Corporate Climate Risk: Measurements and Responses

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Abstract

This paper constructs a novel measure of climate risk at the firm level by adopting a textual analysis method. The measure captures the share of conversations on earnings conference calls that center on climate- and weather-related keywords, allowing us not only to construct a total climate risk measure but also to obtain disaggregated climate risk measures, such as those related to long- versus short-run factors, as well as corporate functions affected by climate risk. We analyze the determinants of firm-level climate risk using natural disasters and firm attributes and find that 60% of its variation is due to within-firm variation, and thus it mostly captures idiosyncratic risk at the firm level. We also examine the relation between climate risk and stock price volatility, as well as firm responses to climate risk. The results suggest that firms with higher unexpected climate risk significantly increase their investment while decreasing their employment in subsequent years.

Keywords: Climate risk, earnings calls, investments, natural disasters, textual analysis

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1. Introduction

Climate issues present severe challenges for businesses and society at large. Scientific evidence shows that the climate is changing, with wildfires raging at an unprecedented scale and sea levels having risen considerably in the past three decades or longer. Climate change is believed to continue to increase the incidence and severity of both chronic and acute climate and weather events, leading to unprecedented risk exposures and disruptions to companies' investment, operations, and financial performance. The magnitudes of such risk at the firm level in the short and long horizons, as well as perspectives on the types of corporate responses that could manage such risk, are now trending topics among not only economists and policymakers, but also business leaders. A recent report by Standard & Poor's (S&P) Ratings reveals that the terms *climate* and *weather* combined were among the most frequently discussed topics among executives, even more common than *Trump*, *the dollar*, *oil*, and *recession* (S&P Ratings (2018)). Nevertheless, quantifying the effects of climate risk on individual firms has often proven difficult due to a lack of firm-level data on climate risk.

In this paper, we quantify, for the first time, climate risk at the firm level, using earnings call transcript data, and then study the impact of climate risk on U.S. public companies. We measure the climate risk faced by a given firm at a given time based on the share of earnings calls conversations centered on both extreme climate events (e.g., wildfires and flooding) and chronic climate changes (e.g., global warming and sea-level rise) associated with risk or uncertainty.[1] Earnings conference calls held between firm management and their analysts contain detailed discussions on the climate risk faced, how the company was and will be affected, as well as the company's responses in the past, present, and future. This information allows us not only to measure the presence and materiality of both the total climate risk and its individual components at the most granular level, but also to explore the company's perspectives regarding climate risk.

In the first part of the paper, we adapt a pattern-based sequence classification method developed in computational linguistics to distinguish between language associated with climate versus non-climate matters, similar to that of Hassan et al. (2019), but for climate risk. A challenge for our analysis is that the measurement of climate risk is not as straightforward as it might seem, due

[1]Firms update beliefs about climate risk through both the rising intensity and severity of extreme climate events, such as wildfires, and chronic changes in climate patterns. We believe both are indispensable components of a valid climate risk measure.

to the ambiguity of the language used in earnings calls. We compiled a comprehensive training library of climate- and weather-related keywords from multiple sources, including Federal Emergency Management Agency (FEMA) disaster announcements, a meteorology textbook, weather.com news, and climate change reports used by Engle et al. (2020). We manually screened the lists through many iterations to reduce the incidence of both false positives (*e.g.*, *wind farms*) and false negatives (*e.g.*, *unseasonably cold*) and eventually arrived at a comprehensive climate dictionary containing 40 single words (unigrams) and 1,384 two-word combinations (bigrams). We use the training dictionary combined with risk synonyms to identify the share of conversations on climate risk in corporate earnings conference calls. We also differentiate between severe and non-severe, long run and short run, backward looking and forward looking, and question-and-answer (Q&A) versus non-Q&A climate risks by 1) using different keywords, 2) analyzing the *tense* of the context of the climate risk discussion, or 3) parsing different parts of the earnings call transcripts. This approach allows us to obtain not only a total climate risk measure, but also a variety of disaggregated climate risk series, all at the firm–quarter level, that can be readily merged with other common, publicly available firm-level data.[2]

After constructing the climate risk measures, we conduct a series of analyses for an accurate interpretation of their properties. We first manually review the transcripts with the highest climate risk and validate that we have correctly identified all conversations regarding climate risk. We then plot the time series of climate risk measures and identify the corresponding topics discussed in the conference calls that contribute to the sharp increase in climate risk. The results show that, while severe and short-run weather events contribute to the spikes in total climate risk, non-severe climate risk dominates severe climate risk during most conference call discussions, and discussions on long-run climate risk intensified from 2008 to 2011.

Using a similar textual analysis method, we further examine the specific corporate functions affected by increasing levels of climate risk. We extract the bigrams surrounding the climate risk discussions in the conference calls and then manually review and classify the top bigrams into four

[2]The increased frequency of climate-related key words in the transcript can be driven by two possibilities. First, managers and/or analysts think that climate risk becomes an important factor for firms' future performance. Second, analysts suddenly pay more attention to the climate issues than before even when the company's business is not affected by climate risk. By decomposing the climate risk into Q&A and non-Q&A, we show that our climate risk measure is driven by the changes in climate risk rather than the attention effects from analysts.

broad corporate functions: 1) market conditions/sales, 2) costs/losses, 3) fixed assets/capital expenditures (CapEx), and 4) supply chain/production/operation. These show great variations across industries and over time. Notably, companies in the retail and food services sector are most concerned about climate risk for its impact on market conditions/sales. Companies in the mining and manufacturing sector most frequently discuss its impact on supply chain/production. Insurance firms highlight costs/losses, and firms in Recreation and Leisure are most concerned about its impact on fixed assets/CAPEX.

In the second part of the paper, we explore the determinants of firm-level climate risk, using natural disaster hits and firm attributes as well as different fixed effects as the explanatory variables. The results show that natural disasters that just occurred in the prior two quarters are an important reason for earnings calls participants to discuss climate risk topics. As for firm characteristics, we find that firms with more physical assets and those with lower leverage ratio, Tobin's Q, and analyst coverage are associated with higher climate risk. The fixed effects of sectors and states show that our measures vary intuitively along these dimensions. For example, we find that agriculture and utilities have the highest climate risk, with droughts and hurricanes being the most important topics discussed in the transcripts. Geographically, firms located in the Midwest and along the coastlines of the South have seen the highest climate risk over the entire sample period. Although all these characteristics have significant relations with our climate risk measures, the model with our finest controls of fixed effects, including firm, sector by year quarter, and state by year quarter fixed effects, only explains 40% of the variation in our main measure, $ClimateRisk_{i,t}$, and the residuals due to within-firm variation account for 60% of the variation, suggesting that climate risk is an idiosyncratic risk at the firm level. With the first-stage analysis, we effectively decompose climate risk into expected and unexpected climate risk, which we use in later analysis.

In the third part of the paper, we first examine the relation between climate risk and the implied stock price volatility that captures uncertainty for equity investors. We find that, although expected climate risk is highly predictive of increases in volatility in the equity market, unexpected climate risk is not. More importantly, we study firms' responses following changes to climate risk, especially the unexpected climate risk component. There exist mixed predictions from the theoretical literature regarding investment under uncertainty. While Bernanke (1983), Pindyck (1991), Pindyck and

Solimano (1993), and Dixit and Pindyck (1994) predict a decline in investment in times of high uncertainty, other studies such as Oi (1961), Hartman (1972, 1976), Abel (1983), and Bar-Ilan and Strange (1996) predict that an increase in uncertainty would increase firm-level investment. Moreover, our textual analysis of firm responses suggests that while some firms "passively" react to climate risk, other firms choose to cope with rising climate risk through active investment and innovation.

Ultimately, how firm investment varies with climate risk is an empirical question. Our results show that, in response to higher unexpected climate risk, firms significantly increase their investment in the following eight quarters. The response is more significant for severe, short-run, forward-looking, and Q&A climate risks. Our last set of analyses finds that firms with high unexpected climate risk have significantly lower employment growth the following year, suggesting that firms' increased investments in response to unexpected climate risk seem to be at the expense of employment growth, likely due to budget constraints.

Our analysis is closely related to two recent studies. The first is that of Engle et al. (2020), who propose and implement a procedure to dynamically hedge aggregate long-run climate change risk. They construct a time-series index that captures news about climate change by adopting a textual-based analysis of the text content of *The Wall Street Journal* and a fixed climate change vocabulary. They then estimate the individual loading factors on common climate risk, that is, (negative) news about climate change. Their analysis yields a dynamic portfolio that overweights stocks that perform well on the arrival of such negative news. Our paper complements theirs, in that our effort aims to quantify climate risk at the firm level, directly capturing the perceptions of climate risk of the firm's management and analysts. Another related paper is that of Hassan et al. (2019), who construct a new measure of political risk, using similar methods. Although both Hassan et al. (2019) and ours construct a new measure of risk that is predictive of firm's stock price uncertainty, they make different inferences. Their main conclusion is that political decision making can incur social costs by creating idiosyncratic political risk for individual firms, in turn decreasing corporate investment. The focus of our study, however, is climate risk, a different type of risk that is related to both chronic and acute climate and weather events.

Since our measures include severe climate risk, this paper is also related to recent literature that studies the effect of natural disasters on corporate operations and profitability. Barrot and Sauvagnat

(2016) document that firms transmit idiosyncratic climate shocks through their production networks. Hsu et al. (2018) find that natural disasters have an immediate negative effect on firm-level operating performance, and technology diversity enhances firm sustainability.[3] The climate risk measure in our paper captures exposure to not only natural disasters, but also to non-severe climate risk, as well as much larger variations at the firm level. More importantly, our evidence suggests that firms' actions in response to unexpected climate risk go beyond just restoring existing production, since we find they subsequently increase investment for up to two years.

More broadly, our paper adds to the new and growing literature on climate finance. Several papers study how climate risk (*e.g.*, the risk of sea-level rise, flooding risk) affects real estate value (*e.g.*, Giglio et al. (2018), Bakkensen and Barrage (2018), Baldauf et al. (2020), Bernstein et al. (2019), Murfin and Spiegel (2020)). A few other studies examine whether capital markets price risks related to long-run temperature shifts, drought, or sea-level rise (*e.g.*, Bansal et al. (2016), Hong et al. (2019), Painter (2020)). Another few studies examine the effects of temperatures on firm sales, earnings, and investments (*e.g.*, Addoum et al. (2019, 2020), Lin et al. (2019)). Choi et al. (2020) analyze how investors update their information about global warming. Different from all these studies, we are the first to construct a new firm-level climate risk measure from earnings calls for all U.S. public firms and study how these firms respond to climate risk. Our measure could be of value to any future research that requires data on corporate climate risk exposures.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 explains the construction of the climate risk measures and our interpretation of their properties. In Section 4, we explore the determinants of climate risk using natural disasters and firm attributes. Section 5 focuses on exploring the relation between climate risk and stock return volatility. Section 6 analyzes corporate responses and strategies related to climate risk. Section 7 concludes the paper.

[3] In addition, Dessaint and Matray (2017) provide evidence that firm managers tend to increase corporate cash holdings after hurricane events. Moreover, a recent paper by Kruttli et al. (2019) studies option market responses to uncertainty regarding both hurricane landfall and the subsequent economic impact.

2. Data

We obtain data on the transcripts of the earnings calls of U.S. public firms from the Thomson Reuters' StreetEvents database. Our sample period is from January 2002 to December 2018. Firms typically have one earnings conference call each fiscal quarter with an earnings release. Thus, most of our analysis is at the firm–quarter level.

We use Python to extract the text of the entire conference calls from the raw XML transcript files, which includes both the presentation by management and the Q&A session. We also extract firm identifiers (*e.g.*, firm names, tickers, CUSIP numbers) and earnings call information (*e.g.*, date and time) from the metadata session of the files. We use firm identifiers to match the earnings call data to other firm-level data from Compustat. Since many financial firms, especially insurance companies, sell insurance products to others to hedge climate- or disaster-related risk, we exclude financial firms (North American Industry Classification System or NAICS 2-digit 52) from our main analysis. We also exclude firms whose headquarters are located outside the United States . Our final sample includes 4,719 unique firms and 139,959 firm–quarter observations. We obtain firms' financial statement data from Compustat, stock information (returns and realized volatility) from the Center for Research in Security Prices, and stock implied volatility data from OptionMetrics.

3. Measuring Climate Risk at the Firm Level

In this section, we introduce our various measures of climate risk at the firm–quarter level.

3.1. Defining the Measures

3.1.1. Climate Risk

Our primary climate risk measure aims to achieve a simple objective: to capture the share of the conversation between firm management and conference call participants regarding exposure and uncertainty related to weather and climate topics. The methodology we use is motivated by a recent study by Hassan et al. (2019), who focus on political risk at the firm level.

The measurement of climate risk–related discussions in earnings calls is not as straightforward a task as it appears, for two reasons. First, climate/weather discussions occur throughout our daily life. The semantic meanings of related keywords have evolved over thousands of years in a greater variety of settings. If we simply search for keywords without careful supervision, even through the application of unsupervised or semi-supervised learning, a significant amount of false positive cases will arise in which keywords are used to describe issues entirely unrelated to climate (*e.g.*, business climate, public cloud, economic storm). Further stressing the importance of supervision, we find that weather and climate irregularities are commonly expressed using combinations of contrasting keywords. There are a large number of false negatives where climate and weather factors could have been missed using typical standalone keywords (*e.g.*, warm winter, unseasonably cold, cool summer).

Second, there are severe and imminent weather events (*e.g.*, hurricanes, floods, drought, wildfire, polar vortex) and less severe but unanticipated meteorological changes (*e.g.*, warm winter, hot summer, fog, precipitation). Both are the indispensable components of climate risk. The former poses significant risk to business in general, but the impact of the latter is less clear and depends on the context. Discussions on both types of issues during the earnings call can provide important perspectives, but how they contribute to the construction of climate risk measures should be evaluated separately.

We address the first challenge by constructing a hybrid dictionary consisting of both single words, or unigrams, and adjacent two-word combinations, or bigrams. The set of unigrams is used unambiguously in climate discussions. The group of bigrams reduces both false positives and false negatives by including general/ambiguous keywords but restricting the context of usage. Specifically, we first list 74 weather- or climate-related seed words (unigrams) from the following three sources: (i) words identified as "incident type" in the Disaster Declarations Summary provided by FEMA, (ii) Wikipedia's list of severe weather phenomena[4], and (iii) additional seed words that we manually added, namely, temperature, cold, unseasonable, and so on. We use this list of seed words to obtain all adjacent two-word combinations that contain at least one of the seed words from the entire sample of earnings call transcripts, and we rank the bigrams by their corresponding frequencies. We then examine the top 500 bigrams related to each seed word to better understand the context of the dis-

[4]See https://en.wikipedia.org/wiki/List_of_severe_weather_phenomena.

cussions. We further identify 34 of the 74 seed words whose contexts are mixed with weather/climate and other non-weather/climate discussions. To limit the likelihood of capturing false positives using our measure, we include only 1,073 of 6,800 (34 $\times$ 200) bigrams that are unambiguously linked to the climate context. This first step yields a dictionary consisting of 40 unigrams (74 -34 = 40) and 1,073 bigrams.

