change exposure, while $CCExposure$ instead reveals that such exposure exists. Results are reported by $CCExposure$ decile. $CCExposure^{Initial}$ is a measure of climate change exposure based on the initial seed bigrams only. Panel A reports results for the overall climate change exposure measure, and Panel B for the topics-based measures. In the table, the exposure measures are calculated at the quarterly (transcript) level.

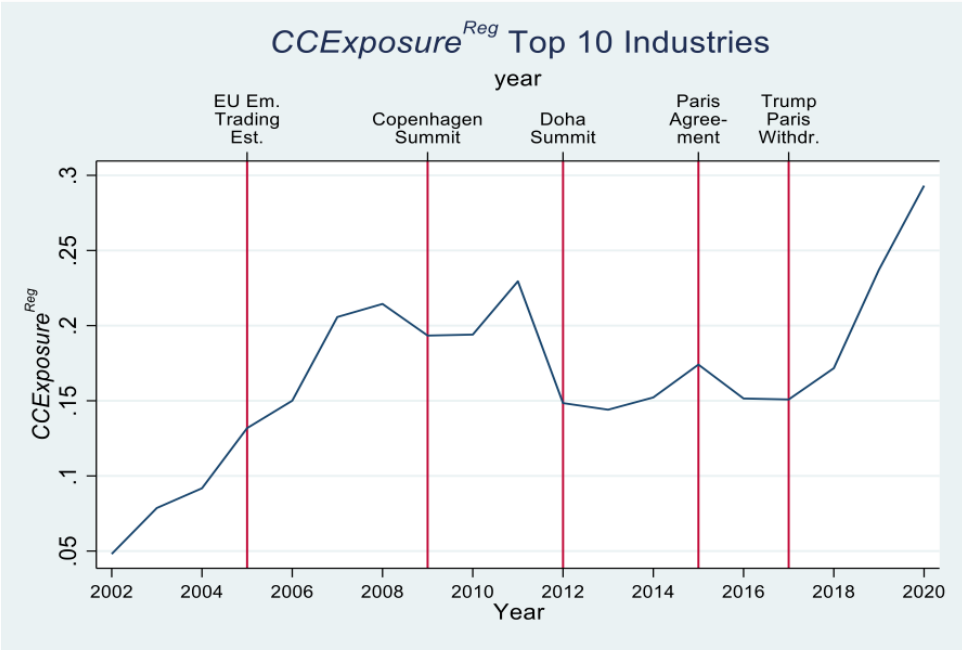

CCExposure Top 10 Industries
year
EU Em. Trading Est./ Hurricane Katrina
Copenhagen Summit
Doha Summit
Paris Agreement/ Hurricane Sandy
Hurricane Harvey
CCExposure
1.5
2
2.5
3
3.5
4
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020

(a)

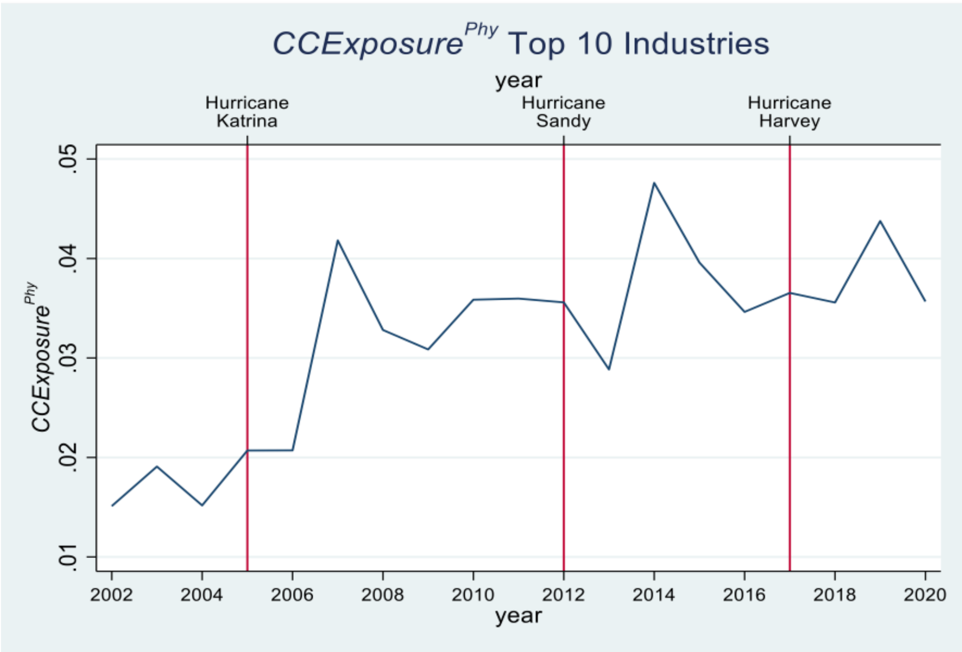

CCExposure^Opp Top 10 Industries
year
EU Em. Trading Est.
Copenhagen Summit
Doha Summit
Paris Agree-ment
Trump Paris Withdr.
CCExposure^Opp
.5
1
1.5
2
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
Year

(b)

Figure 3 continued



(c)



(d)

Figure 3 continued

Figure 3. Climate Change Exposure over Time

These figures report firms' average climate change exposures over time. $CCExposure$ measures the relative frequency with which climate change bigrams occur in earnings calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in earnings calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur earnings calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in earnings calls. For each exposure measure, we construct the time-series for firms in the top-10 industries (see Table III). Appendix A defines all variables in detail.

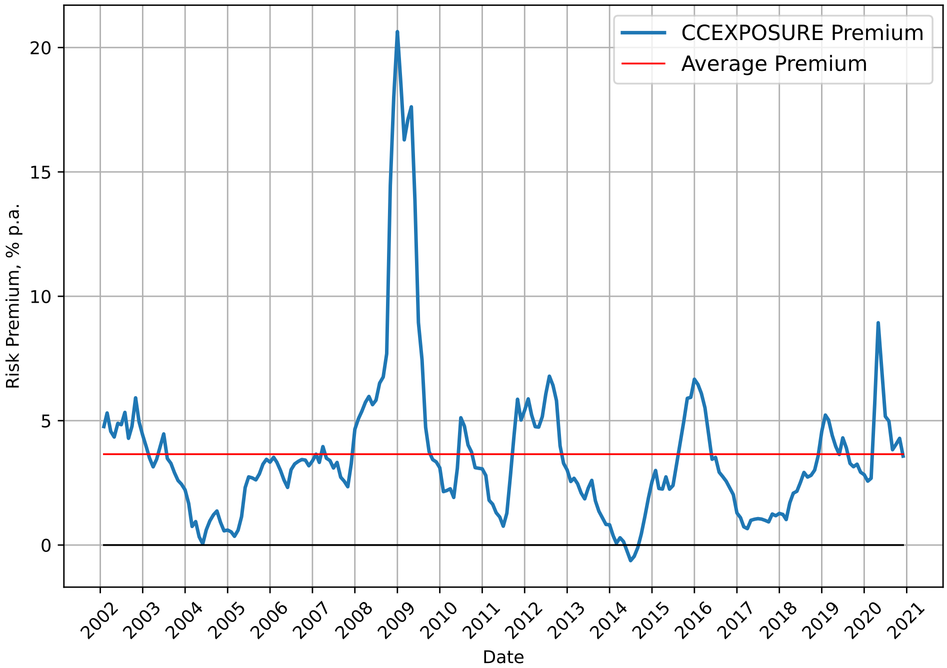


Figure 4. Risk Premium on the Climate Change Exposure Factor

This figure shows the time-series of the risk premium on the *CCEXPOSURE* factor, estimated together with the 4-factor Carhart (1997) model using the conditional framework by Gagliardini, Ossola, and Scaillet (2016). The factor is constructed as the monthly changes in the cross-sectional average of *CCExposure* across U.S.-traded sample firms. The factor is standardized to have zero mean and an annual volatility of 10%.

Table I.
Climate Change Exposure Variables: Summary Statistics

This table reports summary statistics of different measures of climate change exposure, carbon emissions, and public attention to climate change at the firm-year level. For the climate change exposure measures, we average values of the four earnings calls during the year. The sample includes 10,673 unique firms from 34 countries over the period 2002 to 2020. Appendix A defines all variables in detail.