Next, we supplement our training library with the following climate-related bigrams in an effort to reduce false negatives: (i) bigrams extracted from the "title" column of the FEMA Disaster Declarations Summary, (ii) top bigrams extracted from the white papers and reports used by Engle et al. (2020), (iii) top weather or climate bigrams extracted from the news articles of *The Weather Channel* (weather.com), and (iv) top weather or climate bigrams extracted from an undergraduate textbook on meteorology, namely, C. Donald Ahrens' *Meteorology Today: An Introduction to Weather, Climate, and the Environment*, 9^{th} Edition.[5]

Our final dictionary of climate-related words, referred to as C, contains 40 unigrams and 1,384 bigrams.[6] For the small set of single words that unambiguously refer to weather or climate factors, we search for the standalone words directly in the earnings call transcripts. In the majority of cases, we use adjacent two-word combinations (bigrams) to achieve better text classification accuracy.[7]

To address the second challenge, we categorize our dictionary into two subgroups: (i) a dictionary of extreme or catastrophic climate events (*e.g.*, hurricanes, extreme heat, and polar vortex), referred to as SC, and (ii) a dictionary of non-extreme climate events (*e.g.*, weather, temperature, precipitation, greenhouse gas, the atmosphere), referred to as NC. Mentions of unigrams/bigrams in the first subgroup are associated with visible and sizable risk to business operations in general.

[5] We rank the bigrams in each of the training libraries by their corresponding weights (frequency of mentions over the total length of the document). We manually screen (i) the full FEMA list, (ii) the list of bigrams with over 10 mentions in the library of Engle et al. (2020) , (iii) the top 1,000 bigrams in the Weather Channel library, and (iv) the top 1,000 bigrams in the textbook.

[6] We also experiment with two alternative methods of capturing discussions on climate issues. The first method is the Word2Vec model, a semi-supervised approach employed by Li et al. (2020). The second method is Latent Dirichlet Allocation, an unsupervised model employed by Hanley and Hoberg (2019), Lopez-Lira (2019), and Lowry et al. (2020), among others. After comparing the accuracy and efficiency of the alternative methods with the approach we use in the main analysis, we find the alternative methods to be subject to two main limitations: first, many of the words identified by the semi-supervised/unsupervised models are not interpretable, such as *sql*, *waf*, and *petya*; second, many words carry multiple semantic meanings and will significantly increase the likelihood of capturing false positives in the climate risk measure. For example, *wetter*, *drier*, *milder*, and *conditions*.

[7] Prior research suggests that text classification accuracy improves when applying bigrams of words, as opposed to single words (unigrams) (*e.g.*, Bekkerman and Allan (2004)¸ Tan et al. (2002)).

However, mentions of the second group do not necessarily translate into firm risks. To incorporate the distinction in the construction of our measure, we only consider mentions of the second group in the proximity of a risk synonym to be discussions on climate risk. The risk dictionary contains synonyms for *risk*, *risky*, *uncertain*, and *uncertainty*, referred to as R, sourced from the *Oxford English Dictionary*, following Hassan et al. (2019).

Specifically, using a pattern-based sequence classification method developed in computational linguistics (Manning et al. (2008), Song and Wu (2008)), we decompose the transcripts of each earnings call at the firm $\times$ quarter level into a list of unigrams/bigrams contained in the transcript, $b = 1, 2, ..., B_{i,t}$. We then count the number of occurrences of unigrams/bigrams indicating a discussion of risk related to weather or climate factors and divide this by the total number of bigrams in the transcript. For non-severe climate-related words in NC, we require the discussion to be in the proximity of a risk synonym (i.e., within the (-1, 0, 1) sentences of the risk synonym).[8] Unlike non-severe climate events, all of the severe climate events, such as hurricanes, would expose firms to an elevated level of risk or uncertainty, although this might not be discussed explicitly in the immediate vicinity of a risk synonym. We therefore count the occurrences of severe climate keywords without requiring proximity to a risk synonym.[9]

We define the climate risk measure as follows:

$$ClimateRisk_{i,t} = \frac{\sum_{b \in B_{i,t}} (\P[b \in NC] \times \P[\mid b - r \mid < 3 \ Sentences] + \P[b \in SC]])}{B_{i,t}}, \quad (1)$$

where i indexes firms, t refers to the calendar quarter of an earnings conference call, $\P[\cdot]$ is the indicator function, NC is the set of words in the dictionary of non-severe climate events, SC is the set of words in the dictionary of severe climate events, and r is the position of the nearest synonym of risk or uncertainty in the risk synonym dictionary, R. In essence, the first term in the numerator captures the number of occurrences of climate words in the non-severe climate dictionary in proximity to a risk synonym; the second term in the numerator captures the number of occurrences of severe climate event words in the severe climate dictionary (without requiring proximity to a risk keyword).

[8]In robustness analysis, we also construct a climate risk measure requiring non-severe climate words to be in the same sentence as a risk synonym. We find very similar results.

[9]If we were to count only severe climate event words in the proximity of a risk synonym, we find that the measure would miss many discussions of severe climate events that indicate that firms are exposed to risks or uncertainty related to catastrophic climate events.

In short, the climate risk measure defined above captures the share of the conversation in the earnings call regarding the overall risk related to weather and climate factors.

3.1.2. Disaggregated Climate Risk Measures

We also construct disaggregated measures that capture the varieties of climate risk. First, based on whether climate risk is associated with keywords for severe weather events, we create separate measures of severe and non-severe climate risks. Second, based on whether discussions in the earnings calls are associated with long-run climate changes, we separate them into long- and short-run climate risks.[10] Third, we employ Python's NLTK part-of-speech tagging module to determine whether the discussions about climate risk are predominantly surrounded by past or future tense words. Depending on the tense of the context of the climate discussion, we create separate measures of backward- and forward-looking climate risks. Lastly, based on whether the discussion on climate risk occurs during a Q&A interaction session, we create separate measures of Q&A and non-Q&A climate risk. Compared to the non-Q&A component, the Q&A component is less influenced by any strategic disclosure on climate issues by firms' management. These separations could have different implications for firms' perspectives on as well as responses to climate risk.

3.1.3. Climate Sentiments

One challenge to measuring climate risk is that one needs to distinguish information about the mean (first moment) from information about the variance (second moment) of climate-related shocks. To capture information about the mean of climate-related shocks, we construct the measure *Climate-Sentiment*, which counts the number of unigrams/bigrams in the climate dictionary, conditioning on proximity to positive and negative words, scaled by the total number of unigrams/bigrams in the transcript. One advantage of the approach we use (i.e., combining pattern-based sequence classification with conditional word counts) is that we can easily create new variables for additional analysis by modifying the conditioning information in Equation (1). Following Hassan et al. (2019), we use Loughran and McDonald (2011)'s sentiment dictionary for positive and negative words as a

[10]The long-run component is a subgroup of non-severe climate risk. Non-severe climate dictionary consists of long-run bigrams such as *climate change*, *CO2 levels*, *global warming*, and so forth. The remainder of the non-severe climate dictionary consists of short-run bigram/unigrams, such as *snowfall*, *rains*, and so on.

conditioning restriction. Common positive words include *strong*, *good*, and *beneficial*, and negative words include *loss*, *decline*, and *difficult*. In short, we interpret this sentiment measure as information about the mean of climate-related shocks.

3.1.4. Corporate Functions Affected by Climate Risk

We further comb through three sentences before and after any climate or weather keyword that has appeared in the transcripts, resulting in 448,053 unique bigrams. We then manually review the top 2,000 bigrams and classify them, based on their similarity, into four broad corporate functions that could be affected by climate risk: 1) market conditions/sales, 2) costs/losses, 3) fixed assets/CapEx, and 4) supply chain/production/operation.[11] These categories of topics intuitively match with what has been documented and discussed in either the academic literature or industry reports (S&P Ratings (2018)). Table A1 in the Appendix reports the top bigrams associated with each of the functions. For example, call participants could be interested in discussing the impact of climate events on supply chain with keywords such as *raw materials* and *inventory levels*. The assessment of the impact of climate risk also includes adverse effects on a company's capital expenditures and physical assets, with keywords such as *capital expenditures* and *physical damage*.

3.1.5. Climate Risk Measures Using 10-K Data

As a robustness analysis, we use firms' Form 10-K and 10-Q filings as an alternative text source to construct the climate risk measure. In particular, we apply Equation (1) to two sections of 10-Ks/10-Qs, respectively—(i) Management Discussion and Analysis (MD&A) and (ii) Risk Factors—and obtain two alternative climate risk measures.[12]

Both the MD&A and Risk Factors sections of 10-Ks/10-Qs contain discussions about business

[11] While the top 2,000 bigrams manually reviewed only comprise 0.45% of the total number of unique bigrams near weather/climate discussions, their combined instances, 356,780, are 25.9% of the total number of mentions of all bigrams (1,377,826). Given time constraints and the right skewness of bigrams, we focus on identifying and interpreting the most heavily discussed bigrams.

[12] Note that climate risk disclosures have been identified, categorized, and ranked using the rules-based text analysis algorithms developed by Ceres and CookESG Research. Their Climate Risk Disclosure Project provides the narrative disclosures of companies in their annual reports to shareholders filed with the U.S. Securities and Exchange Commission (SEC), which can be purchased. The disclosure data are used by Berkman et al. (2019) to explore the usefulness of the climate risk disclosure measure, which they find to be negatively associated with firm value and positively associated with the implied cost of capital and beta.

risks faced by the firm. However, the disclosures in 10-Ks/10-Qs tend to be highly scripted. Additionally, there are concerns about the lack of informativeness and timeliness in these disclosures (*e.g.*, SEC (1998); Brown and Tucker (2011)). In contrast, earnings conference calls not only include the management's presentation about a business' material factors related to recent earnings, but also management's perspective during the interaction sessions with financial analysts (in the Q&A sections). The content in earnings transcripts is thus timelier and could vary significantly from quarter to quarter, which is critical for us to measure climate risk more accurately in real time. We therefore use the measures based on earnings calls in our main analysis and present the analysis of the alternative measures in the Appendix.

3.2. Constructed Climate Risk Measures

3.2.1. Overall Climate Risk

We now present the constructed measures of $ClimateRisk_{i,t}$. In Table 1, we start by reporting the top climate keywords based on their frequency, to construct our main measure, $ClimateRisk_{i,t}$, and whether they are related to severe climate events. We denote both the frequency of occurrence as well as the frequency weight (fweight, scaled up by 10^4) of individual unigrams/bigrams by $B_{i,t}$. The table shows our climate training library covers a large variety of words (unigrams and bigrams) related to weather and climate factors. In addition, the frequency counts for severe climate words are higher than those for non-severe climate words that are discussed in the proximity of a risk synonym. In terms of individual words, *hurricanes* and *hurricane* are the top severe climate unigrams, based on frequency counts in earnings calls. Their combined fweight comprise 48% of the total fweight of the entire climate dictionary, indicating that hurricanes remain a significant but not a major climate risk factor to firms. The words *storms*, *drought*, *flooding*, *earthquake*, and *wildfire(s)* are also frequently discussed in earnings calls, trending up in the later few years of our sample period. This evidence suggests that a major part of climate risk that firms face consists of exposure to catastrophic climate events or natural disasters. As for non-severe climate words that are in the proximity of a risk synonym, *weather* is the top word in terms of frequency counts, followed by *temperatures* and *climate change*.

Table 2 provides summary statistics of our climate risk measures and other variables in our analysis. We find large variations in climate risk measures across firm–quarter observations. To reduce reliance on a few transcripts with very high values, we cap climate risk measures at the 99th percentile. Additionally, to facilitate interpretation, we standardize all climate risk measures, as well as implied volatility (*i.e.*, the standard deviations (SDs) of these variables all equal one). Besides these two set of variables, we report the statistics of variables on earnings, leverage, Tobin's Q, capital investment, employment change, and other firm fundamental attributes. The summary statistics of these variables are, overall, similar to those reported in the literature. All the variables in the table are at the firm–quarter level, except the variable on employment change, which is at the firm–year level.

Table 3 reports excerpts of the transcripts with the highest $ClimateRisk_{i,t}$, our overall measure of the climate risk discussed in these transcripts. For example, the transcript indicating the highest climate risk, that of Marriott Vacations Worldwide Corporation, on November 2, 2017, discusses Hurricanes Irma and Maria and related storms. The company states that the active hurricane season, and two storms in particular, affected their operations most directly. The transcript indicating the second highest climate risk is that of Cal Dive International Inc, a marine contractor that provides an integrated offshore construction solution, on October 30, 2008. The call discusses both hurricanes and uncertainty associated with variations in non-severe climate conditions that affected the company's operations in Texas and Louisiana. The executives mentioned that they had implemented some emergency plans. The next company, California Water Service Group, in its call on April 27, 2017, discusses the drought conditions in a more positive tone, in the context that drought expenses were minimal in 2017 compared to the highest expenses due to the drought the previous year.

Reflecting the increasing importance of the climate topic of wildfires in California are the transcripts of two companies: Edison International and PG&E Corporation. Edison International's largest subsidiary, Southern California Edison, based in Rosemead, is the primary electricity supply company for much of Southern California, whereas PG&E Corporation, based in San Francisco, serves the northern part of the state. In its earnings call on October 20, 2018, following the height of wildfire season, Edison International executives discussed its responses to mitigate wildfire exposure by stating that they advocate reforms to mitigate the risk of catastrophic wildfires and to fairly allocate financial responsibility among the multiple causes of wildfires. Separately, on November

5, 2018, PG&E not only discussed the impact of recent wildfire and drought events, but also went to great length walking the audience through their Community Wildfire Safety Program proposal targeting wildfire risk mitigation. Although mentioning wildfire and drought, the primary focus of the call from PG&E's perspective was to discuss their responses to address the ongoing risk exposure related to variation in weather conditions.

Having shown the initial promise of our pattern-based classification, we now examine the properties of the constructed measures. In Figure 1, we plot the overall climate risk measure over time. The series shows seven to eight climate risk spikes in the past 17 years. We identify the corresponding topics discussed in the conference calls contributing to the increases in climate risk and label each spike. For example, the spike in 2004Q4 is due to discussions of hurricanes, namely, Hurricanes Charley and Ivan, which struck southwest Florida and Alabama & Florida, respectively, in 2004, causing significant damage. The spike in 2005 reflects the catastrophic and long-lasting effect of Hurricane Katrina, which flooded the vast majority of New Orleans, as well as neighboring parishes. It was estimated that more than 1,200 people died and over 1 million people were displaced. The spike in 2011 has much to do with the Great East Japan Earthquake in March, with disruption and damage that sustained the remainder of the year. The earthquake triggered powerful tsunami waves that killed more than 19,000 people. More importantly, the earthquake and tsunami completely disrupted the Japanese auto industry, which is closely integrated into the supply chains of the U.S. auto industry. The 2012 spike marks Hurricane Sandy, which affected much of New Jersey, New York, and part of Connecticut. Climate risk peaked in 2017, with multiple hurricanes: Hurricane Harvey affected the Houston area, while other hurricanes affected mostly the East Coast, especially Florida and North Carolina. In 2018, while hurricanes continued to be a trending topic in earnings calls, wildfires across California, mostly in the northern part of the state, had become a new focus.

3.2.2. Disaggregated Climate Risk Measures

In Figure 2, we plot the disaggregated climate risk series over time to show that the richness in our climate risk measures goes well beyond just severe or catastrophic weather events that have been extensively explored by the literature. In Panel (a), we separately plot severe and non-severe climate risk over time. Except for the spikes, the magnitude of non-severe climate risk is comparable to that of severe climate risk during most conference call discussions. Non-severe climate risk also shows some spikes in 2014.

In Panel (b), we plot the long- and short-run climate risk over time. We show that short-run climate risk has similar spikes as the severe climate risk measure. Although there is little variation in long-run climate risk most of the time, the discussion intensifies from 2008 to 2011 during the financial crisis years. The discussions of long-run climate risk pick up again starting from 2016 when the Paris Agreement targeting greenhouse-gas-emissions mitigation was signed.

In Panel (c), where backward- and forward-looking climate risks are plotted, we see that the two types of climate risk discussions coexist most of the time. Panel (d) shows distinctions between Q&A and non-Q&A climate risks. While the two measures are entangled with each other and Q&A climate risk clearly dominates most of the time, non-Q&A climate risk shows greater variation than Q&A climate risk after 2013. Goldsmith-Pinkham et al. (2019) show that municipal bond markets began pricing sea level rise exposure following upward revisions in sea level rise projections in the 2013 Intergovernmental Panel on Climate Change report.

We then plot the climate sentiments in Panel (e) of Figure 2, which shows largely similar but also some differentiated patterns. For example, both positive sentiment and negative sentiment are high in 2004, 2005, 2011, 2012, and 2017, coinciding with spikes in climate risk. However, the sentiment series becomes more volatile over time than the climate risk series. When we separate net positive from negative sentiment, net sentiment removes most of the volatility in sentiment, with the remaining spikes mostly corresponding to those for climate risk.

3.2.3. Affected Corporate Functions

We also implement the textual analysis to all transcripts and review how firms in different industries are affected by climate risk. We screen the top 2,000 bigrams in the proximity of climate risk discussions and categorize them into four broad categories. In Figure A1 in the Appendix, we plot the average frequency weights on each of the four affected corporate functions by industry and separate them into two panels, based on their magnitudes. These measures show great variation across industries in terms of being affected by climate risk. For example, market conditions and sales are the most affected in retail trade, food services, and educational services, while finance/insurance is the least affected.[13]

Similarly, Figure 3 plots the average frequency weights on each of the four affected corporate functions over time. Spikes in market conditions and sales are most evident for notable catastrophic climate events, whereas losses are only incurred in distinct periods, such as 2006–2007, 2009–2011, and 2014–2018, reflecting the long-lasting adverse impact of climate risk. There is no apparent pattern in investment and physical assets. We, however, observe that discussions on this topic have increased significantly since 2016Q4. We also notice that discussions on supply chains and operations occur only in several distinct periods. For example, the East Japan Earthquake in 2011 significantly disrupted the supply chain in the auto industry.

While the cross-industry and time-series variations in the discussions of corporate functions are interesting, it is likely that these corporate functions are affected by firm's other risk factors. In Table 4, we calculate the weights of bigrams related to each corporate function, listed in Appendix A1, unconditional on the occurrence of climate risk. We explore the relation between our constructed climate risk measures and affected functions at the firm level by regressing each of the four affected corporate functions on the former series in the same quarter. We control for firm and time fixed effects to isolate any firm- and time-specific characteristics in all 20 regressions based on 4 dependent variables and 5 sets of explanatory variables (e.g., total, severe and non-severe, long-run and short-run, backward-looking and forward-looking, Q&A and non Q&A climate risks).

The results in the first row show that increase in climate risk is significantly associated with more discussions of all four corporate functions. Based on the economic magnitudes of coefficient estimates, we find that market conditions/sales and costs/losses are the functional areas most frequently discussed when the firm sees the rise of total climate risk. This is consistent with the intended purpose of earnings call. Results in the fifth row show that the positive relation between climate risk and discussions of corporate functions is only present in the management voluntary disclosure part (i.e., non Q&A) of the earnings conference call.

The results from the second to the fourth rows show that both severe and non-severe (such as precipitations and warm winter) affect market conditions and sales. Not surprisingly, shocks to costs/losses and supply chain are only concentrated in short-term and backward-looking climate risks.

[13]In addition, costs/losses are the most affected in finance/insurance, utilities, and health care. Supply chains and operations are the most affected in mining and manufacturing.

Lastly, none of the corporate functions are significantly affected by the rise of long-run climate risk. We believe that chronic changes such as sea level rise and global warming are important topics, but are already expected/priced, unlikely driving the discussions of corporate functions during earnings calls.

3.2.4. Alternative Climate Risk Measures Using 10-K/10-Q Data

Figure A2 in the Appendix plots the average of the two alternative climate risk measures constructed from the 10-K/10-Q data over time. As discussed in Section 3.1.5, disclosures in the MD&A and Risk Factors sections of 10-Ks/10-Qs tend to be scripted and do not change much over time. We therefore find that the two alternative climate risk measures display much smaller time-series variations than our main climate risk measure. The quarterly average of the two series does not exceed 0.5 SD. In addition, the climate risk measure constructed from Risk Factors exhibits a significant seasonal pattern, because the Risk Factors sections of 10-K filings of many firms are much more comprehensive than those of 10-Q filings in the same year. [14]

4. Determinants of Climate Risk

In this section, we study determinants of firm-level climate risk by estimating the following regression:

$$ClimateRisk_{i,t} = \beta_1 \cdot Disaster_{c,t-1} + \beta_{12} \cdot X_{i,t-1} + \zeta_t + \zeta_r + \zeta_s + \epsilon_{i,t}, \tag{2}$$

where $Disaster_{c,t-1}$ is a dummy variable indicating any natural disaster events in county c at time $t-1$; $X_{i,t-1}$ includes a set of firm-level time-varying attributes; ζ_t, ζ_r, and ζ_s represent the fixed effects of the firm's year–quarter, industry, and location, respectively. In alternative specifications, we also control for firm, sector by time and state by time fixed effects to capture within-firm variation in climate risk.

The results are reported in Table 5. We include two lagged values of natural disasters, since we find that additional lags are no longer statistically significant. In the first two columns, no fixed effects

[14]For instance, Walmart Inc. has very comprehensive Risk Factors sections in its 10-Ks, but very short ones in its 10-Qs.

are controlled for, and the coefficients on natural disasters and firm attributes therefore capture the correlation between them in prior quarters and climate risk discussed in the current quarter. In Columns (3) to (5), we gradually add time fixed effects, sector (at the NAICS two-digit level) fixed effects, and state fixed effects, respectively. In Columns (6) and (7), we control for sector by time and state by time fixed effects, which capture time-varying market conditions at both the industry and geographic levels. Column (6) only includes natural disasters, while Column (7) includes natural disasters and firm attributes. In Columns (8) to (10), we control for firm fixed effects, along with year–quarter fixed effects in Column (8), sector by year–quarter fixed effects in Column (9), and to both sector by year–quarter and state by year–quarter fixed effects in Column (10).

4.1. Natural Disaster Exposure

Recent literature on climate risk in economics or finance has mostly focused on the effect of natural disasters on the labor market, the housing market, and corporate outcomes. Thus, the first determinant of climate risk we explore is natural disasters sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS[15]), which has been used in several recent studies (*e.g.*, Barrot and Sauvagnat (2016)). The most recent SHELDUS data are reconciled with natural disasters declared by FEMA. SHELDUS provides data on the county, beginning/end dates of the disaster, its main synonyms (*e.g.*, flooding, rain, hurricane, storm, snow), and the name of the disaster event, which allows us to match it to our firm–quarter panel data, using the headquarter county. By regressing the climate risk in the current quarter on natural disasters in the past, the coefficients β_1 capture the effect of disaster exposure on the discussion of climate risk during the earnings calls.

Throughout all specifications in Table 5, the coefficient on the natural disasters are all significant and positive, suggesting the natural disasters that just occurred in the prior quarters are an important reason why the earnings call participants discuss climate risk topics. The presence of natural disasters in the prior quarter are associated with an SD of 0.1–0.3 in climate risk, while the disasters two quarters ago have only a third or a quarter of the effect. Nevertheless, natural disasters alone

[15]Originally created at the University of South Carolina, SHELDUS is now maintained by Arizona State University

explain only 0.4% of the variation in climate risk, highlighting much larger variations in our climate risk measures at the firm level.

4.2. Firm Attributes

Firms with certain characteristics could be more likely to discuss climate risk. Our second set of determinants of climate risk contains several important firm–time attributes in the prior quarter. First are the attributes that capture a firm's climate exposure, that is, firms with large quantities of physical assets are more exposed to changes in climate conditions. We include three variables: a firm's total assets (logarithm), CapEx scaled by assets, and property, plant, and equipment (PPE) scaled by assets. All three variables have a positive relation with climate risk in the current quarter, with assets and PPE being statistically significant at the 1% level when we control for time, sector, and state fixed effects, and CapEx being statistically significant when we control for firm fixed effects. The results suggest that firms with more investments in physical assets have greater exposure to changes in climate conditions and are thus more likely to discuss climate risk.

The second attribute is a firm's leverage, measured by its book leverage ratio. When a firm has high leverage, it could be more motivated to please capital market participants by avoiding discussing climate risk exposure. We find that this variable is negative and statistically significant when we control for firm fixed effects, suggesting that, when a firm is highly levered, it is less likely to discuss climate risk. The third set of attributes measures firm types, where certain firms perform well either financially or in the capital market, so that they are more or less likely to discuss climate risk. The coefficient on the return on assets (ROA) is significant and positive when we control for sector and state fixed effects in Columns (5) and (7), suggesting that firms with higher returns are more likely to discuss climate risk. We do not find any significant coefficients on firms' quarterly cumulative stock returns. Our next attribute is Tobin's Q, which captures firms' growth opportunities (relative to assets in place). We find a significant and negative coefficient on Tobin's Q when we control for sector and state fixed effects in Columns (5) and (7), but significant and positive coefficients on Tobin's Q when we control for firm fixed effects in Column (10). The results suggest that firms with a lower Tobin's Q, that is, which have more assets in place, are less likely to discuss climate risk topics. However, when Tobin's Q increases within a firm (i.e., it gains more growth opportunities), the firm is more likely to discuss climate risk.

Our last set of firm attributes captures firms' external characteristics. We include the number of analysts covering the firm, the firm's share of institutional ownership, and its concentration of institutional ownership, as measured by the Herfindahl–Hirschman Index (HHI). Generally, the more analysts covering a firm, the lower the information asymmetry about the firm. Institutional ownership is the opposite of individual ownership. Firms with higher or more concentrated institutional ownership might not need to pay as much attention to earnings calls as a platform for disseminating information. We find that the coefficients on the number of analysts are significant and negative in Columns (2) to (8), suggesting that firms with high analyst coverage are less likely to discuss climate risk. The coefficients on both the share and concentration of institutional ownership are not significant at all, suggesting that these characteristics have little relation with corporate climate risk being discussed during earnings calls.

4.3. Sector and Geographic Variations

In Figure 4, we plot the coefficients for the sector, state, and year–quarter dummies, estimated from Column (5) in Table 5. Panel (a) shows significant cross-sectional variation across sectors in climate risk. Relative to agriculture sector, the average climate risk of all other industries are significantly lower. Utilities (NAICS 22) have the second highest climate risk while three sectors, including information, real estate, and professional services, have the lowest climate risk.

In Panel (b) of Figure 4, we plot the coefficients on the state dummies. The results show that firms located in the Midwest (*e.g.*, Nebraska and Missouri), West South Central (*e.g.*, Texas, Arkansas, Louisiana), and Southeast (*e.g.*, Tennessee, Mississippi, Alabama, and Florida) regions experience the greatest climate risk. Besides these regions, the states of Vermont, New Jersey, and Wisconsin as well as Puerto Rico have higher climate risk than the rest of the country. These states are the most exposed to severe weather events, as well as dramatic changes in climate, such as the polar vortex. Although the overall climate risk in California is not among the highest over the sample period from 2002 to 2018, it has been trending up due to exposure to wildfires and earthquakes in recent years.

In Panel (c) of Figure 4, we plot the coefficients on year–quarter dummies after controlling for state and sectoral variations. Different from the series in Figure 1, they reflect the time trend of climate risk that affects the entire country and economy at large. There are six clear and visible spikes, at 2004Q4, 2005Q5, 2006Q1, 2008Q4, 2012Q4, and 2017Q4. They correspond to the five most severe climate events at the time (*e.g.*, hurricanes).

4.4. Analysis of Disaggregated Climate Risk Measures

In Panel B of Table 5, we conduct a similar analysis of individual climate risk measures following the specification in Column (5) in Panel A, where we control for time, sector, and state fixed effects. In Columns (1) and (2), as expected, severe climate risk is much more affected by natural disasters in the past than non-severe climate risk, since natural disasters are severe weather events. Most of the coefficients in Column (1) are similar to those in Panel A, suggesting the determinants of overall climate risk are mostly driven by those of severe climate risk. Some covariates have a significant relation with non-severe climate risk: PPE have a significant and positive effect; the number of analysts has a significant and negative effect; the market concentration of institutional ownership has a significant and negative effect. While the concentration of institutional ownership has no significant effect on severe climate risk, firms with a higher concentration of institutional ownership are less likely to discuss non-severe climate risk during earnings calls.

In Columns (3) and (4) in Panel B of Table 5, only short-run, and not long-run, climate risk is affected by natural disasters. Most of the coefficients in Column (4) are similar to those in Panel A, suggesting the determinants of overall climate risk are mostly driven by those of short-run climate risk. Two covariates have a significant relation with long-run climate risk: both book leverage and the number of analysts have a significant and negative effect, suggesting that firms with lower leverage and fewer analysts covering it are more likely to discuss long-run climate risk.

In Columns (5) and (6) in Panel B of Table 5, both backward- and forward-looking climate risk are affected by natural disasters with similar magnitudes, suggesting that the determinants of overall climate risk are driven by those of both backward- and forward-looking climate risks.

In Columns (7) and (8) in Panel B of Table 5, both Q&A and non-Q&A climate risk are affected by natural disasters, but with a much greater magnitude in Column (7), suggesting that Q&A climate risk is affected more by actual disasters than non-Q&A climate risk. Some firm attributes have different effects on the two climate risk measures. For example, while the ROA has a significant and positive effect on Q&A climate risk, it does not have any effect on non-Q&A climate risk. The concentration of institutional ownership has a significant and negative effect on Q&A climate risk, but not on non-Q&A climate risk. In contrast, Tobin's Q has a significant and negative effect on non-Q&A climate risk, but not on Q&A climate risk.

4.5. Variance Decomposition

We estimate $ClimateRisk_{i,t}$ in additional specifications and summarize all of their R^2 values to capture the exact portion of the variation in $ClimateRisk_{i,t}$ that can be explained by observable characteristics. These results are summarized in Table 6.

The results shows that, while natural disasters have a significant effect on corporate climate risk, they only explains 0.4% of the variation, largely due to much smaller variations in natural disasters than in our firm-level climate risk. Firm attributes explain an additional 4.5% of the variation. Time trends play an even larger role, with 8% of the additional variation being explained by the year–quarter dummies with or without firm attributes. Sectoral fixed effects account for another 1.8% of the variation in climate risk, and a firm's geographic location accounts for only 1.1% of the variation, in addition to the time and sector. Since we are concerned about market conditions by sector and geography, we also control for sector by time as well as state by time fixed effects. Adding sector by time fixed effects explains 3.7% of the variation, in addition to controlling for time, sector, and state fixed effects, whereas adding state by time fixed effects explains 4–6% of the variation, depending on whether we include natural disasters and firm attributes.

Nevertheless, the interaction of sector and time combined with the interaction of state and time explain at most 25% of the variation in $ClimateRisk_{i,t}$, leaving 75% of the variation to firm-level idiosyncratic factors. This result suggests that, unlike natural disasters that are commonly used by the literature or the news about long-run climate risk of Engle et al. (2020), our climate risk is a firm-level risk measure. When we add firm and time fixed effects, the model captures another 3% of the variation. Finally, we also try to replace time fixed effects with sector by time or state by time fixed effects to control for sector- or geographic-specific time trends, respectively. We find the additional time controls explain another 7–11% of the variation in $ClimateRisk_{i,t}$. In summary, even with our finest controls of fixed effects, the model only explains 40% of the variation in $ClimateRisk_{i,t}$, and residuals due to within-firm variation still account for 60% of the variation, bolstering our confidence that this risk is truly idiosyncratic at the firm level.