	Mean	STD	25%	Median	75%	N
CC Measures ($\times 10^3$)						
$CCExposure_{i,t}$	1.01	2.53	0.10	0.30	0.78	86152
$CCExposure^{Opp}_{i,t}$	0.40	1.36	0.00	0.04	0.24	86152
$CCExposure^{Reg}_{i,t}$	0.05	0.27	0.00	0.00	0.00	86152
$CCExposure^{Phy}_{i,t}$	0.01	0.10	0.00	0.00	0.00	86152
CC Measures (TFIDF Version) ($\times 10^3$)						
$CCExposure_{i,t}$	7.99	19.69	0.77	2.44	6.26	86152
$CCExposure^{Opp}_{i,t}$	3.06	10.15	0.00	0.31	1.93	86152
$CCExposure^{Reg}_{i,t}$	0.38	1.93	0.00	0.00	0.00	86152
$CCExposure^{Phy}_{i,t}$	0.09	0.75	0.00	0.00	0.00	86152
CC Q&A Measure ($\times 10^3$)						
$CCExposure^{Q\&A}_{i,t}$	0.67	1.95	0.00	0.12	0.54	86152
CC Sentiment and Risk Measures ($\times 10^3$)						
$CCSentiment^{Pos}_{i,t}$	0.38	1.10	0.00	0.07	0.32	86152
$CCSentiment^{Neg}_{i,t}$	0.19	0.55	0.00	0.00	0.16	86152
$CCRisk_{i,t}$	0.04	0.17	0.00	0.00	0.00	86152
Carbon Emissions and Climate Change Attention						
$Total\ Emissions_{i,t}$	2961549	13608989	27472	133847	751772	33789
$WSJ\ CC\ News\ Index_t$	0.007	0.001	0.006	0.006	0.008	68794

Table II.
Top-100 Bigrams Captured by Climate Change Exposure (*CCExposure*)

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 earnings calls. Appendix A defines all variables in detail.

Bigram	Frequency	Bigram	Frequency	Bigram	Frequency
renewable energy	15605	onshore wind	878	carbon intensity	641
electric vehicle	9508	electric motor	869	energy application	615
clean energy	6430	provide energy	851	produce electricity	604
new energy	4544	efficient solution	839	help state	604
climate change	4374	global warm	837	environmental standard	593
wind power	4253	power generator	828	power agreement	586
wind energy	4035	solar pv	827	supply energy	585
energy efficient	3899	scale solar	827	electric hybrid	585
greenhouse gas	3416	need clean	821	source power	575
solar energy	2511	coastal area	816	sustainability goal	572
air quality	2409	energy star	793	energy reform	571
clean air	2301	environmental footprint	792	plant power	564
carbon emission	2088	design use	777	compare conventional	560
gas emission	1910	area energy	777	gas vehicle	560
extreme weather	1773	charge station	762	effort energy	560
carbon dioxide	1583	clean water	759	pass house	559
water resource	1423	major design	747	carbon free	558
autonomous vehicle	1394	vehicle manufacturer	740	driver assistance	545
energy environment	1279	future energy	737	electrical energy	543
wind resource	1245	motor control	726	solar installation	541
government india	1201	combine heat	718	snow ice	538
battery power	1147	electric bus	709	renewable natural	536
air pollution	1127	distribute power	703	promote use	536
battery electric	1121	environmental benefit	695	farm project	531
integrate resource	1052	eco friendly	695	laser diode	528
clean power	1008	electrical vehicle	695	deliver energy	526
carbon price	999	carbon neutral	690	protect environment	525
world population	977	fast charge	675	sustainable energy	523
solar farm	971	cell power	657	manage energy	522
energy regulatory	967	energy team	650	invest energy	521
obama administration	957	cycle gas	646	electric energy	519
heat power	941	coal gasification	643	forest land	512
carbon tax	928	environmental concern	643	capacity energy	512
unite nation	925				

Table III. Industry Distribution of Climate Change Exposure Measures

This table reports firms' climate change exposure measures for the top-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 climate change bigrams occur in earnings calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in earnings calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in earnings calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in earnings calls. For all measure, we average values of the four earnings calls during the year. We report only those industries for which we have more than 20 firm-year observations. Appendix A defines all variables in detail.

Panel A: $CCExposure$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	N
49 Electric, Gas, & Sanitary Services	6.95	6.23	5.34	3259
16 Heavy Construction, Except Building	3.04	4.35	1.53	537
17 Construction	2.26	2.95	1.16	131
37 Transportation Equipment	2.12	3.17	1.07	2021
36 Electronic & Other Electric Equipment	2.07	4.20	0.57	5812
12 Coal Mining	2.05	1.48	1.70	253
29 Petroleum Refining	1.72	2.14	1.06	730
41 Local & Suburban Transit	1.69	2.06	0.84	94
55 Automative Dealers & Service Stations	1.63	3.90	0.69	484
33 Primary Metal	1.56	1.54	1.14	1149
Panel B: $CCExposure^{Opp}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	N
49 Electric, Gas, & Sanitary Services	3.05	3.62	1.83	3259
16 Heavy Construction, Except Building	1.54	2.96	0.43	537
17 Construction	1.19	1.95	0.43	131
36 Electronic & Other Electric Equipment	1.07	2.55	0.19	5812
37 Transportation Equipment	1.07	1.98	0.43	2021
75 Auto Repair, Services, & Parking	0.68	1.59	0.32	171
55 Automative Dealers & Service Stations	0.67	1.41	0.27	484
29 Petroleum Refining	0.61	1.10	0.23	730
35 Industrial Machinery & Equipment	0.58	1.95	0.13	4056
12 Coal Mining	0.49	0.64	0.35	253

Table III continued

Panel C: $CCExposure^{Reg}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	N
49 Electric, Gas, & Sanitary Services	0.41	0.71	0.13	3259
12 Coal Mining	0.18	0.28	0.07	253
29 Petroleum Refining	0.17	0.37	0.00	730
32 Stone, Clay, & Glass Products	0.14	0.39	0.00	622
10 Metal Mining	0.11	0.34	0.00	1465
37 Transportation	0.10	0.30	0.00	2021
33 Primary Metal	0.09	0.25	0.00	1149
35 Industrial Machinery & Equipment	0.09	0.54	0.00	4056
41 Local & Suburban Transit	0.09	0.31	0.00	94
24 Lumber & Wood	0.08	0.52	0.00	471
Panel D: $CCExposure^{Phy}$ ($\times 10^3$)				
Industry (SIC2)	Mean	Std.Dev.	Median	N
26 Paper & Allied Products	0.08	0.35	0.00	852
24 Lumber & Wood	0.07	0.24	0.00	471
14 Nonmetallic Minerals, Except Fuels	0.05	0.14	0.00	208
49 Electric, Gas, & Sanitary Services	0.04	0.16	0.00	3259
12 Coal Mining	0.04	0.22	0.00	253
64 Insurance Agents, Brokers, & Service	0.03	0.15	0.00	297
15 General Building Contractors	0.03	0.11	0.00	600
10 Metal Mining	0.03	0.12	0.00	1465
22 Textile Mill Products	0.03	0.10	0.00	159
35 Industrial Machinery & Equipment	0.03	0.26	0.00	4056

Table IV.
Climate Change Exposure Measures: Effects of Carbon Emissions and Climate Change News

This table reports regressions that relate carbon emissions and climate change news to the climate change exposure measures. Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which bigrams related to climate change occur in earnings calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in earnings calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in earnings calls. For all measure, we average values of the four earnings calls during the year. $Total\ Emissions$ is the sum of a firm's Scope 1 and Scope 2 carbon emissions. $WSJ\ CC\ News\ Index$ is a time-series index developed in Engle et al. (2020) that captures climate change news in the *Wall Street Journal*. We divide the coefficient on *WSJ Climate Change News Index* by 100. The regressions control for *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets* *Capex/Assets*, and *R&D/Assets* (all in $t-1$). In Panel B, we do not include time-varying industry fixed effects, as *WSJ CC News Index* only varies in the time-series. Standard errors, clustered at the industry-by-year level, are in parentheses. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

Panel A: Carbon Emissions				
	$CCExposure_{i,t}$	$CCExposure^{Opp}_{i,t}$	$CCExposure^{Reg}_{i,t}$	$CCExposure^{Phy}_{i,t}$
	(1)	(2)	(3)	(4)
$Log(1 + Total\ Emissions_{i,t-1})$	0.169***	0.050***	0.028***	-0.001
	(0.023)	(0.010)	(0.004)	(0.001)
Model	OLS	OLS	OLS	OLS
Sample	All	All	All	All
Controls	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No
Country Fixed Effects	Yes	Yes	Yes	Yes
N	30905	30905	30905	30905
Adj. R-sq.	0.390	0.304	0.164	0.020
Panel B: Public Attention to Climate Change				
	$CCExposure_{i,t}$	$CCExposure^{Opp}_{i,t}$	$CCExposure^{Reg}_{i,t}$	$CCExposure^{Phy}_{i,t}$
	(1)	(2)	(3)	(4)
$WSJ\ CC\ News\ Index_t$	0.427**	0.186*	0.044***	0.004
	(0.168)	(0.101)	(0.011)	(0.003)
Model	OLS	OLS	OLS	OLS
Sample	All	All	All	All
Controls	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	No	No	No	No
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
N	54824	54824	54824	54824
Adj. R-sq.	0.298	0.217	0.097	0.019

Table V.
Variance Decomposition of Climate Change Exposure Measures

This table provides a variance decomposition of the climate change exposure measures. Regressions are estimated at the firm-year level. In Panel A, the table reports the incremental R-squared from adding a specific fixed effect. In Panel B, the table decomposes the variation into a firm fixed effect and residual component. $CCExposure$ measures the relative frequency with which climate change bigrams occur in earnings calls. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in earnings calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in earnings calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in earnings calls. For all measure, we average values of the four earnings calls during the year. Appendix A defines all variables in detail.

Variable	$CCExposure_{i,t}$	$CCExposure^{Opp}_{i,t}$	$CCExposure^{Reg}_{i,t}$	$CCExposure^{Phy}_{i,t}$
	(1)	(2)	(3)	(4)
	Panel A: Incremental R-Squared			
Year Fixed Effect	0.7%	0.7%	0.6%	0.03%
Industry Fixed Effect	27.1%	19.9%	8.3%	1.6%
Industry x Year Fixed Effect	1.9%	2.5%	1.7%	1.2%
Country Fixed Effect	0.6%	0.8%	0.5%	0.2%
"Firm Level"	69.7%	76.2%	89.0%	97.1%
Sum	100.0%	100.0%	100.0%	100.0%
	Panel B: Fraction of Variation			
Firm Fixed Effect: Permanent differences across firms within sector and countries	51.6%	54.9%	46.2%	47.4%
Residual: Variation over time in the identity of firms within industries and countries most affected by exposure variable	48.4%	45.1%	53.8%	52.6%
Sum	100.0%	100.0%	100.0%	100.0%

Table VI.
Quantifying Measurement Error in Climate Change Exposure Measures

This table shows AR(1) regressions of climate change exposure. Regressions are estimated at the firm-year level. $CCExposure$ measures the relative frequency with which climate change bigrams occur in earnings calls. We average values of the four earnings calls during the year. $CCExposure^{10K}$ measures climate change exposure by applying our algorithm to the "Management Discussion and Analysis" (MD&A) section in firms' annual 10K filings. Following Hassan et al. (2019), $CCExposure$ and $CCExposure^{10K}$ in this table are standardized by subtracting the sample mean and dividing by the sample standard deviation. Implied Share Measurement Error is calculated as $1 - (\hat{\beta}_{OLS}/\hat{\beta}_{IV})$ where $\hat{\beta}_{OLS}$ is the estimated coefficient in $CCExposure_{i,t} = \alpha + \beta CCExposure_{i,t-1} + \epsilon$ and where $\hat{\beta}_{IV}$ is the coefficient on the instrumented $CCExposure_{i,t}$ in the same specification. To obtain bootstrapped standard errors for Implied Share Measurement Error, we repeat the following procedure 500 times: draw a random sample of the same sample size (with replacement and clustered by firm) from our regression sample, run the two regressions, and obtain the implied share of measurement error. These standard errors are clustered at the firm level. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

Panel A: Overall Variation	$CCExposure_{i,t}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t-1}$	0.922***	1.008***	0.991***	0.958***
	(0.002)	(0.003)	(0.003)	(0.002)
Model	OLS	IV	IV	IV
Instrument		$CCExpo^{10K}_{i,t-1}$	$CCExpo^{10K}_{i,t-2}$	$CCExpo_{i,t-2}$
Sample	US	US	US	US
Industry x Year Fixed Effects	No	No	No	No
N	47589	47589	41794	41794
Implied Share Measurement Error		0.085	0.069	0.037
		(0.007)	(0.007)	(0.005)

Panel B: Firm-level Variation	$CCExposure_{i,t}$			
	(1)	(2)	(3)	(4)
$CCExposure_{i,t-1}$	0.886***	0.992***	0.966***	0.932***
	(0.002)	(0.004)	(0.002)	(0.003)
Model	OLS	IV	IV	IV
Instrument		$CCExpo^{10K}_{i,t-1}$	$CCExpo^{10K}_{i,t-2}$	$CCExpo_{i,t-2}$
Sample	US	US	US	US
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes
N	47502	47502	41712	41712
Implied Share Measurement Error		0.107	0.083	0.050
		(0.002)	(0.012)	(0.007)

Table VII.
Green Technology Jobs and Climate Change Exposure Measures

This table reports regressions that relate green technology jobs to the climate change exposure measures. Regressions are estimated at the firm-year level. *#Green Tech Jobs* is the number of job postings for disruptive green tech jobs. *I(Green Tech Jobs)* is an indicator that equals one if *#Green Tech Jobs* is positive, and zero otherwise. *#Non-Green Tech Jobs* is the number of job postings for non-green disruptive tech jobs. $Green\ Tech\ Ratio_{i,t+1}$ is the number of job postings for disruptive green jobs relative to the total number of all disruptive job postings. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are defined as in previous tables. The regressions control for *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets* *Capex/Assets*, and *R&D/Assets* (all in t). In Columns 5 to 7, we use the same observations as in Columns 1 to 4. In Columns 1 to 4 and 7, the economic effects are computed as the percentage change in the dependent variable for a one-standard-deviation change in the exposure variable of interest. In Columns 5 and 6, the economic effect is computed as the effect of a one-standard deviation change in the exposure variable relative to the standard deviation of the dependent variable. We use the within-fixed-effect standard deviations. Standard errors, clustered at the industry-by-year level, are in parentheses. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\ Tech\ Jobs_{i,t+1}$				$I(\#Green\ Tech\ Jobs)_{i,t+1}$	$Green\ Tech\ Ratio_{i,t+1}$	$\#Non\text{-}GreenTech\ Jobs_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Log(1 + CCExposure_{i,t})$	1.564***				0.077***	0.015***	-0.204***
	(0.199)				(0.006)	(0.003)	(0.060)
$Log(1 + CCExposure^{Opp}_{i,t})$		1.869***					
		(0.221)					
$Log(1 + CCExposure^{Reg}_{i,t})$			1.432***				
			(0.398)				
$Log(1 + CCExposure^{Phy}_{i,t})$				1.071			
				(0.939)			
Model	Poisson	Poisson	Poisson	Poisson	OLS	OLS	Poisson
Sample	US	US	US	US	US	US	US
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	23870	23870	23870	23870	23870	23870	23870
Adj./ps. R-sq.	0.754	0.770	0.688	0.684	0.116	0.049	0.526
Dep. Variable: Mean	2.82	2.82	2.82	2.82	0.07	0.003	845.09
Dep. Variable: STD	89.56	89.56	89.56	89.56	0.26	0.042	3613.42
Economic Effect, %	108.7	89.6	21.6	6.6	14.0	16.9	-9.1

Table VIII.
Green Patents and Climate Change Exposure Measures

This table reports regressions that relate green patents to the climate change exposure measures. Regressions are estimated at the firm-year level. $\#Green\,Patents$ is the number of green patents. $I(Green\,Patents)$ is an indicator that equals one if $\#Green\,Patents$ is positive, and zero otherwise. $Green\ Patents\ Ratio_{i,t+1}$ is the number of green patents relative to the total number of all patents. $\#Non\text{-}Green\ Patents$ is the number of non-green patents. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are defined as in previous tables. The regressions control for *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets Capex/Assets*, and *R&D/Assets* (all in t). In Columns 5 to 7, we use the same observations as in Columns 1 to 4 (the Poisson estimation in Column 7 drops some observations). In Columns 1 to 4 and 7, the economic effects are computed as the percentage change in the dependent variable for a one-standard-deviation change in the exposure variable of interest. In Columns 5 and 6, the economic effect is computed as the effect of a one-standard deviation change in the exposure variable relative to the standard deviation of the dependent variable. We use the within-fixed-effect standard deviations. Standard errors, clustered at the industry-by-year level, are in parentheses. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\ Patents_{i,t+1}$				$I(Green\ Patents)_{i,t+1}$	$Green\ Patents\ Ratio_{i,t+1}$	$\#Non\text{-}Green\ Patents_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Log(1+CCExposure_{i,t})$	1.102***				0.025***	0.006***	-0.436***
	(0.231)				(0.003)	(0.001)	(0.118)
$Log(1+CCExposure^{Opp}_{i,t})$		0.691**					
		(0.314)					
$Log(1+CCExposure^{Reg}_{i,t})$			2.656***				
			(0.279)				
$Log(1+CCExposure^{Phy}_{i,t})$				1.257**			
				(0.491)			
Model	Poisson	Poisson	Poisson	Poisson	OLS	OLS	Poisson
Sample	US	US	US	US	US	US	US
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21914	21914	21914	21914	21914	21914	21776
Adj./ps. R-sq.	0.617	0.602	0.611	0.598	0.078	0.023	0.752
Dep. Variable: Mean	0.28	0.28	0.28	0.28	0.03	0.003	22.10
Dep. Variable: STD	4.07	4.07	4.07	4.07	0.18	0.040	224.23
Economic Effect, %	71.7	27.4	44.1	8.0	7.0	7.4	-19.3