4.6. Expected versus Unexpected Climate Risk

By analyzing what determines climate risk, using natural disasters and firm attributes along with fixed effects, we effectively decompose climate risk into two parts: expected and unexpected climate risk. Expected climate risk, constructed using the regression in Column (5) in Table 5, Panel A, is conditional on the public information known to the earnings call participants, such as natural disasters, firm attributes, time, sector, and state, and thus should be reflected in any market reactions, such as the stock price and volatility. The residuals capture what is unexpected to the market participants. In Panel (a) of Figure 5, we plot the SDs of the two series. This plot shows that most of the variation in the overall climate risk is captured in the unexpected component, whereas the variation in expected climate risk is largely flat over time, confirming that $ClimateRisk_{i,t}$ is predominantly a firm-level idiosyncratic risk. In our second-stage analysis, we are interested in exploring the relation between unexpected $ClimateRisk_{i,t}$ and corporate outcomes.

Panel (b) of Figure 5 plots the histogram of unexpected climate risk, showing significant dispersion of unexpected climate risk. While most of the values lie within two SDs, some unexpected climate risk values extend beyond four SDs in both tails.

5. Validating Climate Risks

In this section, we provide external validation of the $ClimateRisk_{i,t}$ measures using the implied stock price volatility that captures the uncertainty for equity investors.

5.1. Correlation with Volatility

We next analyze whether $ClimateRisk_{i,t}$ correlates with the implied volatility of stock returns. Our main specification takes the form

$$Y_{i,t} = \beta \cdot ClimateRisk_{i,t} + \gamma \cdot X_{i,t-1} + \zeta_i + \zeta_t + \epsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ is the corporate outcome variable (i.e., implied volatility, $Vol_{i,t}$) in the quarter when climate risk is discussed; ζ_i and ζ_t represent the firm and time fixed effects, respectively; $X_{i,t-1}$ is a set of firm attributes, as included in Equation (2), that is, the logarithm of the firm's assets, CapEx (scaled by assets), PPE (scaled by assets), the book leverage ratio, Tobin's Q, the ROA, the number of analysts covering the firm, and the share and concentration of institutional ownership (HHI). It is worth noting that, although $ClimateRisk_{i,t}$ is in the contemporaneous quarter of the outcome variable, since the earnings calls typically occur in the first month of the quarter to discuss the results in the prior quarter and implied volatility is measured using 90-day at-the-money options, β actually captures a relation between the current $ClimateRisk_{i,t}$ and future volatility.

Panel A of Table 7 reports the results, using implied stock return volatility as the dependent variable. Column (1) shows our most parsimonious specification, where we regress implied $Vol_{i,t}$ on $ClimateRisk_{i,t}$ and the firm attributes. The coefficient of interest is negative and statistically significant at the 1% level, suggesting that a one-SD increase in climate risk at the firm level is associated with a 0.028-SD decrease in the firm's stock return volatility. Column (2), however, shows a nonsignificant relation between $ClimateRisk_{i,t}$ and $Vol_{i,t}$ once we control for firm and year–quarter fixed effects, suggesting no significant correlation between climate risk and stock return volatility.

In Columns (3) and (4) in Panel A of Table 7, we adopt similar specifications, but replace the overall $ClimateRisk_{i,t}$ with the expected $ClimateRisk_{i,t}$, measured using the predicted value from the first-stage regression, as the main explanatory variable. In both specifications, the coefficient on the expected $ClimateRisk_{i,t}$ is positive and statistically significant at the 1% level, suggesting that a one-SD increase in the expected climate risk at the firm level is associated with a 0.011-SD (= 0.0952*0.12) increase in the firm's implied volatility of stock returns, based on Column (4). In Columns (5) and (6), we conduct similar regressions on the unexpected $ClimateRisk_{i,t}$, measured using the residuals from the first-stage regression, as the main explanatory variable. Although the coefficient is negative and statistically significant in Column (5) when we only control for firm attributes, it is not significant at all in Column (6) when we control for firm fixed effects, suggesting no significant correlation between unexpected climate risk and stock return volatility.

Taking stock of the results, we find a positive correlation between firm's expected $ClimateRisk_{i,t}$ and its stock return volatility in the near future. However, there is no significant relation between unexpected $ClimateRisk_{i,t}$ and stock price volatility. Our evidence suggests that the stock and option markets only react to expected variations in climate risk, given a firm's fundamental exposure as captured by our first-stage analysis, but not to any "abnormal" climate risk discussions in firms' earnings calls.

5.2. Robustness Tests

We next conduct robustness tests to demonstrate that the results in Panel A of Table 7 are not driven by confounding firm-level risks. Panel B reports the tests where we control for other risks, including total risk, but not related to climate risk, political risk, or non-political risk, which have been studied in the literature. In all specifications, we control for firm and time fixed effects, as well as firm-level time-varying attributes. The results show that, while we control for other risk measures, the coefficients on all three $ClimateRisk_{i,t}$ values remain very similar to those in Panel A and are little affected by the inclusion of additional risk measures, suggesting that the constructed climate risk measure captures a new kind of risk that has not been explored by the literature, and its expected component is highly predictive of future stock return volatility.

6. Climate Risk and Corporate Responses

In this section, we explore how firms respond to changes in climate risk using two approaches. First, we conduct case studies based on simple textual analysis of 50 earnings call transcripts with highest levels of climate risk to identify and interpret corporate responses. Second, guided by the anecdotal evidence from the first step, we conduct empirical tests over the full sample to study the relation between corporations' climate risk and their future actions, using investment and employment growth as the primary empirical measures.

6.1. Textual Analysis of Corporate Responses

In this section, we conduct case studies based on the 50 transcripts with the highest climate risk measures and investigate firm responses to elevated climate risk exposure. In Table A2, we summarize the main response keywords based on industry. As expected, the responses vary by industry, since each industry can have different constraints, capacities, resources, and climate risks. These dimensions also vary across firms within a sector. For example, in agriculture, where drought is one of the major climate risk factors, some firms discuss innovation, such as developing drought-tolerant crops. In the oil and gas extraction industry, where hurricanes are a primary climate risk factor, some firms focus on repair work, inspection, and revising production guidance, while others take more proactive approaches, such as accelerating idle well abandonment as a way to reduce future exposure. In the manufacturing sector, which has to cope with hurricanes and flood risk, some firms focus on passive responses, including discussions to shut down business, evacuation, and insurance claims, while others consider launching a hurricane-resistant product and investments.

In the utilities and health care sectors, we see a great deal of heterogeneity in responses across different types of climate events. For example, company executives discuss repairs and service restoration as more passive responses, and hedging with swap contracts as a more proactive one. However, in relation to wildfires, the topics differ and include conducting patrols, as a passive action, and more proactive measures, such as preemptively shutting off power (controversial in PG&E's case), advocating legislative reforms, investigating potential origins and causes, system upgrades, vegetation management, and system hardening.

Taking stock of the textual analysis, we find great heterogeneity in firm responses to climate risk. Although many responses are passive, with the objective to repair and maintain existing production, others explore innovation and investment strategies. This motivates us to focus on our empirical analysis of firm responses using investment and employment, which are the two essential elements in a Cobb–Douglas production function, as well as the readily available data. Investment captures a firm's efforts beyond just restoring its existing production, such as opening/closing plants, developing alternative products, and upgrading existing equipment to ultimately improve productivity in the face of rising climate risk. Investment can be achieved at the expense of labor, especially when the firm faces budgetary constraints. We investigate these issues in the sections below.

6.2. Climate Risk and Corporate Investment

In this section, we focus on corporate investments, measured using CapEx, as a main dimension of corporate responses, to explore the relation between our constructed climate risk series and corporate responses. The theoretical literature has mixed predictions regarding investment under uncertainty. While Bernanke (1983), Pindyck (1991), Pindyck and Solimano (1993) and Dixit and Pindyck (1994) predict a decline in investment in times of high uncertainty, other studies such as Oi (1961), Hartman (1972, 1976), Abel (1983), Roberts and Weitzman (1981) and Bar-Ilan and Strange (1996) predict that an increase in uncertainty would increase firm-level investment. Moreover, our textual analysis of firm responses suggests that while some firms "passively" react to climate risk, other firms choose to cope with rising climate risk through active investment and innovation. Ultimately, how firm investment varies with climate risk exposure is an empirical question.

6.2.1. Investment

In Table 8, we report the regression results on firm investment using CapEx scaled by capital stock as the dependent variable and following the specification in Equation (3). In Panel A, we report the results using total climate risk as the explanatory variable, where Columns (1) and (2) report the effects of overall climate risk, Columns (3) and (4) report the effects of expected climate risk, and Columns (5) and (6) report the effects of unexpected climate risk. In Columns (1), (3), and (5), we only control for firm–time attributes and in Columns (2), (4), and (6), we control for firm–time attributes as well as firm and time fixed effects.

The results in Columns (2), (4), and (6) show a positive and significant relation between overall as well as unexpected $ClimateRisk_{i,t}$ and corporate investment, suggesting that a one-SD increase in both overall and unexpected climate risk at the firm level is associated with a 0.168 (=0.1682*1.00) and 0.158 (=0.1701*0.93) percentage-point increase in the firm's CapEx as a percentage of capital stock, respectively. In contrast, there is a negative and significant relation between the expected $ClimateRisk_{i,t}$ and corporate investment, suggesting that a one-SD increase in the expected climate risk at the firm level is associated with a 0.190 (=1.5796*0.12) percentage-point decrease in the firm's CapEx.

In Table A3 in the Appendix, we report the results using CapEx as well as research and development (R&D) investment, both scaled by firm assets, as the dependent variable. The results show a similarly positive and significant relation between overall as well as unexpected $ClimateRisk_{i,t}$ and corporate investment, measured by CapEx/assets, and there is no significant relation between expected $ClimateRisk_{i,t}$ and corporate investment. We do not find a significant relation between any of the climate risk measures and corporate R&D investment, which could be driven by limited variation in R&D investment due to missing values.

We also explore the nonlinear relation between unexpected climate risk and corporate investment by regressing CapEx scaled by capital stock on a set of dummy variables defined based on quintiles of unexpected $ClimateRisk_{i,t}$. The coefficients are plotted in Figure 7. This figure shows a direct relation between the unexpected $ClimateRisk_{i,t}$ and corporate investment. As unexpected risk rises, the firm increases its CapEx in response.

6.2.2. Dynamics of the Relation

We further examine the dynamics between $ClimateRisk_{i,t}$ and capital investment, using CapEx scaled by capital stock as the dependent variable. We run the same regressions specified in Equation (3), but including a set of lagged values of $ClimateRisk_{i,t}$ in addition to the contemporaneous value. The coefficients on the lagged $ClimateRisk_{i,t}$ can be interpreted as the persistent effect of climate risk on future corporate investment. The results in Figure 6 are plotted with those on overall climate risk in Panel (a), those on expected climate risk in Panel (b), and those on unexpected climate risk in Panel (c), respectively.

From these dynamic relations, we find that, first, the coefficient on the contemporaneous value of three $ClimateRisk_{i,t}$ measures is very similar to those reported in Table 8 when we control for a set of lagged values, suggesting very limited serial correlation in the climate risk measures. Second, the relation between overall climate risk and corporate investment is largely driven by that between unexpected climate risk and corporate investment. Both measures have a positive and significant relation with CapEx over most of the eight quarters in the future, decaying over time. Thus, firms significantly increase their CapEx in the next two years following a rise in unexpected climate risk. Our evidence suggests that it takes a significant amount of time and resources to actively manage and respond to the challenges of rising climate risk exposures.

6.2.3. Disaggregated Climate Risk Measures and Investment

In the remaining panels of Table 8, we report the results on the relation between disaggregated climate risk measures and corporate investment, using CapEx scaled by capital stock as the dependent variable. In all the specifications, we control for firm and time fixed effects as well as firm attributes. We decompose each of the climate risk components into expected and unexpected, using the specification of column (5) in Table 5.

In Panel B, we report separate regressions on severe and non-severe climate risks. The results show a positive and significant relation between overall as well as unexpected severe $ClimateRisk_{i,t}$ and corporate investment, suggesting that a one-SD increase in both overall and unexpected climate risk at the firm level is associated with 0.156- and 0.149-percentage-point increases in the firm's CapEx as a percentage of capital stock, respectively. There is no significant relation between the overall as well as unexpected non-severe $ClimateRisk_{i,t}$ and corporate investment.

Panel C reports the regression results on long- and short-run climate risks. The results show a positive and significant relation between overall as well as unexpected long-run $ClimateRisk_{i,t}$, and between overall as well as unexpected short-run $ClimateRisk_{i,t}$ and corporate investment. The relation between short-run $ClimateRisk_{i,t}$ and CapEx is more significant and of greater magnitude than that between long-run $ClimateRisk_{i,t}$ and CapEx. A one-SD increase in both overall and unexpected short-run climate risk at the firm level is associated with a 0.16-percentage-point increase in the firm's CapEx. A one-SD increase in both overall and unexpected long-run climate risk at the firm level is only associated with a 0.06-percentage-point increase in the firm's CapEx. The relation between the expected long-run $ClimateRisk_{i,t}$ and CapEx is positive and significant, with a one-SD increase in the expected long-run climate risk at the firm level associated with a 0.618-percentage-point increase in the firm's CapEx, while the relation between the expected short-run $ClimateRisk_{i,t}$ and CapEx is negative and significant, with a one-SD increase in short-run climate risk at the firm level associated with a 0.191-percentage-point decrease in the firm's CapEx.

Panel D reports the regression results on backward- and forward-looking climate risk. The results show a positive and significant relation between overall as well as unexpected backward-looking $ClimateRisk_{i,t}$, and between overall as well as unexpected forward-looking $ClimateRisk_{i,t}$ and corporate investment. All the relations between the four $ClimateRisk_{i,t}$ measures and CapEx are of similar magnitude, with a one-SD increase in any of the climate risks at the firm level associated with an approximately 0.15-percentage-point increase in the firm's CapEx. The relations between the expected backward-looking $ClimateRisk_{i,t}$ and expected forward-looking $ClimateRisk_{i,t}$ and CapEx are negative and significant, with a one-SD increase in either of the expected climate risk measures at the firm level associated with a 0.194- and a 0.189-percentage-point decrease in the firm's CapEx, respectively.

Panel E reports the regression results on the Q&A and non-Q&A climate risks. The results show a positive and significant relation between overall as well as unexpected Q&A $ClimateRisk_{i,t}$, and between overall as well as unexpected non-Q&A $ClimateRisk_{i,t}$ and corporate investment. The relation between the Q&A $ClimateRisk_{i,t}$ and CapEx is more significant and of greater magnitude than that between non-Q&A $ClimateRisk_{i,t}$ and CapEx. A one-SD increase in both overall and unexpected Q&A climate risk at the firm level is associated with a 0.12-percentage-point increase in the firm's CapEx as a percentage of capital stock. A one-SD increase in both overall and unexpected non-Q&A climate risk at the firm level is associated with only a 0.09-percentage-point increase in the firm's CapEx as a percentage of capital stock. The relations between the expected Q&A $ClimateRisk_{i,t}$ as well as expected non-Q&A $ClimateRisk_{i,t}$ and CapEx are negative and significant, with a one-SD increase in expected Q&A and non-Q&A climate risk at the firm level associated with a 0.15- and a 0.34-percentage-point decrease in the firm's CapEx, respectively.