Table IX.
Forward-looking Risk Measures and Climate Change Exposure Measures

This table reports regressions that relate forward-looking risk measures to the climate change exposure measures. Regressions are estimated at the firm-quarter level. $IVar$ is implied variance, $ISkew$ is implied skewness, $IKurt$ is implied kurtosis, $SlopeD$ and $SlopeU$ are implied volatility slopes on the left and right of the distribution, and VRP is the variance risk premium. The construction of the option-implied measures is detailed in Internet Appendix B. $CCExposure$, $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$ are defined as in previous tables. The regressions control for *Log(Assets)*, *Debt/Assets*, *Cash/Assets*, *PP&E/Assets*, *EBIT/Assets Capex/Assets*, and *R&D/Assets* (all in t). The economic effect is computed as the effect of a one-standard-deviation change in the exposure variable of interest relative to the standard deviation of the dependent variable (in %). We use the within-fixed-effect standard deviation. Standard errors, clustered at the industry-by-year level, are in parentheses. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$IVar_{i,t+1}$	$ISkew_{i,t+1}$	$IKurt_{i,t+1}$	$SlopeD_{i,t+1}$	$SlopeU_{i,t+1}$	$VRP_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: $CCExposure$						
$Log(1 + CCExposure_{i,t})$	-0.005	-0.028***	0.185***	0.017***	-0.014***	0.001
	(0.003)	(0.007)	(0.035)	(0.005)	(0.005)	(0.002)
N	39191	39191	39191	39191	39191	39191
Adj. R-sq.	0.429	0.142	0.351	0.232	0.239	0.095
Economic Effect, %	-1.08	-2.65	4.33	2.30	-2.24	0.30
Panel B: $CCExposure^{Opp}$						
$Log(1 + CCExposure^{Opp}_{i,t})$	-0.005	-0.026***	0.264***	0.026***	-0.024***	0.005*
	(0.005)	(0.008)	(0.048)	(0.008)	(0.007)	(0.003)
N	39191	39191	39191	39191	39191	39191
Adj. R-sq.	0.428	0.142	0.352	0.232	0.239	0.095
Economic Effect, %	-0.79	-1.81	4.53	2.58	-2.81	1.10
Panel C: $CCExposure^{Reg}$						
$Log(1 + CCExposure^{Reg}_{i,t})$	-0.004	-0.014	0.217***	0.026**	-0.029**	-0.006
	(0.007)	(0.017)	(0.082)	(0.013)	(0.012)	(0.011)
N	39191	39191	39191	39191	39191	39191
Adj. R-sq.	0.428	0.142	0.350	0.231	0.238	0.095
Economic Effect, %	-0.30	-0.46	1.76	1.22	-1.61	-0.62
Panel D: $CCExposure^{Phy}$						
$Log(1 + CCExposure^{Phy}_{i,t})$	-0.027**	-0.006	0.268*	0.009	-0.043**	-0.019**
	(0.012)	(0.037)	(0.154)	(0.027)	(0.022)	(0.009)
N	39191	39191	39191	39191	39191	39191
Adj. R-sq.	0.428	0.142	0.350	0.231	0.238	0.095
Economic Effect, %	-0.83	-0.08	0.89	0.17	-0.98	-0.81
Model	OLS	OLS	OLS	OLS	OLS	OLS
Sample	S&P500	S&P500	S&P500	S&P500	S&P500	S&P500
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Variable: Mean	0.175	-0.573	4.685	0.319	-0.103	0.041
Dep. Variable: STD	0.197	0.450	1.821	0.315	0.267	0.143

Table X.
Climate Change Exposure Factor: Components of F and ν.

This table reports the estimated annualized components of F and ν for the 4-factor Carhart (1997) model augmented by a *CCEXPOSURE* factor. The estimation is based on the conditional framework by Gagliardini, Ossola, and Scaillet (2016). The factor is constructed as the monthly changes in the cross-sectional average of $CCExposure$ across U.S.-traded sample firms. The factor is standardized to have zero mean and an annual volatility of 10%. All instruments are centered and standardized in the time-series. The common instruments are the default spread and the term spread, and the firm-specific instrument is the log of the book-to-market ratio. *p< .1; **p< .05; ***p< .01.

Factors	*Instruments*	F	$SE(F)$	ν	$SE(\nu)$
		(1)	(2)	(3)	(4)
Market	Constant	8.9838***	3.4981	2.3908***	0.7110
	Default Spread	-1.0201	5.4550	2.4676***	0.8715
	Term Spread	-1.9715	3.3962	1.4489**	0.6705
SMB	Constant	2.3669	1.9164	2.6523*	1.3459
	Default Spread	2.5406	2.0404	-1.3983	1.0227
	Term Spread	2.1356	1.8985	-4.6391***	0.9302
HML	Constant	-2.1553	2.0893	-3.5959***	1.0965
	Default Spread	-3.6834	3.9437	3.7360***	0.8545
	Term Spread	4.8748**	2.2504	-0.0444	0.8434
MOM	Constant	1.3199	3.5668	7.2011***	1.6444
	Default Spread	-14.359*	8.2567	7.8356***	1.7552
	Term Spread	2.4766	2.9728	-0.6825	1.2843
CCEXPOSURE	Constant	-0.0032	2.3008	3.7273***	1.1654
	Default Spread	0.0805	2.7644	3.1262***	1.0855
	Term Spread	-0.2941	2.6282	-0.1834	0.9978

Internet Appendix

for

Firm-level Climate Change Exposure

ZACHARIAS SAUTNER, LAURENCE VAN LENT, GRIGORY VILKOV,
and RUISHEN ZHANG*

*Citation format: Sautner, Zacharias, van Lent, Laurence, Vilkov, Grigory, and Zhang, Ruishen, Internet Appendix to "Firm-level Climate Change Exposure," *Journal of Finance* [DOI STRING]. Please note: Wiley is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

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:

$$RoughCCExposure_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left(1[b \in \mathbb{C}^{\mathbb{R}} \setminus \mathbb{N}] \right), \tag{8}$$

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

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

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

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

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

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

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

B. Construction of Option-Implied Measures

A. Data

Data on option-implied variables are from the Volatility Surface File of Ivy DB OptionMetrics. We focus these tests on S&P500 firms, for which data on liquid options is available. We match options data through the historical CUSIP link of OptionMetrics. The high frequency of the option-implied measures allows us to use quarterly values of $CCExposure$. To prepare the Volatility Surface, we select OTM options with absolute deltas strictly (weakly) smaller than 0.5 for puts (calls) for maturities of 30 days. We interpolate the implied volatilities available as a function of moneyness between the available moneyness points. We then extrapolate the data by filling in the missing extreme data using the implied volatility values from the left and right boundaries. This method enables us to fill in the moneyness range of [1/3,3] with a total of 1,001 points. For the interpolations, we use a piece-wise cubic Hermite interpolating polynomial.

B. Measures

Implied Variance, Skewness, Kurtosis. To measure implied variance (IV) of log returns, we take the Bakshi, Kapadia, and Madan (2003) variance swap rate $IVar_{t,t+\Delta t}$ for a given maturity $t + \Delta t$, constructed from the prices of out-of-the-money (OTM) calls $C(t, t+\Delta, K)$ and puts $P(t, t+\Delta, K)$ with strike prices K observed at t.

$$IVar_{t,t+\Delta t} = R_{t,t+\Delta t} \int_0^{S_t} \frac{2(1 - \ln K/S_t)}{K^2} P(t, t + \Delta, K)dK + R_{t,t+\Delta t} \int_{S_t}^{\infty} \frac{2(1 - \ln K/S_t)}{K^2} C(t, t + \Delta, K)dK \tag{9}$$

where $R_{t,t+\Delta t}$ if the gross risk-free rate of return and S_t is the spot price of the underlying stock. We use a similar approach for the implied skewness, $ISkew$, and for the implied kurtosis, $IKurt$, applying the formulas for the log returns provided in Bakshi, Kapadia, and Madan (2003). We approximate each integral in Equation (9) for IV using a finite sum of 1001 option prices (we do likewise for similar integrals in the formulas for $ISkew$ and $IKurt$).

Implied Volatility Slope. We measure the steepness of the implied volatility slope on the left (*SlopeD*) and right (*SlopeU*) from the at-the-money (ATM) point. As in Kelly, Pastor, and Veronesi (2016), the measures are the slopes of functions relating implied volatilities of OTM options to their deltas. We estimate *SlopeD* by regressing implied volatilities of puts with deltas between -0.1 and -0.5 on their deltas (and a constant). For *SlopeU*, we regress implied volatilities of calls with deltas between 0.1 and 0.5 on their deltas. Note that for *SlopeD* the independent variable (delta) is *increasing* for more OTM options, so a positive (and a higher) slope coefficient indicates more expensive tail protection, while for *SlopeU* the independent variable is *decreasing* for more OTM options, and, hence, a more negative slope coefficient indicates higher cost of obtaining right-tail exposure. *SlopeD* is on average positive and *SlopeU* is on average negative as far OTM options are typically more expensive (in terms of implied volatilities) than ATM options.

Variance Risk Premium. We calculate risk premiums for particular risks by comparing expected quantities under the physical and risk-neutral probability measures as follows. (The theoretically sound definition of the finite-period risk premium is the expectation under the risk-neutral (Q) measure minus expectation under the physical (P) measure; for convenience, we follow an informal tradition of computing the finite-period risk premium as the Q minus P expectation.) The variance risk premium (VRP) allows us to evaluate the cost of protection against general variance risk (or uncertainty, as suggested in Bali and Zhou (2016)). VRP is computed as the difference between the risk-neutral expected and the past realized variances (the latter acting as a proxy for expected variance under the physical measure):

$$VRP_{t,t+\Delta t} = IVar_{t,t+\Delta t} - RVar_{t-\Delta t,t}, \tag{10}$$

where $RVar_{t-\Delta t,t}$ is computed from daily simple returns over the rolling window $[t - \Delta t, t]$.

C. Costs and Benefits of Measures

While these "risk quantities" do not directly reflect expectations of risk in the real (physical) world, they efficiently aggregate the forward-looking consensus of market participants with respect to the future return distribution. A key benefit is their forward-looking character. For example, $IVar$ is a strong predictor of the future realized variance (Poon and Granger (2003)), $ISkew$ allows for the quantification of the asymmetry of the risk-neutral distribution, and $SlopeD/SlopeU$ represent heuristic proxies for the relative price of protection against tail risk (Kelly, Pastor, and Veronesi (2016)). A cost is potential bias stemming from the risk premium effect (see Vanden (2008), Chang et al. (2012), Cremers, Halling, and Weinbaum (2015), DeMiguel et al. (2013)).

Table IA. I.
Firm-Years Across Countries

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

Country/Region	N	Percent
Australia	1,460	1.69
Austria	193	0.22
Belgium	262	0.3
Bermuda	727	0.84
Brazil	1,049	1.22
Canada	5,924	6.88
Chile	227	0.26
China	1,459	1.69
Denmark	428	0.5
Finland	472	0.55
France	1,314	1.53
Germany	1,320	1.53
Greece	234	0.27
Hong Kong	450	0.52
India	1,227	1.42
Ireland; Republic of	646	0.75
Israel	738	0.86
Italy	553	0.64
Japan	1,675	1.94
Korea; Republic (S. Korea)	296	0.34
Luxembourg	271	0.31
Mexico	542	0.63
Netherlands	798	0.93
New Zealand	206	0.24
Norway	450	0.52
Russia	335	0.39
Singapore	256	0.3
South Africa	480	0.56
Spain	504	0.59
Sweden	930	1.08
Switzerland	975	1.13
Taiwan	344	0.4
United Kingdom	3,300	3.83
United States of America	56,107	65.13
Total	86,152	100

Table IA. II.
Firm-Years with/without Trucost Emissions Data

This table reports summary statistics of climate change exposure measures and firm characteristics depending on whether or not a firm-year is included in the Trucost database on carbon emissions. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	Firm-Year Observations with Trucost Emissions Data (N=33,789)			Firm-Year Observations without Trucost Emissions Data (N=52,363)			
	Mean	Std.Dev.	Median	Mean	Std.Dev.	Median	Difference-in-Means
$CCExposure_{i,t}$	1.190	2.831	0.350	0.899	2.312	0.277	0.291***
$CCExposure^{Opp}_{i,t}$	0.481	1.505	0.081	0.346	1.256	0.000	0.134***
$CCExposure^{Reg}_{i,t}$	0.066	0.296	0.000	0.046	0.252	0.000	0.019***
$CCExposure^{Phy}_{i,t}$	0.015	0.110	0.000	0.012	0.091	0.000	0.003***
$Assets_{i,t}$	23616	57774	4798	4976	22603	707	18640***
$Debt/Assets_{i,t}$	0.260	0.193	0.239	0.252	0.241	0.204	0.008***
$Cash/Assets_{i,t}$	0.139	0.160	0.083	0.203	0.225	0.110	-0.064***
$PPE/Assets_{i,t}$	0.265	0.242	0.189	0.236	0.247	0.136	0.028***
$EBIT/Assets_{i,t}$	0.069	0.118	0.070	0.003	0.203	0.049	0.066***
$Capex/Assets_{i,t}$	0.044	0.046	0.031	0.042	0.053	0.024	0.002***
$R\&D/Assets_{i,t}$	0.026	0.064	0.000	0.051	0.106	0.000	-0.025***
$USfirm_{i,t}$	0.488	0.500	0.000	0.756	0.429	1.000	-0.268***

Table IA. III.
Initial Bigrams for Searching Climate Change Bigrams

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

Table IA. IV.
Initial Bigrams for Opportunity, Regulatory, and Physical Climate Change Exposure Measures

Panel A: 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		
Panel B: Initial Regulatory Bigrams				
greenhouse gas	gas emission	carbon tax	emission trade	carbon reduction
reduce emission	air pollution	carbon price	dioxide emission	carbon market
carbon emission	reduce carbon	environmental standard	epa regulation	mercury emission
carbon dioxide	energy regulatory	nox emission	energy independence	
Panel C: 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	

Table IA. V.
Climate Change Exposure Measures: Correlations

This table shows correlations across different climate change exposure measures. We report correlations for frequency-unweighted ("EW") and TFIDF-adjusted ("TFIDF") versions of climate change exposure. Appendix A defines all variables in detail.

		Frequency-Unweighted Measures (EW Measures)				TFIDF-Adjusted Measures (TFIDF Measures)			
		$CCExpo_{i,t}$	$CCExpo_{i,t}^{Opp}$	$CCExpo_{i,t}^{Reg}$	$CCExpo_{i,t}^{Phy}$	$CCExpo_{i,t}$	$CCExpo_{i,t}^{Opp}$	$CCExpo_{i,t}^{Reg}$	$CCExpo_{i,t}^{Phy}$
EW Measures	$CCExposure_{i,t}$	1.000							
	$CCExposure_{i,t}^{Opp}$	0.892	1.000						
	$CCExposure_{i,t}^{Reg}$	0.534	0.329	1.000					
	$CCExposure_{i,t}^{Phy}$	0.135	0.058	0.073	1.000				
TFIDF Measures	$CCExposure_{i,t}$	0.997	0.876	0.534	0.134	1.000			
	$CCExposure_{i,t}^{Opp}$	0.890	0.995	0.336	0.057	0.879	1.000		
	$CCExposure_{i,t}^{Reg}$	0.527	0.321	0.992	0.072	0.528	0.328	1.000	
	$CCExposure_{i,t}^{Phy}$	0.131	0.056	0.069	0.996	0.131	0.055	0.069	1.000

Table IA. VI.
Earnings-Call Observations across Countries

This table reports the distribution of earnings calls (earnings calls with $CCExposure > 0$) across sample countries. The sampling criteria are specified in Section I.A.

Country/Region	# Calls	# Calls with $CCExposure > 0$	Percentage of Calls with $CCExposure > 0$
Argentina	468	199	42.52
Australia	3881	2319	59.75
Austria	938	538	57.36
Belgium	1047	548	52.34
Bermuda	2855	1433	50.19
Brazil	4619	2396	51.87
Canada	20995	11524	54.89
Chile	831	513	61.73
China	5024	2516	50.08
Denmark	1845	879	47.64
Finland	2024	1068	52.77
France	3931	2525	64.23
Germany	5539	3169	57.21
Greece	987	445	45.09
Hong Kong	1325	664	50.11
India	4921	2892	58.77
Ireland; Republic of	2386	1228	51.47
Israel	2759	972	35.23
Italy	2772	1525	55.01
Japan	7688	2463	32.04
Korea; Republic (S. Korea)	1304	625	47.93
Luxembourg	1102	660	59.89
Mexico	2301	1225	53.24
Netherlands	2959	1611	54.44
New Zealand	477	274	57.44
Norway	2088	1116	53.45
Poland	673	372	55.27
Portugal	486	255	52.47
Russia	1193	683	57.25
Singapore	1086	561	51.66
South Africa	1445	960	66.44
Spain	2240	1389	62.01
Sweden	4250	2065	48.59
Switzerland	3197	1759	55.02
Taiwan	1377	531	38.56
Turkey	586	244	41.64
United Kingdom	10116	6109	60.39
United States of America	217191	109531	50.43
Total	330906	169786	51.31

Table IA. VII.
Earnings-Call Observations across Years

This table reports the distribution of earnings calls (earnings calls with $CCExposure > 0$) across sample years. The sampling criteria are specified in Section I.A.

Year	# Calls	# Calls with $CCExposure > 0$	Percentage of Calls with $CCExposure > 0$
2002	6188	2739	44.26
2003	11908	5377	45.15
2004	14339	6668	46.50
2005	15431	7391	47.90
2006	16388	7990	48.76
2007	17405	8487	48.76
2008	18737	9597	51.22
2009	18247	9439	51.73
2010	18291	9378	51.27
2011	18642	9796	52.55
2012	18736	9777	52.18
2013	16737	8606	51.42
2014	17752	9136	51.46
2015	17785	9220	51.84
2016	17234	8996	52.20
2017	19580	10107	51.62
2018	22073	11587	52.49
2019	22757	12157	53.42
2020	22676	13338	58.82
Total	330906	169786	51.31

Table IA. VIII.
Earnings-Call Observations across Industries

This table reports the distribution of earnings calls (earnings calls with $CCExposure > 0$) across industries. The sampling criteria are specified in Section I.A.