6.3. Climate Risk and Corporate Employment

Besides investment, the other strategy at a firm's disposal in response to rising climate risk can be to adjust employment through plant closings, mass layoffs, hiring freezes, and pay reduction. Layoffs and plant closings have been commonly adopted by executives at public companies as ways to increase productivity, address ongoing risks, and appeal to the capital market. Our second measure of corporate strategy is the level of employment, which is only available at the firm by year level. In the analysis, we take the averages of our climate risk measures to derive firm by year–level climate risk and use them as the main explanatory variables, following the specifications in Equation (3) at the firm-year level. The results are reported in Table 9.

In Panel A, we report the results using total climate risk as the main explanatory variable, where the specification in each column is the same as in Table 8, Panel A. The results in Columns (2), (4), and (6) show a negative and significant relation between the overall as well as expected $ClimateRisk_{i,t}$ and corporate employment, suggesting that a one-SD increase in overall and expected climate risk at the firm level is associated with a 0.287- and a 6.12-percentage-point increase in the firm's employment the next year, respectively. In contrast, there is no significant relation between the unexpected $ClimateRisk_{i,t}$ and corporate employment.

In Panels B to E, we report the results using disaggregated climate risk as the explanatory variable, where we control for firm and time fixed effects, as well as other firm attributes. The results in all five panels suggest that, while there is a negative and significant relation between most of the expected $ClimateRisk_{i,t}$ series, except for the expected long-run climate risk, and corporate employment, firms also respond to unexpected climate risk by reducing their employment. Specifically, firms adjust their employment downward when facing unexpected severe as well as non-Q&A climate risks. A one-SD increase in unexpected severe and non-Q&A climate risks at the firm level is associated with a 0.209- and a 0.355-percentage-point decrease in the firm's employment the next year, respectively.

6.4. Alternative Climate Risk Measures

We also explore the relation between two alternative climate risk measures based on 10-Ks/10-Qs and corporate responses. Following the specification in Table 5, Panel B, where we control for time, sector, and state fixed effects, we decompose these measures into expected and unexpected components. Table A4 in the Appendix reports the results on climate risk constructed from the MD&A and Risk Factors sections of the 10-Ks/10-Qs. We find the two unexpected climate risk measures from the 10-K/10-Q data have different relations with the firm's CapEx. Similar to our baseline analysis based on earnings call, we find a positive and significant relation between climate risk from the MD&A section and CapEx. In contrast, the relation between climate risk from the Risk Factors section and CapEx is negative and significant. This evidence is likely driven by the lack of time-series variation and the seasonality due to differences in the disclosure length of the Risk Factors sections of 10-Ks versus 10-Qs. Lastly, we find that the relation between both climate risk measures and changes in employment is not statistically significant.

Table A5 in the Appendix reports the results on the net climate sentiment we constructed from the earnings call data. The results suggest no significant relation between the net climate sentiment and a firm's responses measured using investment and change in employment.

7. Conclusion

Climate risk presents an increasingly severe challenge for businesses, frequently disrupting companies' investment, operations, and financial performance. Climate risk can be exacerbated or mitigated by a firm's own actions and those of other firms. The economics and finance literature has largely focused on the adverse effects of natural disasters on corporate operations. Little research has been conducted on quantifying firm-level climate risk or analyzing corporate actions in response to changes in climate risk, partly due to a lack of credible measurements at the firm level.

In this paper, we quantify climate risk at the firm level by applying a textual analysis method to earnings call transcript data. This measure allows us not only to measure the presence and materiality of climate risk at the most granular level, but also to explore the company's perspectives regarding climate risk. Our climate risk measures include an overall measure as well as disaggregated ones that include severe versus non-severe, long- versus short-run, backward- versus forward-looking, and Q&A versus non-Q&A climate risks.

We first analyze the different climate risk measures to understand their determinants. The results suggest that the climate risk measures are positively affected by natural disasters that just occurred in the prior two quarters. However, we find that natural disasters alone only explain 0.5% of the variation in climate risk, highlighting much larger variations in our climate risk measures at the firm level. Firms with certain characteristics, such as those with larger assets, are more likely to discuss climate risk during earnings calls. Variance decomposition based on R^2 values from different specifications suggest that, even with our finest controls of fixed effects, the model only explains 40% of the variation in $ClimateRisk_{i,t}$ and residuals due to within-firm variation still account for 60% of the variation, suggesting that climate risk is primarily idiosyncratic.

Based on our first-stage analysis, we effectively decompose climate risk into two parts: expected and unexpected climate risk. We use these series as the main explanatory variable in the second stage to explore firms' responses following changes in climate risk. A simple textual analysis of the topics discussed surrounding climate keywords shows great heterogeneity across firms in terms of the responses related to climate risk. We then conduct empirical analyses to explore the relation between climate risk and firm responses, using investments and employment growth as the primary metrics. We find that, in response to higher unexpected climate risk, firms significantly increase their investment in the following quarters, supporting the idea that firms actively respond to climate risk challenges. We also find that firms with high unexpected climate risk are associated with significantly slower employment growth in the following year. Together, our evidence suggests that, likely due to budget constraints, firms with high climate risk actively increase investments at the expense of employment growth.

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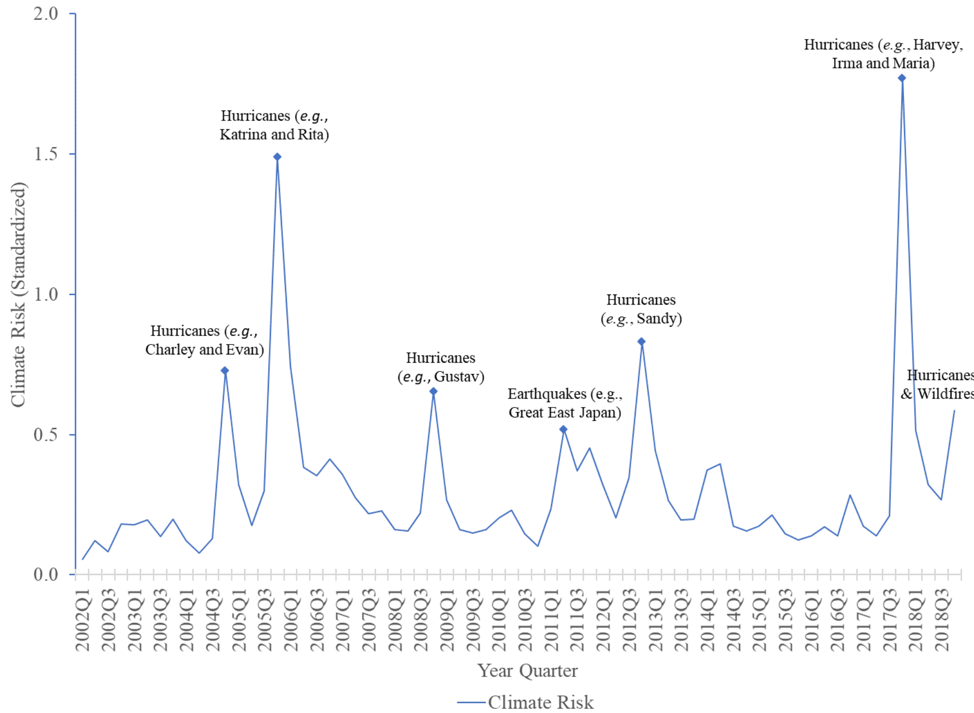
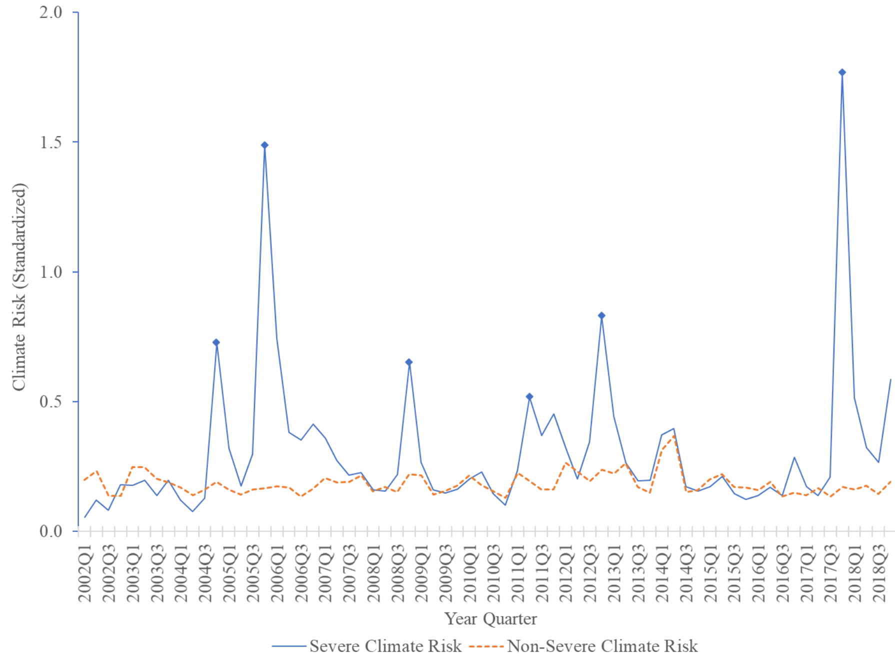
Figure 1. Corporate Climate Risk



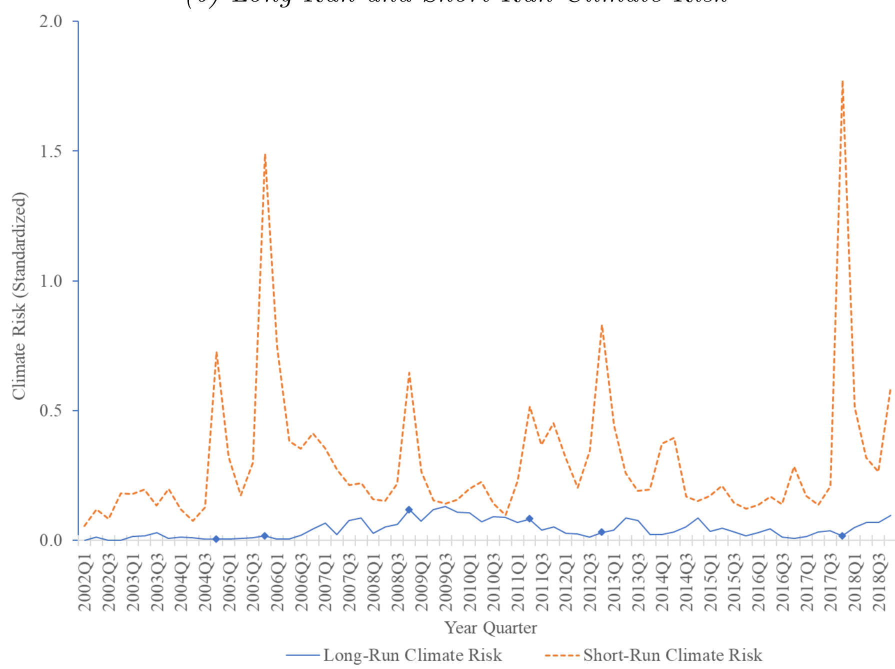
The figure shows the time-average of $ClimateRisk_{i,t}$ (standardized by its standard deviation in the time series) across firms in each quarter. We label each spike with the corresponding topics discussed in the conference calls which contribute to the increase in climate risk.

Figure 2. Varieties in Climate Risk

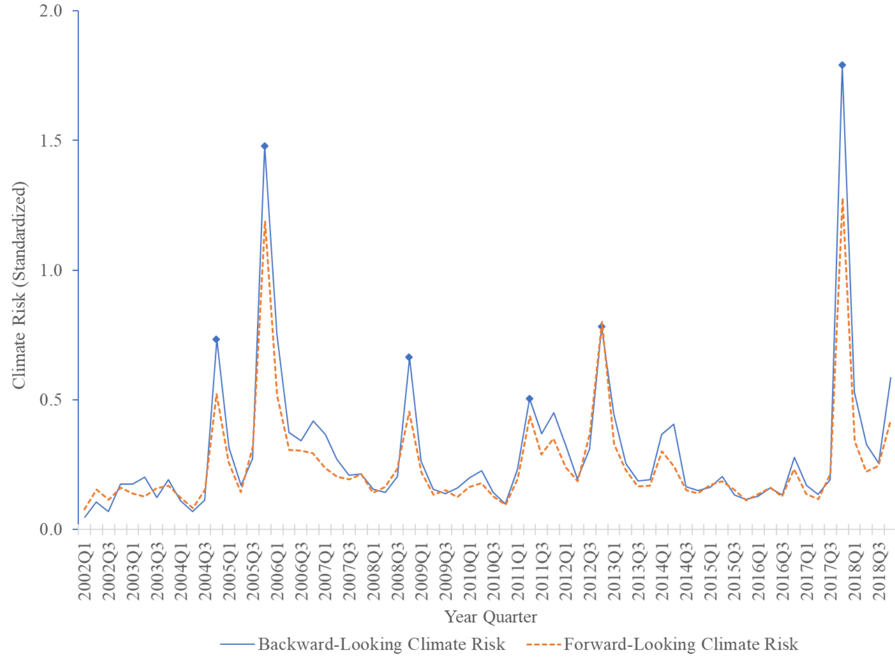
(a) Severe and Non-Severe Climate Risk



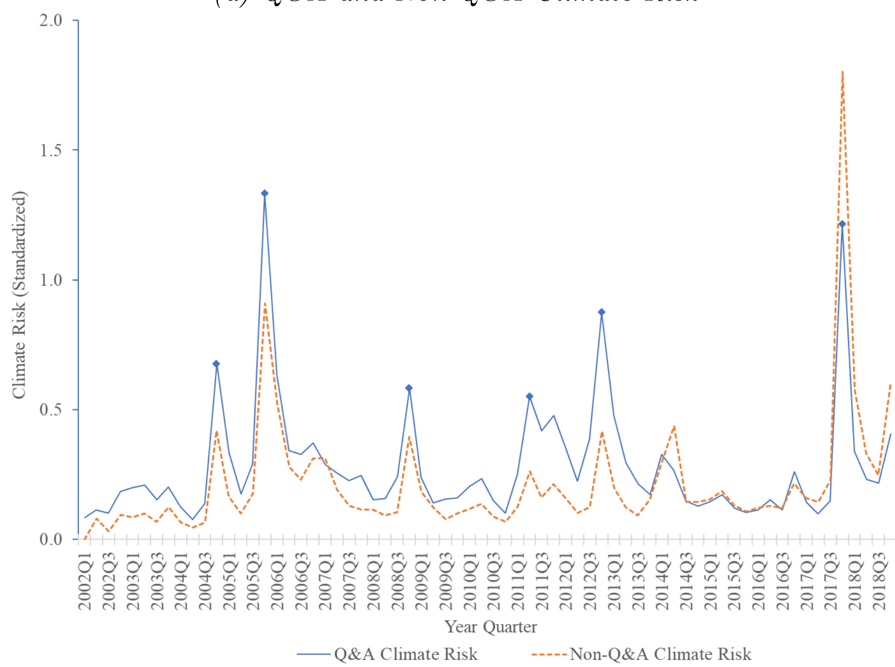
(b) Long-Run and Short-Run Climate Risk



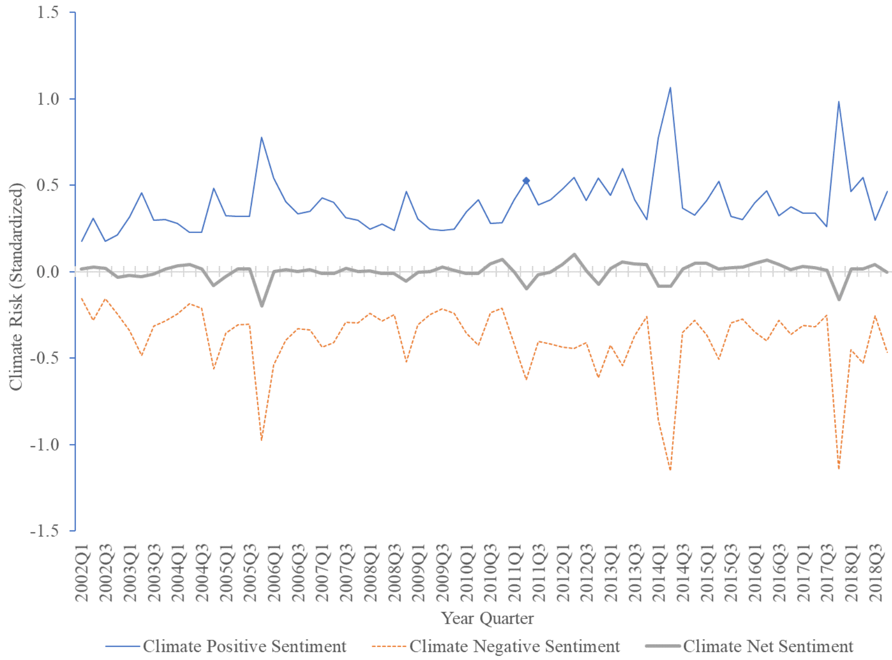
(c) Backward-Looking and Forward-Looking Climate Risk



(d) Q&A and Non-Q&A Climate Risk

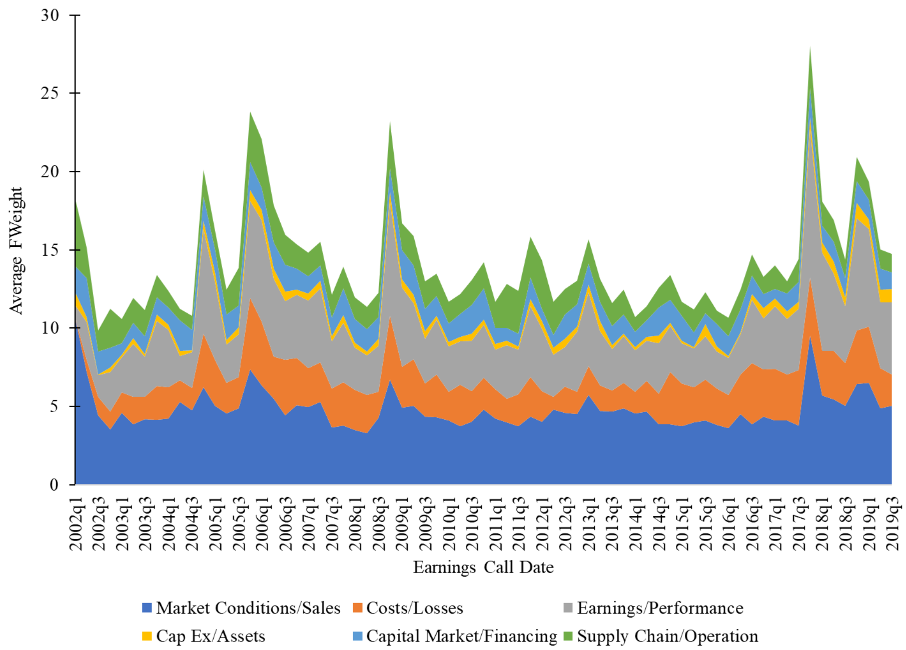


(e) Climate Sentiments



The figure plots different types of disaggregated climate risk series over time. Each climate risk measure is standardized by its standard deviation in the time series. Panel (a) plots the time-average of severe and non-severe climate risk across firms in each quarter. Panel (b) plots the long-run and short-run climate risk over time. Panel (c) plots the backward-looking and forward-looking climate risk over time. Panel (d) plots the Q&A and non-Q&A climate risk during our sample period. Panel (e) plots the time-average of $ClimateSentiment_{i,t}$ across firms in each quarter, including positive, negative and net sentiment series.

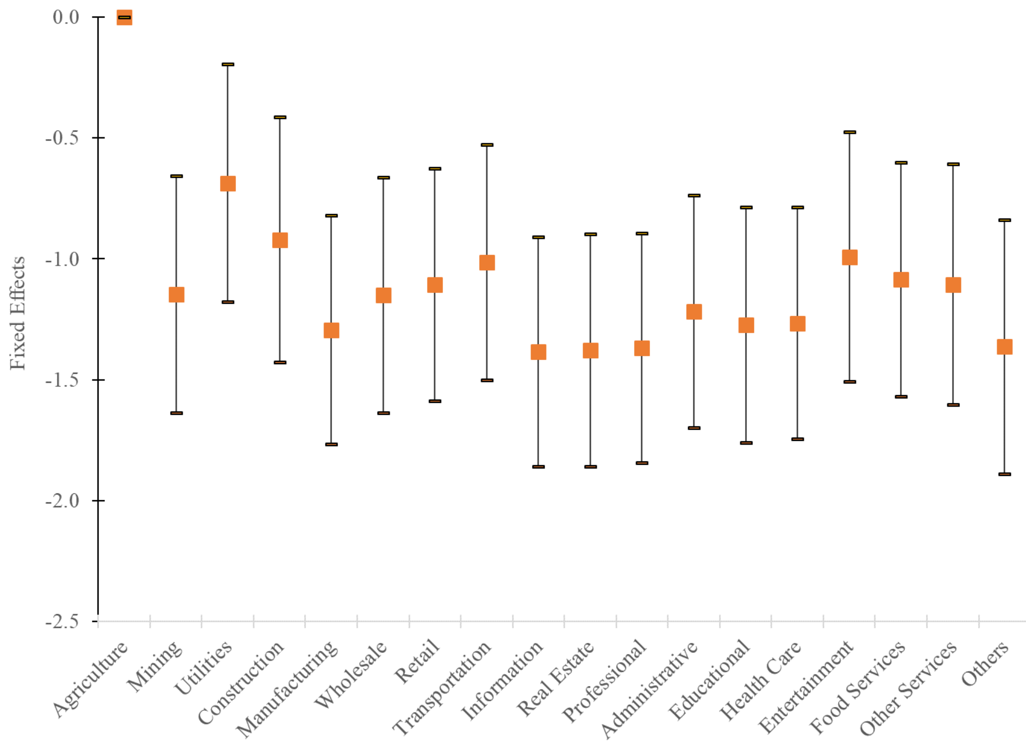
Figure 3. Evolution of Affected Corporate Functions



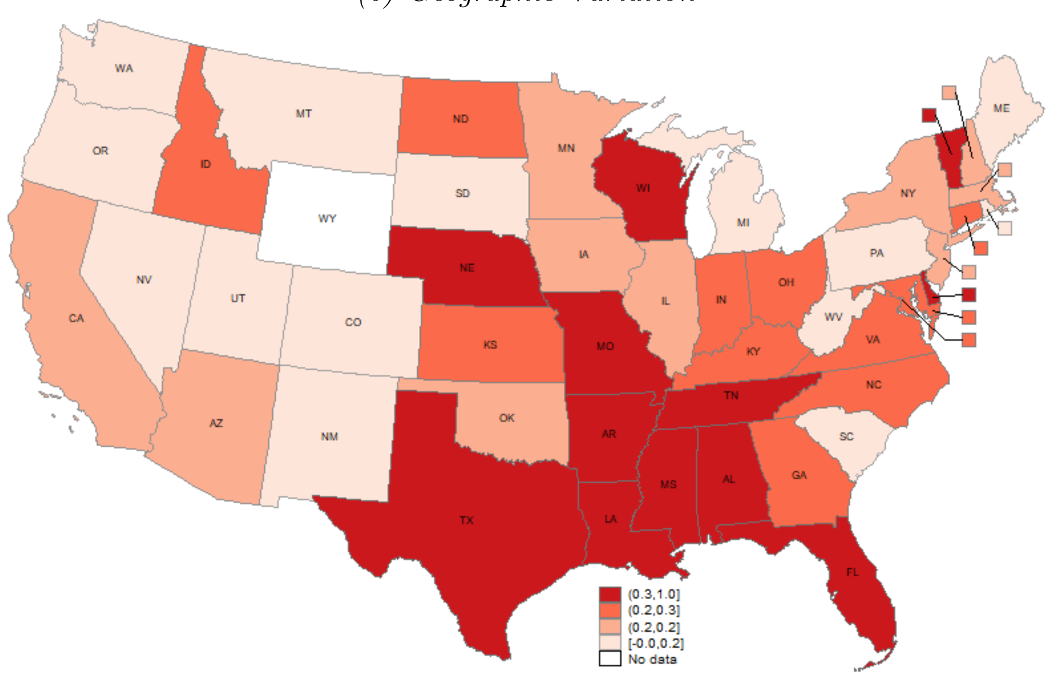
The figure plots the time-average of frequency weight of corporation functions affected by climate risk. We manually review the top 2,000 bigrams before and after climate keywords in the earnings call transcripts and classify them, based on their similarity, into four broad corporate functions that might be affected by climate risk. The list of bigrams in each group is reported in Appendix Table A1.

Figure 4. Variation in Climate Risk

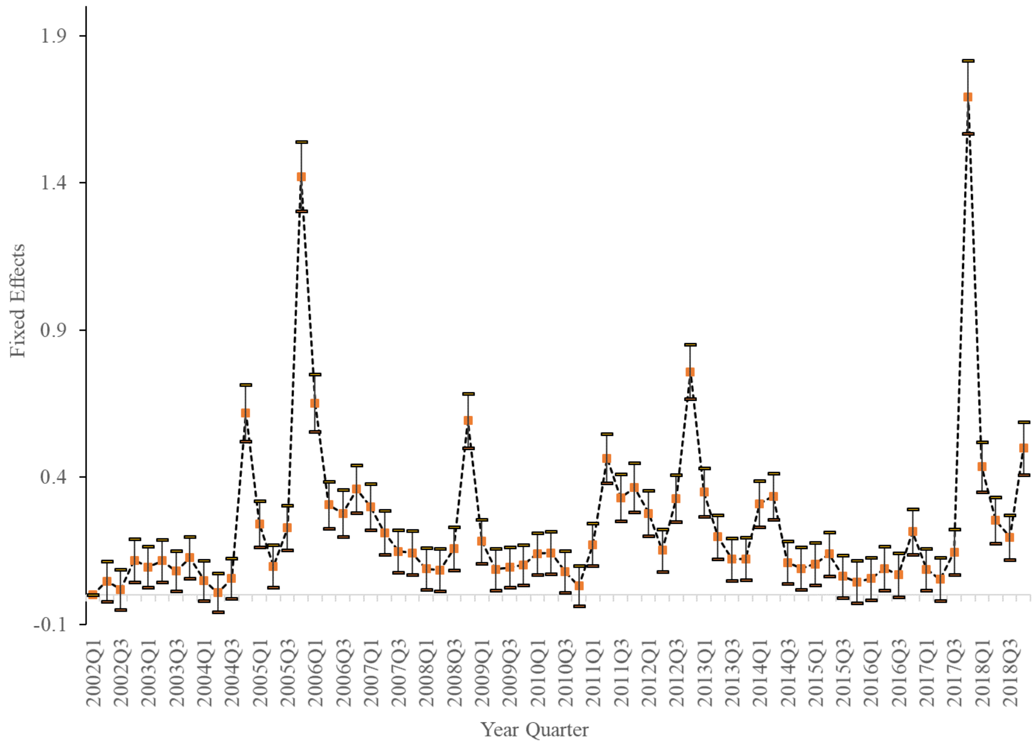
(a) Sectoral Variation



(b) Geographic Variation



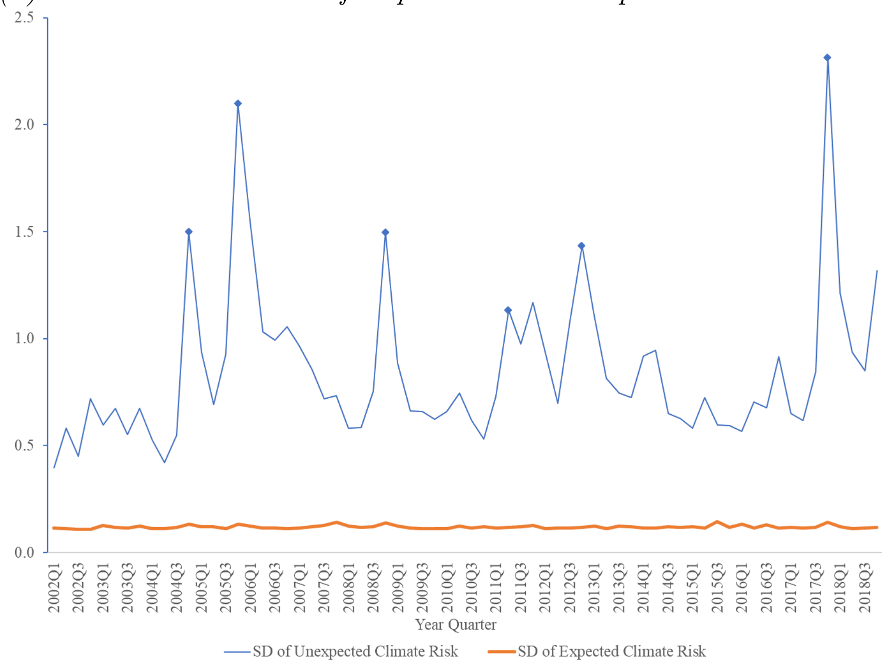
(c) Time Variation



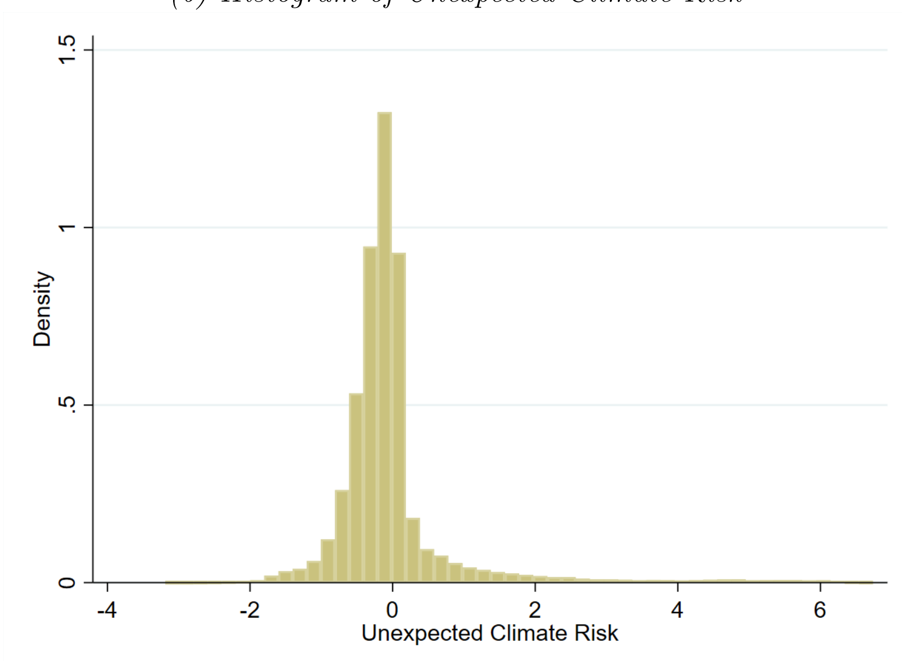
This figure plots the coefficients of sector, state and year-quarter fixed effects estimated from Column (5) in Table 5 Panel A. Panel (a) shows the variation across sectors in climate risk by plotting the coefficients and 95% confidence intervals of sector dummies. Panel (b) plots the coefficients of state dummies in a map. Panel (c) plots the coefficients and 95% confidence intervals of year-quarter dummies.