Industry (SIC2)	# Calls	# Calls with $CCExposure > 0$	Percentage of Calls with $CCExposure > 0$
01 Agricultural Production – Crops	371	234	63.07
07 Agricultural Services	129	38	29.46
09 Fishing, Hunting, & Trapping	27	23	85.19
10 Metal, Mining	4891	3403	69.58
12 Coal Mining	834	751	90.05
13 Oil & Gas Extraction	11941	7335	61.43
14 Nonmetallic Minerals, Except Fuels	742	577	77.76
15 General Building Contractors	2018	1117	55.35
16 Heavy Construction, Except Building	1874	1615	86.18
17 Construction	471	361	76.65
20 Food & Kindred Products	7614	3894	51.14
21 Tobacco Products	678	239	35.25
22 Textile Mill Products	569	245	43.06
23 Apparel & Other Textile Products	2338	859	36.74
24 Lumber & Wood	1735	918	52.91
25 Furniture & Fixtures	1428	595	41.67
26 Paper & Allied Products	3263	1987	60.89
27 Printing & Publishing	2643	879	33.26
28 Chemical & Allied Products	30174	13134	43.53
29 Petroleum Refining	3062	2329	76.06
30 Rubber & Miscellaneous Plastics Products	2041	1221	59.82
31 Leather & Leather Products	941	384	40.81
32 Stone, Clay, & Glass Products	2058	1494	72.59
33 Primary Metal	3998	3097	77.46
34 Fabricated Metal Products	2996	1882	62.82
35 Industrial Machinery & Equipment	15292	9588	62.70
36 Electronic & Other Electric Equipment	22426	14200	63.32
37 Transportation	7796	6043	77.51
38 Instruments & Related Products	15524	7721	49.74
39 Miscellaneous Manufacturing Industries	1831	738	40.31
40 Railroad Transportation	723	601	83.13
41 Local & Suburban Transit	241	190	78.84
42 Trucking & Warehousing	1599	853	53.35
44 Water Transportation	2656	1579	59.45
45 Transportation by Air	3063	1827	59.65
46 Pipelines, Except Natural Gas	767	423	55.15
47 Transportation Services	1686	819	48.58
48 Communications	13528	5734	42.39
49 Electric, Gas, & Sanitary Services	11798	11122	94.27
50 Wholesale Trade – Durable Goods	5353	2674	49.95

Table IA. VIII continued

51 Wholesale Trade – Nondurable Goods	3449	1827	52.97
52 Building Materials & Gardening Supplies	531	334	62.90
53 General Merchandise Stores	2316	918	39.64
54 Food Stores	1817	800	44.03
55 Automative Dealers & Service Stations	1747	1256	71.89
56 Apparel & Accessory Stores	3173	976	30.76
57 Furniture & Homefurnishings Stores	1095	395	36.07
58 Eating & Drinking Places	3655	1359	37.18
59 Miscellaneous Retail	5147	1833	35.61
60 Depository Institutions	17204	6168	35.85
61 Nondepository Institutions	3405	1325	38.91
62 Security & Commodity Brokers	6553	2899	44.24
63 Insurance Carriers	10060	4226	42.01
64 Insurance Agents, Brokers, & Service	1071	519	48.46
65 Real Estate	3573	1394	39.01
67 Holding & Other Investment Offices	18046	7526	41.70
70 Hotels & Other Lodging Places	1246	388	31.14
72 Personal Services	820	299	36.46
73 Business Services	36858	15186	41.20
75 Auto Repair, Services, & Parking	626	435	69.49
78 Motion Pictures	982	281	28.62
79 Amusement & Recreation Services	2636	1067	40.48
80 Health Services	4674	1943	41.57
81 Legal Services	134	73	54.48
82 Educational Services	1728	656	37.96
83 Social Services	281	93	33.10
87 Engineering & Management Services	4953	2882	58.19
89 Services, Not Elsewhere Classified	7	5	71.43
Total	330906	169786	51.31

Table IA. IX.
Top Bigrams for Topics-Based Climate Change Exposure Measures

Panel A: Top-100 Opportunity Climate Change Bigrams ($CCExposure^{Opp}$)

Bigrams	Frequency	Bigrams	Frequency	Bigrams	Frequency
renewable energy	15605	clean efficient	348	solar storage	272
electric vehicle	9508	hybrid technology	339	opportunity clean	272
clean energy	6430	energy vehicle	338	solar program	272
new energy	4544	vehicle lot	337	safe clean	272
wind power	4253	gigawatt install	337	geothermal power	270
wind energy	4035	gas clean	332	vehicle good	269
solar energy	2511	focus renewable	331	supply industrial	268
plug hybrid	1130	vehicle type	327	cost renewable	267
battery electric	1121	renewable electricity	326	grid technology	265
solar farm	971	meet energy	326	solar battery	263
heat power	941	bus truck	326	ton carbon	262
renewable resource	933	energy commitment	325	subsidy receive	261
carbon neutral	690	battery charge	324	vehicle electric	260
electric hybrid	585	vehicle place	319	vehicle small	260
carbon free	558	clean supply	310	vehicle hybrid	259
sustainable energy	523	vehicle space	309	demand wind	259
rooftop solar	498	expand energy	308	power world	258
grid power	493	vehicle future	308	term electric	257
solar generation	491	pure electric	305	incremental content	256
vehicle charge	476	fully electric	303	carbon energy	254
issue rfp	475	energy research	302	energy target	252
reinvestment act	474	invest renewable	298	target gigawatt	252
charge infrastructure	469	cell electric	297	energy landscape	249
construction megawatt	468	electronic consumer	291	customer clean	248
guangdong province	431	install solar	290	conventional energy	247
recovery reinvestment	407	community solar	288	mild hybrid	245
energy standard	406	ton waste	287	vehicle talk	243
ev charge	403	power solar	284	charge network	243
hybrid car	403	type energy	282	medical electronic	242
generation renewable	381	energy goal	281	vehicle offer	238
grid connect	376	vehicle development	280	free energy	237
vehicle battery	374	energy important	279	plus storage	237
micro grid	370	energy bring	277	vehicle opportunity	237
energy wind	352				

Table IA. IX continued

Panel B: Top-100 Regulatory Climate Change Bigrams ($CCExposure^{Reg}$)

Bigrams	Frequency	Bigrams	Frequency	Bigrams	Frequency
greenhouse gas	3416	reduce nox	194	emission issue	133
reduce emission	2354	emission year	192	emission monitor	133
carbon emission	2088	target energy	191	china air	132
gas emission	1910	air resource	186	capture carbon	131
reduce carbon	1715	implement energy	183	quality permit	126
carbon dioxide	1583	control regulation	180	available control	123
air pollution	1127	global climate	179	efficient combine	122
carbon price	999	think carbon	173	environmental goal	122
energy regulatory	967	efficient natural	170	comply environmental	121
carbon tax	928	promote energy	169	nox sox	121
environmental standard	593	source electricity	167	oxide emission	119
carbon reduction	558	gas regulation	162	way comply	118
emission trade	480	issue air	162	install low	118
dioxide emission	478	florida department	161	relate climate	116
nox emission	475	nitrous oxide	160	clean electricity	115
energy independence	399	produce carbon	156	hill wind	112
epa regulation	381	reduce sulfur	156	glacier hill	111
development renewable	344	effective energy	154	tax australia	111
deliver clean	322	product carbon	152	high hydrocarbon	108
know clean	309	impact clean	152	emission ton	107
standard requirement	309	regulation low	151	reduce methane	106
carbon market	298	emission rate	150	wait commission	105
trade scheme	283	commission license	150	gas carbon	104
emission intensity	268	recovery pollution	150	stability reserve	103
impact climate	265	appeal district	148	eu ets	102
reduce air	254	emission compare	147	weight fuel	101
emission free	223	emission increase	147	commission public	101
save technology	222	achieve carbon	144	talk climate	100
mercury emission	221	capture sequestration	139	expect carbon	100
place energy	219	clean job	137	castle peak	98
carbon economy	217	emission improve	137	emission carbon	97
talk clean	216	emission come	135	additive process	97
energy alternative	214	nation energy	135	request public	96
change climate	207				

Table IA. IX continued

Panel C: Top-50 Physical Climate Change Bigrams ($CCExposure^{Phy}$)					
Bigrams	Frequency	Bigrams	Frequency	Bigrams	Frequency
global warm	837	sea water	232	especially coastal	68
coastal area	816	ice product	202	golf ground	67
snow ice	538	management district	193	plant algeria	67
friendly product	527	water act	187	area coastal	63
forest land	512	management water	172	large desalination	61
provide water	429	weather snow	165	solution act	57
sea level	421	service reliable	161	combine sewer	54
area florida	402	ability party	147	sewer overflow	53
nickel metal	375	ice control	142	sell forest	52
supply water	352	inland area	134	fluorine product	52
natural hazard	295	value forest	130	warm product	52
storm water	292	non coastal	117	area inland	48
air water	290	sale forest	110	exposure coastal	41
heavy snow	260	storm january	109	city coastal	39
warm climate	245	fight global	86	marina east	37
security energy	238	land forest	84	keppel marina	28
water discharge	233	particularly coastal	70		