Figure 5. Dispersion of Unexpected Climate Risk

(a) Standard Deviation of Expected and Unexpected Climate Risk



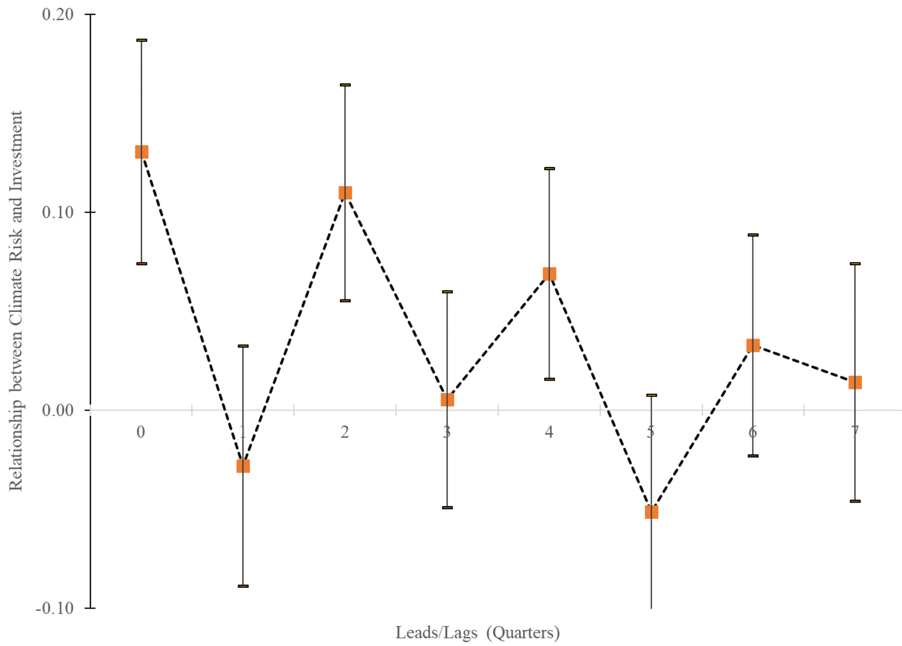
(b) Histogram of Unexpected Climate Risk



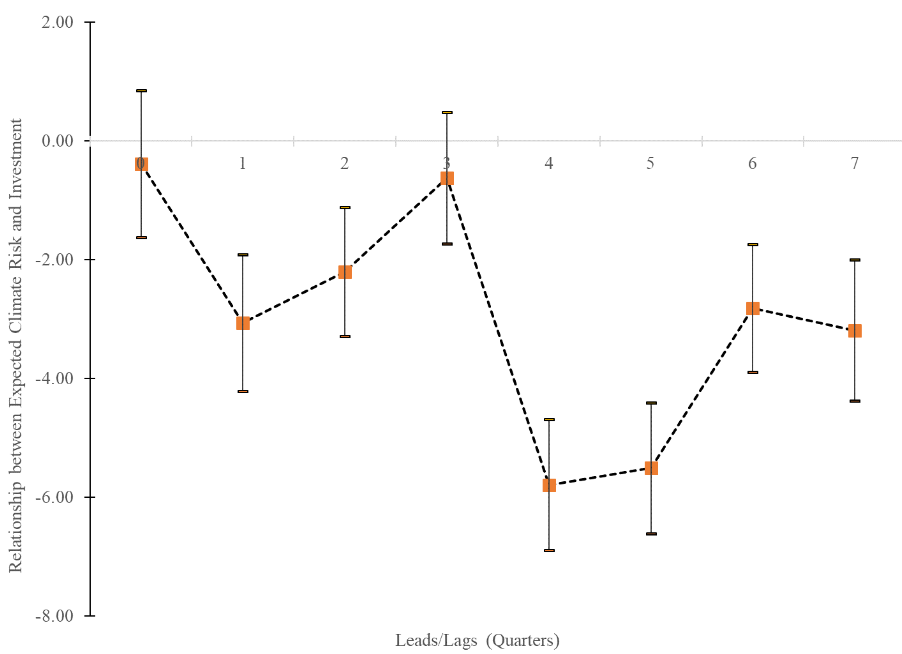
Panel (a) plots the standard deviation of expected and unexpected climate risk over time. Expected climate risk is the predicted value estimated from the first-stage regression as specified in column (5) of Panel A in Table 5. Unexpected climate risk is the residual estimated from the same regression. Panel (b) shows a histogram of the estimated residuals.

Figure 6. Dynamic Relation between Climate Risk and Cap Ex / Capital

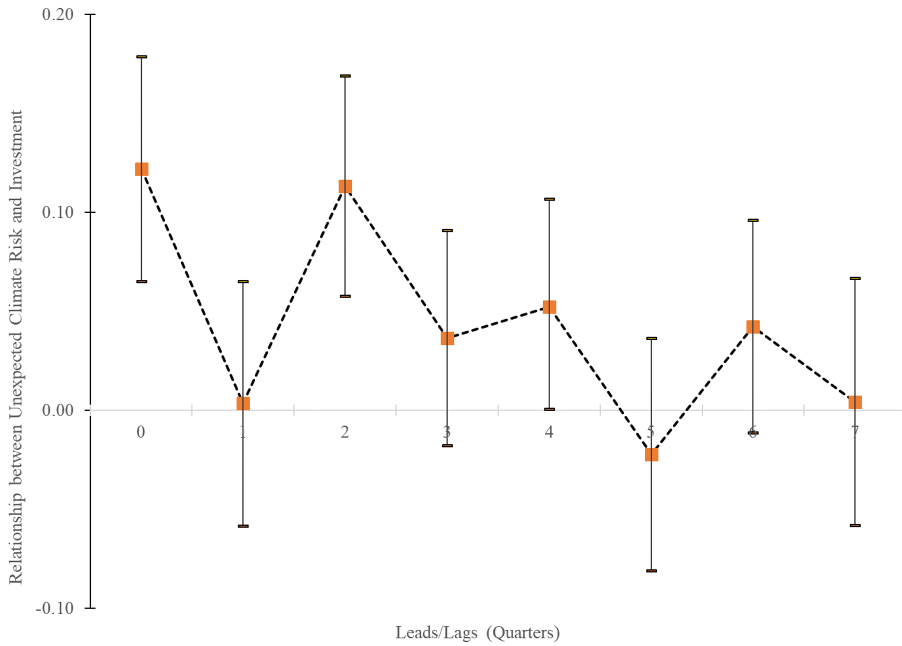
(a) Climate Risk



(b) Expected Climate Risk

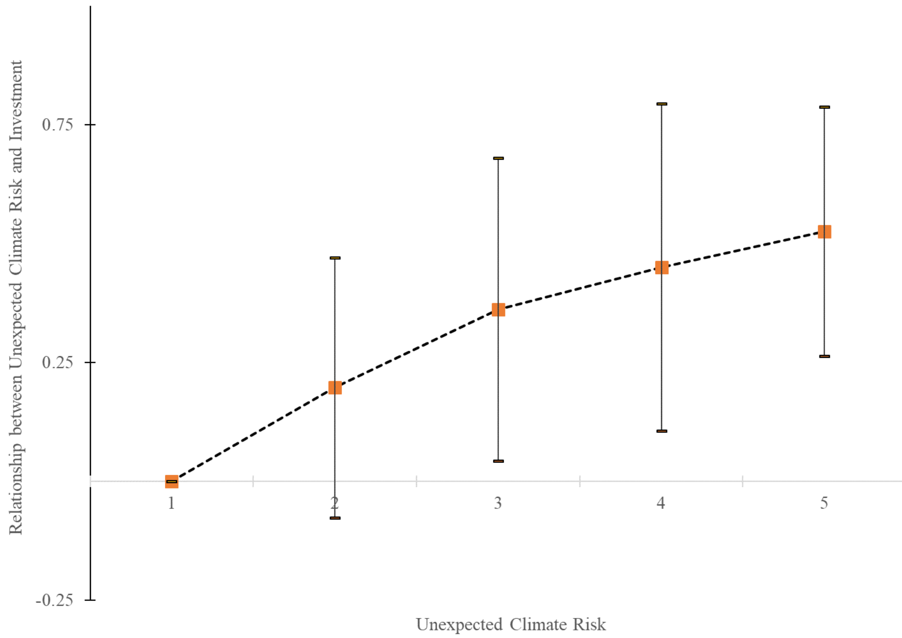


(c) Unexpected Climate Risk



The figure plots the coefficients and 95% confidence intervals from a regression of capital investment (Cap Ex scaled by capital stock) on the contemporaneous and 7 lagged values of climate risk measures. The regression follows the specification of Equation (3). Panel (a) shows the coefficients on overall climate risk $ClimateRisk_{i,t}$. Panel (b) and (c) plot the coefficients on expected and unexpected climate risk, respectively.

Figure 7. Nonlinear relation between Climate Risk and Investment



The figure plots the coefficients and 95% confidence intervals from regressing CapEx scaled by capital stock on a set of dummy variables defined based on the quintiles of the unexpected climate risk measure while controlling for firm-time attributes as well as firm and time fixed effects.

Table 1: Top Seeds or Bigrams Used in Constructing $ClimateRisk_{i,t}$

Severe Climate Events = 1			Non-Severe Climate Events = 0		
Unigram or Bigram	fweight	Frequency	Unigram or Bigram	fweight	Frequency
hurricane	131615.15	32358	weather	27805.21	6488
hurricanes	58098.81	14514	temperatures	654.82	132
storms	32356.28	7991	climate change	479.89	122
drought	20051.06	4832	the flood	447.09	110
earthquake	16459.00	3957	the snow	306.53	77
flooding	15273.25	3826	precipitation	280.60	51
severe winter	5605.61	1345	heating season	278.79	52
tsunami	5228.59	1307	greenhouse gas	276.31	72
wildfire	3657.77	1052	high water	269.97	73
wildfires	3652.17	918	air quality	241.66	59
storm related	3183.99	803	the ice	231.03	61
storm losses	2485.17	416	degree days	216.56	41
the floods	2420.79	614	snowfall	198.20	44
polar vortex	2195.62	545	air pollutants	196.48	47
storm activity	2111.31	507	mild winter	188.77	48
snowstorm	1978.01	488	rainfall	178.90	43
tropical storm	1914.30	466	normal winter	170.70	36
earthquakes	1854.27	464	winter conditions	170.45	43
snowstorms	1833.40	447	carbon dioxide	161.06	39
windstorm	1796.94	391	warm winter	161.00	36
storm damage	1730.99	397	air pollution	158.63	40
storm costs	1562.63	386	rains	157.82	38
extreme cold	1452.48	332	the arctic	149.91	37
extremely cold	1364.03	307	cold winter	126.36	33
ice storm	1343.98	305	hot summer	124.89	30
winter storm	1337.63	332	global warming	122.16	30
extreme winter	951.66	219	fossil fuel	114.78	26
storm season	857.54	196	unseasonably warm	110.12	24
major storm	853.45	172	the fog	107.43	28
extremely warm	830.93	156	harsh winter	106.58	28
droughts	810.67	199	the clouds	104.26	25
the volcano	737.00	195	unseasonably cold	99.60	19
thailand flood	732.31	163	water flood	82.40	22
storm cost	681.46	167	carbon emissions	79.99	21
wind storm	654.80	154	the warmest	79.35	14
extreme heat	594.02	162	the atmosphere	79.10	19
some storm	585.33	142	early winter	74.14	13
storm impact	575.55	157	cool summer	72.32	13
thailand floods	551.61	139	cold season	70.92	17
hailstorm	535.79	119	climate risk	69.19	17
storm clouds	499.04	135	the winds	68.80	19
hailstorms	485.85	111	wind hail	68.53	12
significant storm	484.08	128	the rain	67.82	17
the storm's	449.11	109	co2 emissions	67.00	17
andrew storm	441.94	109	greenhouse gases	66.71	14
the monsoon	422.67	97	water levels	61.59	15
lightning strike	422.63	107	fossil fuels	57.69	13
storm levels	421.55	92	wind exposure	56.55	12
storm events	387.42	85	the coldest	54.51	10

The table reports the top words with the highest frequency weight in the construction of the $ClimateRisk_{i,t}$ measure. The frequency of non-extreme seeds/bigrams only counts the mentions of those words in the proximity of the risk words.

Table 2: Summary Statistics

	N	Mean	P50	SD	Min	P1	P99	Max
			Climate Risk Measures					
Climate Risk$_{i,t}$	139,959	0.32	0.00	1.00	0.00	0.00	6.55	6.55
Climate Risk$_{i,t}$ - Severe	139,959	0.29	0.00	1.00	0.00	0.00	6.70	6.70
Climate Risk$_{i,t}$ - Non-Severe	139,959	0.18	0.00	1.00	0.00	0.00	7.10	7.10
Climate Risk$_{i,t}$ - Long-Run	139,959	0.05	0.00	1.00	0.00	0.00	0.00	44.54
Climate Risk$_{i,t}$ - Short-Run	139,959	0.31	0.00	1.00	0.00	0.00	6.56	6.56
Climate Risk$_{i,t}$ - Backward-Looking	139,959	0.31	0.00	1.00	0.00	0.00	6.57	6.57
Climate Risk$_{i,t}$ - Forward-Looking	139,959	0.26	0.00	1.00	0.00	0.00	6.67	6.67
Climate Risk$_{i,t}$ - Q&A	139,959	0.29	0.00	1.00	0.00	0.00	6.60	6.60
Climate Risk$_{i,t}$ - Non-Q&A	139,959	0.23	0.00	1.00	0.00	0.00	7.13	7.13
Climate Risk$_{i,t}$ - MD&A	113,568	0.34	0.00	1.00	0.00	0.00	6.10	6.10
Climate Risk$_{i,t}$ - Risk Factors	94,151	0.31	0.00	1.00	0.00	0.00	6.48	6.48
Climate Risk$_{i,t}$ - Expected	117,938	0.33	0.31	0.12	-0.06	0.10	0.62	0.88
Climate Risk$_{i,t}$ - Unexpected	117,938	0.00	-0.13	0.93	-3.19	-1.49	4.87	6.74
			Other Measures					
Total Risk$_{i,t}$	126,972	1.23	1.01	1.00	0.00	0.00	5.14	5.14
Political Risk$_{i,t}$	126,972	0.69	0.36	1.00	0.00	0.00	6.10	6.10
Non-Political Risk$_{i,t}$	126,972	0.76	0.42	1.00	0.00	0.00	5.98	5.98
Climate Sentiment$_{i,t}$	139,959	-0.04	0.00	1.00	-4.58	-4.58	3.86	3.86
			Firm Outcomes					
Implied Vol$_{i,t}$	100,393	2.10	1.87	1.00	0.76	0.76	5.69	5.69
Cap Ex$_{i,t}$/ Capital$_{i,t-1}$	132,230	13.40	9.91	14.00	0.08	0.08	94.34	94.34
Cap Ex$_{i,t}$/ Assets$_{i,t-1}$	136,121	2.90	1.60	3.79	0.00	0.00	22.16	22.16
R&D$_{i,t}$/ Assets$_{i,t-1}$	76,472	2.51	1.41	3.42	0.00	0.00	19.09	19.09
Change in Employment$_{i,t}$	34,730	0.06	0.03	0.23	-0.51	-0.51	1.22	1.22
			Firm Attributes					
Total Assets$_{i,t-1}$	138,208	5,0697	924	23,096	0	12	78,327	846,988
Log(Total Assets)$_{i,t-1}$	138,208	6.84	6.83	1.92	-1.62	2.49	11.27	13.65
PPE$_{i,t-1}$/ Assets$_{i,t-1}$	134,158	0.25	0.16	0.24	0.00	0.00	0.90	0.90
Book Leverage$_{i,t-1}$	130,244	0.24	0.21	0.23	0.00	0.00	1.04	1.04
Tobin's Q$_{i,t-1}$	130,354	2.02	1.56	1.37	0.67	0.67	8.38	8.38
ROA$_{i,t-1}$	136,881	0.06	0.11	0.23	-1.02	-1.02	0.45	0.45
Stock Cum Return$_{i,t-1}$	135,982	0.031	0.023	0.232	-0.551	-0.551	0.889	0.889
No of Analyst$_{i,t-1}$	139,959	7.72	6.00	6.90	0.00	0.00	30.00	50.00
Log (No Analyst+1)$_{i,t-1}$	139,959	1.83	1.95	0.89	0.00	0.00	3.43	3.93
Institutional Ownership$_{i,t-1}$	135,371	0.67	0.75	0.27	0.00	0.00	1.00	1.00
Institution HHI$_{i,t-1}$	134,970	0.10	0.05	0.13	0.01	0.02	0.80	1.00