Table IA. X.
Snippets of Top Climate Change Exposure Firms

Firm	HQ	SIC	Time	Assets ($ millions)	Bigrams	Top Snippet
China Longyuan Power Group Corp Ltd	China	4991	2013Q4	18,136	good wind; wind speed	in general the experience is the good wind results year probably will follow a low wind speed year and if the wind speed in the northern part is good probably in the southern parts the wind speed would be lower.
Xinjiang Goldwind Science & Technology Co Ltd	China	3510	2019Q4	14,750	grid tariff; potential wind; renewable energy; tariff wind; wind power	the last slide here presents research results of china renewable energy engineering institute, showing that on-grid tariff of wind power in majority of regions in china has reached the same level with benchmark coal-fired power tariff, demonstrating the potential of wind power marketed transaction.
ECOtality Inc	U.S.	3620	2009Q2	20	charge infrastructure; development electric; electric vehicle; promote development; vehicle charge	we also achieved significant operational milestones with our partnerships with nissan; the maricopa county association of governments, which represents the phoenix metropolitan area, as well as the pima county association of government, which represents the tucson metropolitan area; in order to advance zero emission mobility by promoting the development of electric vehicle and charging infrastructure.
China Ming Yang Wind Power Group Ltd	China	3510	2015Q2	2567	biomass energy; clean energy; consumption energy; development wind; energy china; solar biomass	it was stated clearly in the government's 2015 work report that the development of wind, solar and biomass energy should be strongly promoted, and we should accelerate the consumption of clean energy to boost our revolution in the consumption of energy in china.
Advanced Battery Technologies Inc	U.S.	3690	2009Q3	158	advance battery; electric vehicle; focus electric; vehicle china	as we move through 2009, our key initiatives include aligning ourselves to benefit from the increasing focus on electric vehicles in china and worldwide, especially in china, where government initiatives will provide meaningful incentives; leveraging our current leadership to secure new contracts, especially large-scale rechargeable polymer lithium-ion battery sales, and ultimately driving revenue mix shift to reflect higher-margin sales; ensuring an improving operational efficiency at both advanced battery and wuxi zq entities.
Ocean Power Technologies Inc	U.S.	3511	2008Q4	97	energy requirement; increase renewable; population center; powerbuoy wave; renewable energy; wave condition; wave power	these areas represent strong potential markets for our powerbuoy wave power stations because they combine favorable wave conditions, political and economic stability, large population centers, high levels of industrialization, and significant and increasing renewable energy requirements.

Table IA. X continued

Firm	**HQ**	**SIC**	**Time**	**Assets ($ millions)**	**Bigrams**	**Top Snippet**
Otter Tail Corp	U.S.	4911	2015Q3	1,821	dioxide mercury; emission nitrogen; oxide sulfur; regional haze; sulfur dioxide	remember, the state-of-the-art control system will reduce emissions of nitrogen oxide, sulfur dioxide, and mercury by 80% to 90% to meet the epa's regional haze and mats requirements.
FuelCell Energy Inc	U.S.	3690	2010Q4	151	cell power; coal derive; emission coal; gas emission; greenhouse gas; solid oxide	another deal we contract, we are working toward a long range goal of developing megawatt class, solid oxide, fuel cell power plants filled with coal-derived synthesis gas, thereby reducing greenhouse gas emissions from coal up to 90%.
ALLETE Inc	U.S.	4931	2019Q3	5,483	carbon free; clean energy; double wind; wind energy; wind facility	with approximately 555 megawatts of carbon-free wind generation already in operation, allete clean energy is on schedule with its planned construction of several new wind facilities that upon completion will roughly double its wind energy fleet, adding almost 500 megawatts in total generation capability.
Clean Energy Fuels Corp	U.S.	5500	2017Q3	792	air quality; clean air; fuel renewable; nox engine; renewable natural	moving on to the clean air action plan that is being drafted by the ports of la and long beach, we believe ultimately that any final plan must immediately address the horrendous air quality by requiring the thousands of trucks that operate on dirty diesel at the ports to be replaced with new zero nox engines fueled by renewable natural gas.

Table IA. XI.
Top-100 Unigrams and Bigrams Captured by $CCExposure^{EGKLS}$

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

Uni/Bigrams	Frequency	Uni/Bigrams	Frequency	Uni/Bigrams	Frequency
market	7271737	reduction	837331	land	242464
increase	6125831	unit	809445	party	239304
time	4859969	potential	794827	national	234016
term	4527681	effect	779984	weather	229339
cost	4508616	set	633825	natural	228976
result	4422260	world	613867	develop	227216
high	3834354	gas	597801	response	219786
impact	2759159	global	593695	establish	208680
net	2539728	international	583436	water	199055
include	2407273	measure	575794	define	151324
level	2403504	event	549727	implementation	148991
base	2290149	country	541835	wind	138807
project	1658992	region	495348	air	129668
area	1465194	plant	488014	scenario	129584
balance	1415498	pressure	479484	chemical	100768
report	1348573	power	471925	feedback	92600
future	1335014	energy	461752	assessment	86797
development	1309010	condition	451798	social	83111
range	1271805	organic	436245	solar	75186
benefit	1266657	economic	433424	environmental	74964
current	1200773	relative	427686	mass	72671
activity	1193239	cycle	383043	human	60708
process	1188852	action	373261	mechanism	57164
average	1120217	produce	368668	layer	53525
production	1081807	form	368562	framework	52067
group	1014513	refer	357518	sea	48936
technology	1001416	resource	341490	concentration	48560
reduce	986884	fuel	303120	carbon	44655
place	933857	source	293965	surface	44483
number	917925	industrial	291517	protocol	41692
state	880937	occur	273066	ecosystem	35182
environment	877466	live	270116	emission	34987
capacity	859368	policy	259081	warm	34698
model	857032				

Table IA. XII.
Climate Change Exposure Measures: Comparison with Measure using EGLKS's Keywords

This table reports summary statistics for a climate change exposure measure constructed from the list of *pre-specified* climate change keywords in listed in Engle et al. (2020) (EGKLS)'s Figure 1. To create the alternative measure, labeled $CCExposure^{EGKLS}$, we replace our bigrams set $\mathbb{C}$ with $\mathbb{C}^{EGKLS}$, and then recompute the relative frequency with which the alternative terms appear in the transcripts. We construct a frequency-unweighted and a TFIDF version, denoted as $CCExposure^{EGKLS-EW}$ or $CCExposure^{EGKLS-TFIDF}$, respectively. Panel A reports summary statistics, and Panel B correlations. In Panel B, we report overall sample correlations and correlations depending on whether the time-series index by EGKLS of public climate change attention indicates that such attention is high (*WSJ CC News Index* is in the top quartile) or low. Appendix A defines all variables in detail.

Panel A: Summary Statistics (x10^3)	Mean	STD	25%	Median	75%	N
$CCExposure_{i,t}^{EGLKS-EW}$	54.0	11.0	47.4	52.9	59.8	86152
$CCExposure_{i,t}^{EGLKS-TFIDF}$	17.3	8.5	12.1	15.0	20.0	86152

Panel B: Correlations	$CCExposure_{i,t}$	$CCExposure_{i,t}^{EGLKS-EW}$
$CCExposure_{i,t}^{EGLKS-EW}$	0.35	1.00
$CCExposure_{i,t}^{EGLKS-TFIDF}$	0.59	0.73
	WSJ Climate Change Index High (Top 25%)	
$CCExposure_{i,t}^{EGLKS-EW}$	0.38	1.00
$CCExposure_{i,t}^{EGLKS-TFIDF}$	0.62	0.73
	Low (WSJ Climate Change Index Bottom 75%)	
$CCExposure_{i,t}^{EGLKS-EW}$	0.33	1.00
$CCExposure_{i,t}^{EGLKS-TFIDF}$	0.55	0.73

Table IA. XIII.
Green Tech Jobs and Green Patents Results: Controlling for Emissions

This table reports regressions that relate green tech jobs and green patents to the climate change exposure measures. Regressions are estimated at the firm-year level. The regressions complement those in Tables VII and VIII by additionally controlling for a firm's carbon emissions (*Total Emissions*). Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\ Tech\ Jobs_{i,t+1}$				$\#Green\ Patents_{i,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Log(1 + CCExposure_{i,t})$	1.390***				1.505***			
	(0.192)				(0.241)			
$Log(1 + CCExposure^{Opp}_{i,t})$		1.824***				1.224***		
		(0.256)				(0.247)		
$Log(1 + CCExposure^{Reg}_{i,t})$			1.060***				2.915***	
			(0.304)				(0.339)	
$Log(1 + CCExposure^{Phy}_{i,t})$				-1.478				-1.220
				(1.971)				(1.540)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Sample	US	US	US	US	US	US	US	US
Carbon Emissions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8767	8767	8767	8767	5417	5417	5417	5417
Ps. R-sq.	0.778	0.793	0.730	0.728	0.597	0.568	0.576	0.552

Table IA. XIV.

Green Tech Jobs Results: Alternative Model Specifications

This table reports regressions that relate green tech jobs to the climate change exposure measures. Regressions are estimated at the firm-year level. The table estimates different alternative model specifications of the regressions in Tables VII. Column 1 additionally controls for proxies for strategic disclosure, notably the firm's overall sentiment (the share of positive and negative tone words across the full earnings call transcript) and two proxies for the firm's recent financial performance. We measure performance as the pre-call stock returns (accumulated over the seven days before the earnings call), and the earnings surprise. Earnings surprise is defined as earnings per share before extraordinary items minus earnings per share in the same quarter of the prior year, divided by the price per share at the beginning of the quarter (Ball and Bartov (1996)). We average the two performance variables across the earnings calls of a firm-year to obtain an annual measure. Column 2 is estimated within the Burning Glass (BG) sample (i.e., when we do not impute missing *#Green Tech Jobs* data). The OLS models with industry-by-year fixed effects permit for more observations (the linear model averages out the incidental parameter problem) than the Poisson models. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\,Tech\,Jobs_{i,t+1}$							$Log(1+\#Green\,Tech\,Jobs_{i,t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Log(1+CCExposure_{i,t})$	1.679***	1.511***				10.006***		0.218***	0.187***
	(0.219)	(0.193)				(2.641)		(0.020)	(0.019)
$Log(1+CCExposure^{Q\&A}_{i,t})$			1.114***						
			(0.175)						
$Log(1+CCSentiment^{Pos}_{i,t})$				1.052***					
				(0.313)					
$Log(1+CCSentiment^{Neg}_{i,t})$				0.568					
				(0.370)					
$Log(1+CCRisk_{i,t})$					3.281***				
					(0.579)				
$CCExposure_{i,t}$							1.642***		
							(0.451)		
Model	Poisson	Poisson	Poisson	Poisson	Poisson	OLS	OLS	OLS	OLS
Sample	US	US, BG	US	US	US	US	US	US	US
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes
N	16892	15840	23870	23870	23870	28963	28963	28963	28934
Adj./ps. R-sq.	0.778	0.766	0.735	0.719	0.712	0.007	0.006	0.085	0.112

Table IA. XV.
Green Patents Results: Alternative Model Specifications

This table reports regressions that relate green patents to the climate change exposure measures. Regressions are estimated at the firm-year level. The table estimates different alternative model specifications of the regressions in Tables VIII. Column 1 additionally controls for proxies for strategic disclosure, notably the firm's overall sentiment (the share of positive and negative tone words across the full earnings call transcript) and two proxies for the firm's recent financial performance. We measure performance as the pre-call stock returns (accumulated over the seven days before the earnings call), and the earnings surprise. Earnings surprise is defined as earnings per share before extraordinary items minus earnings per share in the same quarter of the prior year, divided by the price per share at the beginning of the quarter (Ball and Bartov (1996)). We average the two performance variables across the earnings calls of a firm-year to obtain an annual measure. Column 2 is estimated within the Google Patent (GP) sample (i.e., when we do not impute missing *#Green Patents* data). The OLS models with industry-by-year fixed effects permit for more observations (the linear model averages out the incidental parameter problem) than the Poisson models. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\ Patents_{i,t+1}$							$Log(1 + \#Green\ Patents_{i,t+1})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Log(1 + CCExposure)_{i,t}$	1.442***	0.955***				0.147***		0.028***	0.016***
	(0.183)	(0.142)				(0.032)		(0.004)	(0.003)
$Log(1 + CCExposure^{Q\&A}_{i,t})$			0.878***						
			(0.201)						
$Log(1 + CCSentiment^{Pos}_{i,t})$				0.754***					
				(0.225)					
$Log(1 + CCSentiment^{Neg}_{i,t})$				1.028***					
				(0.388)					
$Log(1 + CCRisk)_{i,t}$					2.534***				
					(0.723)				
$CCExposure_{i,t}$							0.013***		
							(0.004)		
Model	Poisson	Poisson	Poisson	Poisson	Poisson	OLS	OLS	OLS	OLS
Sample	US	US, GP	US	US	US	US	US	US	US
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes
N	15020	3692	21914	21914	21914	43390	43390	43390	43348
Adj./ps. R-sq.	0.639	0.687	0.612	0.615	0.601	0.009	0.009	0.029	0.043

Table IA. XVI.
Green Tech Jobs and Green Patents Results: $CCExposure^{Initial} = 0$ Subsample

This table reports regressions that relate green tech jobs and green patents to the climate change exposure measures. Regressions are estimated at the firm-year level. The table estimates the same model specifications as used in Tables VII and VIII, but within the sample where $CCExposure^{Initial} = 0$ (or the corresponding topics-based measures). $CCExposure^{Initial}$ is the climate change exposure score computed, based on the initial seed bigrams in Table III only. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	$\#Green\ Tech\ Jobs_{i,t+1}$				$\#Green\ Patents_{i,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Log(1 + CCExposure_{i,t})$	1.161*				1.966***			
	(0.702)				(0.336)			
$Log(1 + CCExposure^{Opp}_{i,t})$		2.286***				1.270**		
		(0.559)				(0.575)		
$Log(1 + CCExposure^{Reg}_{i,t})$			4.034***				4.488***	
			(0.972)				(0.904)	
$Log(1 + CCExposure^{Phy}_{i,t})$				0.868				2.466*
				(1.886)				(1.288)
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Sample	US	US	US	US	US	US	US	US
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18704	20885	22036	22981	16470	18708	19738	21054
Ps. R-sq.	0.442	0.450	0.687	0.678	0.686	0.652	0.617	0.608

Table IA. XVII.
Comparison of Observations with and without Within-Fixed Effects Variation

This table compares observations with and without variation within industry-by-year groups. The Poisson regressions in Tables VII and VIII base the estimation only on observations with at least one non-zero value within a given industry-by-year group. This restriction is desirable to avoid biased estimators. It restricts the usable sample to those groups that are informative about the effects of $CCExposure$ (Cohn, Liu, and Wardlaw (2022)). Panel A reports statistics for the green tech job estimation, and Panel B for the green patent estimation. Appendix A defines all variables in detail. *p< .1; **p< .05; ***p< .01.

Panel A: Green Tech Jobs Estimation

	Observations Included in the Estimation (N=23,870)			Observations Excluded from the Estimation (N=5,093)			
	Mean	Std.Dev.	Median	Mean	Std.Dev.	Median	Difference-in-Means
$CCExposure_{i,t}$	1.100	2.784	0.306	0.536	1.112	0.258	0.564***
$CCExposure^{Opp}_{i,t}$	0.431	1.433	0.075	0.175	0.514	0.000	0.256***
$CCExposure^{Reg}_{i,t}$	0.056	0.297	0.000	0.025	0.122	0.000	0.031***
$CCExposure^{Phy}_{i,t}$	0.013	0.106	0.000	0.013	0.072	0.000	-0.001
$Assets_{i,t}$	8872	30271	1223	10732	36266	1721	-1860***
$Debt/Assets_{i,t}$	0.246	0.232	0.203	0.324	0.249	0.287	-0.077***
$Cash/Assets_{i,t}$	0.199	0.221	0.112	0.115	0.143	0.061	0.084***
$PPE/Assets_{i,t}$	0.216	0.239	0.118	0.282	0.267	0.199	-0.066***
$EBIT/Assets_{i,t}$	0.013	0.202	0.056	0.071	0.111	0.070	-0.058***
$Capex/Assets_{i,t}$	0.041	0.051	0.024	0.045	0.051	0.031	-0.004***
$R\&D/Assets_{i,t}$	0.057	0.110	0.001	0.006	0.030	0.000	0.051***

Panel B: Green Patents Estimation

	Observations Included in the Estimation (N=21,914)			Observations Excluded from the Estimation (N=21,476)			
	Mean	Std.Dev.	Median	Mean	Std.Dev.	Median	Difference-in-Means
$CCExposure_{i,t}$	1.107	2.653	0.336	0.781	2.236	0.253	0.327***
$CCExposure^{Opp}_{i,t}$	0.430	1.365	0.083	0.281	1.105	0.000	0.149***
$CCExposure^{Reg}_{i,t}$	0.056	0.311	0.000	0.039	0.199	0.000	0.016***
$CCExposure^{Phy}_{i,t}$	0.012	0.116	0.000	0.013	0.074	0.000	-0.001
$Assets_{i,t}$	5142	19303	653	11384	36924	1730	-6241***
$Debt/Assets_{i,t}$	0.213	0.222	0.168	0.284	0.240	0.245	-0.071***
$Cash/Assets_{i,t}$	0.253	0.239	0.171	0.124	0.159	0.063	0.128***
$PPE/Assets_{i,t}$	0.207	0.227	0.119	0.252	0.253	0.166	-0.045***
$EBIT/Assets_{i,t}$	-0.008	0.228	0.057	0.059	0.127	0.064	-0.067***
$Capex/Assets_{i,t}$	0.044	0.053	0.026	0.042	0.048	0.027	0.002***
$R\&D/Assets_{i,t}$	0.085	0.122	0.037	0.011	0.051	0.000	0.074***

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities.*

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html