The table reports the summary statistics of all variables used in the subsequent analysis. All variables are at the firm-quarter level, except that *Change in Employment*$_{i,t}$ is at the firm-year level. All the climate risk and climate sentiment variables are explained in Section 3 and have been standardized here and in regressions for easier interpretations. Expected and unexpected $ClimateRisk_{i,t}$ are the fitted value and residual from the regression in column (5) of Table 5 Panel A, respectively. *Total Risk*$_{i,t}$, *Political Risk*$_{i,t}$, and *Non-Political Risk*$_{i,t}$ are sourced from Hassan et al. (2019). $ImpliedVol_{i,t}$ is the implied volatility of 90-day at-the-money options. $CapEx_{i,t}/Capital_{i,t-1}$ is the ratio of capital expenditure over capital stock calculated recursively using a perpetual-inventory method as in Hassan et al. (2019). *Change in Employment*$_{i,t}$ is the % change in the number of employment from last to current year and divides by the employment of the last year. *Tobin's* $Q_{i,t}$ is calculated as (Total Assets + Market Value of Equity - Book Value of Equity)/Total assets. $ROA_{i,t-1}$ is return on assets calculated as Operating Income Before Depreciation (OIBDPQ) divides by Total Assets of the previous quarter end. *Institutional Ownership*$_{i,t}$ and *Institution HHI*$_{i,t}$ are the sum and the HHI of 13F institutional ownership as a percentage of shares outstanding, respectively.

Table 3: Transcript Excerpts with the Highest Climate Risk

Firm name	Climate risk	Call date	Extreme climate risk	Non-extreme climate risk	Text surrounding bigram with highest weight
Marriott Vacations Worldwide Corp	218.23	2-Nov-17	hurricane, hurricanes, storms		has obviously been a very active hurricane season, 2 storms in particular, Hurricanes Irma and Maria, affected our operations most directly
Kerr-Mcgee Corp	205.48	28-Sep-05	hurricane, hurricanes, storms, flooding		Kerr-McGee typically builds in an allowance of about 3% of our expected annual Gulf of Mexico production volumes to allow for weather-related disruptions during the July through October hurricane season
Superior Energy Services Inc	194.86	3-Nov-05	hurricanes, storm related, storm activity, storm levels		We were producing better than 7500 a day during the quarter on days that were unaffected by hurricanes, and I say that because, lest you all forget, we did have a little hurricane in July so we were shut in for a few days
Cal Dive International Inc	193.80	30-Oct-08	hurricane, hurricanes, storms	uncertainty + weather	for Cal Dive after hurricanes all four operations bases in Texas and Louisiana were damaged and took on water but we had implemented our emergency plans
California Water Service Group	188.98	27-Apr-17	drought, mudslide		and so the drought expense is really minimal for this quarter in 2017 as compared to the height of the drought last year
Fortress Investment Group LLC	186.21	3-Nov-04	hurricane, hurricanes, storms		Hurricanes interrupted service at the railroad and also interrupted many of our customers' businesses
Conn's Inc	185.92	26-Nov-08	hurricane, hurricanes, storms		Sales were negatively impacted by two hurricanes and mandatory evacuations for most of the Gulf Coast
Aaron's Inc	168.34	27-Oct-17	hurricane, hurricanes, storms, flooding		Hurricanes Irma and Harvey presented extraordinary challenges for our teams
Chevron Corp	157.37	28-Oct-05	hurricanes, storms, storm effects		Weaker marketing margins particularly in Asia resulted from escalating spot product prices largely attributable to the impact of the U.S. hurricanes. Volume effects resulted in a positive variance of $30 million between quarters
Home Depot Inc	157.12	14-Nov-17	hurricane, hurricanes, storms, Storm Sandy, flooding, wildfires, earthquake		because of our outperformance in the third quarter and the expectation of additional sales from the rebuilding efforts associated with the storms, we are increasing our sales and earnings per share guidance for the year
Edison International	156.67	30-Oct-18	mudslides, wildfire		we advocated for reforms to mitigate the risk of catastrophic wildfires and fairly allocate financial responsibility among the multiple causes which contribute to wildfires.
PGT Innovations Inc	154.44	2-Nov-17	hurricane, hurricanes, storms, flooding		Due to the first major hurricanes that hit our market in 12 years, which we believe negatively impacted sales by $13 million in the quarter
Floor & Decor Holdings Inc	153.90	2-Nov-17	hurricane, hurricanes, storms, flooding		including both full and partial store closures across our 24 stores affected by the hurricanes. We estimate the hurricanes cost us approximately $6 million to $7 million in sales

The table lists the top transcripts based on $ClimateRisk_{i,t}$ (non-standardized), together with firm name, earnings call date, climate words, and selected text surrounding the climate words in the transcript.

Table 4: Affected Functions and Climate Risk Measures

	(1)	(2)	(3)	(4)
Dep Var	Market/ Sales	Costs/ Losses	CapEx/ Assets	Supply Chain
Climate $\text{Risk}_{i,t}$	0.0052***	0.0036***	0.0010*	0.0040***
	(2.823)	(2.830)	(1.684)	(3.345)
Severe Climate $\text{Risk}_{i,t}$	0.0036**	0.0043***	0.0012*	0.0044***
	(1.988)	(3.366)	(1.960)	(3.745)
Non-Severe Climate $\text{Risk}_{i,t}$	0.0055**	-0.0020*	-0.0007	-0.0018*
	(2.493)	(-1.754)	(-1.186)	(-1.812)
Long-Run Climate $\text{Risk}_{i,t}$	0.0003	-0.0019*	-0.0004	-0.0011
	(0.230)	(-1.773)	(-0.700)	(-1.484)
Short-Run Climate $\text{Risk}_{i,t}$	0.0052***	0.0038***	0.0010*	0.0040***
	(2.807)	(2.955)	(1.716)	(3.406)
Backward-Looking Climate $\text{Risk}_{i,t}$	0.0050**	0.0057***	0.0027***	0.0057***
	(2.350)	(3.891)	(3.849)	(4.097)
Forward-Looking Climate $\text{Risk}_{i,t}$	0.0002	-0.0028**	-0.0022***	-0.0022*
	(0.089)	(-2.219)	(-3.446)	(-1.832)
Q&A Climate $\text{Risk}_{i,t}$	0.0010	-0.0007	-0.0002	-0.0001
	(0.555)	(-0.557)	(-0.302)	(-0.135)
Non-Q&A Climate $\text{Risk}_{i,t}$	0.0052***	0.0046***	0.0010*	0.0057***
	(3.013)	(3.794)	(1.765)	(5.152)
N	139,785	139,785	139,785	139,785
YQ FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

This table reports the results of regressions of a variety of affected corporate functions on our constructed climate risk measures in the same quarter. For each transcript, the dependent variables are the weights of bigrams (frequency of mentions $\times$ 100 over length of transcript) related to four categories of affected corporate functions: market conditions or sales, costs or losses, CapEx or assets, and supply chain or operation. The related bigrams within each category are listed in Appendix Table A1. In each column, there are five regressions on different climate risk measures at firm-level (standardized): total and four pairs of disaggregated $ClimateRisk_{i,t}$, respectively. Each regression specification controls for time and firm fixed effects. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 5: Determinants of Corporate Climate Risk

Panel A: Total Climate Risk Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep Var	Climate $\text{Risk}_{i,t}$									
$\text{Disaster}_{c,t-1}$	0.3059***	0.3131***	0.2117***	0.2040***	0.1972***	0.0998***	0.1005***	0.2053***	0.1807***	0.1000***
	(13.561)	(13.105)	(10.253)	(10.089)	(10.215)	(4.802)	(4.420)	(10.732)	(9.841)	(4.652)
$\text{Disaster}_{c,t-2}$	0.0170	0.0266*	0.0569***	0.0497***	0.0435***	0.0341**	0.0368**	0.0469***	0.0462***	0.0299*
	(1.206)	(1.769)	(3.880)	(3.481)	(3.182)	(2.144)	(2.099)	(3.614)	(3.589)	(1.934)
$\text{Asset}_{i,t-1}$		0.0570***	0.0508***	0.0341***	0.0326***		0.0288***	0.0130	0.0132	0.0143
		(8.309)	(7.380)	(5.508)	(5.328)		(4.642)	(1.239)	(1.298)	(1.417)
Cap $\text{Ex}_{i,t-1}$		0.0046**	-0.0014	0.0007	0.0016		-0.0023	0.0069***	0.0028*	0.0024
		(2.185)	(-0.639)	(0.362)	(0.818)		(-1.148)	(4.163)	(1.743)	(1.604)
$\text{PPE}_{i,t-1}$		0.6532***	0.7215***	0.3800***	0.3089***		0.3613***	-0.1108	-0.0311	0.0165
		(14.381)	(15.633)	(6.994)	(5.620)		(6.529)	(-1.220)	(-0.361)	(0.199)
Book $\text{Leverage}_{i,t-1}$		0.0164	0.0119	0.0360	0.0104		0.0235	-0.1511***	-0.1003**	-0.0855**
		(0.402)	(0.293)	(0.914)	(0.276)		(0.616)	(-3.559)	(-2.475)	(-2.168)
Tobin's $\text{Q}_{i,t-1}$		-0.0087*	-0.0147***	-0.0104**	-0.0074*		-0.0080*	0.0038	0.0041	0.0075**
		(-1.935)	(-3.189)	(-2.365)	(-1.733)		(-1.840)	(1.047)	(1.174)	(2.116)
$\text{ROA}_{i,t-1}$		0.0546**	0.0523**	0.0685***	0.0542**		0.0482**	0.0063	-0.0214	-0.0263
		(2.253)	(2.199)	(3.004)	(2.448)		(2.256)	(0.254)	(-0.908)	(-1.163)
Cum $\text{Return}_{i,t-1}$		-0.0116	-0.0071	-0.0066	-0.0102		-0.0090	-0.0176	-0.0203*	-0.0141
		(-1.088)	(-0.581)	(-0.561)	(-0.875)		(-0.794)	(-1.555)	(-1.883)	(-1.295)
No $\text{Analysts}_{i,t-1}$		-0.0787***	-0.0656***	-0.0424***	-0.0423***		-0.0332***	-0.0204*	0.0026	0.0034
		(-6.504)	(-5.427)	(-3.720)	(-3.713)		(-2.912)	(-1.892)	(0.256)	(0.348)
Institution $\%_{i,t-1}$		0.0501	0.0434	0.0455	0.0329		0.0168	0.0093	-0.0220	-0.0272
		(1.526)	(1.313)	(1.437)	(1.086)		(0.560)	(0.269)	(-0.689)	(-0.877)
Institution $\text{HHI}_{i,t-1}$		-0.0427	-0.0724	-0.0343	-0.0590		-0.0733*	-0.0200	-0.0248	-0.0288
		(-0.895)	(-1.497)	(-0.791)	(-1.343)		(-1.751)	(-0.454)	(-0.598)	(-0.684)
N	139,959	117,938	117,938	117,938	117,938	139,561	117,558	117,758	117,742	117,379
R^2	0.00425	0.049	0.129	0.146	0.158	0.211	0.249	0.306	0.350	0.395
YQ FE	No	No	Yes	Yes	Yes	No	No	Yes	No	No
Sector FE	No	No	No	Yes	Yes	No	No	No	No	No
State FE	No	No	No	No	Yes	No	No	No	No	No
Sector × YQ FE	No	No	No	No	No	Yes	Yes	No	Yes	Yes
State × YQ FE	No	No	No	No	No	Yes	Yes	No	No	Yes
Firm FE	No	No	No	No	No	No	No	Yes	Yes	Yes

Panel B: Disaggregated Climate Risk Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var	Climate Risk$_{i,t}$							
	Severe	Non-Severe	Long Run	Short Run	Past-Tense	Forward-Looking	Q&A	Non-Q&A
Disaster$_{c,t-1}$	0.1978***	0.0398***	-0.0176	0.1984***	0.1984***	0.1479***	0.1709***	0.1159***
	(10.050)	(2.684)	(-1.414)	(10.253)	(10.151)	(8.023)	(8.936)	(6.552)
Disaster$_{c,t-2}$	0.0506***	-0.0252*	-0.0076	0.0442***	0.0450***	0.0332**	0.0254*	0.0423***
	(3.670)	(-1.863)	(-0.584)	(3.225)	(3.268)	(2.366)	(1.768)	(3.061)
Asset$_{i,t-1}$	0.0332***	0.0077	0.0034	0.0327***	0.0338***	0.0205***	0.0215***	0.0311***
	(5.665)	(1.139)	(0.629)	(5.360)	(5.596)	(3.734)	(3.818)	(5.078)
CapEx$_{i,t-1}$	0.0017	0.0005	0.0012	0.0015	0.0013	0.0024	0.0013	0.0006
	(0.894)	(0.265)	(0.772)	(0.786)	(0.712)	(1.334)	(0.703)	(0.331)
PPE$_{i,t-1}$	0.3030***	0.1415**	0.0496	0.3076***	0.3163***	0.2052***	0.2437***	0.2952***
	(5.712)	(2.529)	(1.476)	(5.587)	(5.863)	(4.108)	(4.965)	(5.429)
Book Leverage$_{i,t-1}$	0.0060	0.0252	-0.0883***	0.0147	0.0072	0.0260	0.0394	-0.0205
	(0.163)	(0.540)	(-3.868)	(0.392)	(0.194)	(0.742)	(1.117)	(-0.544)
Tobin's Q$_{i,t-1}$	-0.0062	-0.0065*	-0.0030	-0.0072*	-0.0072*	-0.0061	-0.0036	-0.0090**
	(-1.490)	(-1.747)	(-0.812)	(-1.691)	(-1.747)	(-1.475)	(-0.867)	(-2.343)
ROA$_{i,t-1}$	0.0484**	0.0195	-0.0449*	0.0568**	0.0481**	0.0600***	0.0847***	0.0023
	(2.278)	(0.670)	(-1.680)	(2.568)	(2.254)	(2.753)	(3.954)	(0.111)
Cum Return$_{i,t-1}$	-0.0089	-0.0077	0.0221	-0.0115	-0.0142	0.0078	0.0011	-0.0173
	(-0.764)	(-0.570)	(1.508)	(-0.985)	(-1.226)	(0.625)	(0.089)	(-1.436)
No Analysts$_{i,t-1}$	-0.0343***	-0.0368***	0.0091	-0.0430***	-0.0413***	-0.0278***	-0.0217**	-0.0438***
	(-3.259)	(-2.707)	(0.649)	(-3.796)	(-3.724)	(-2.638)	(-2.035)	(-4.308)
Institution %$_{i,t-1}$	0.0415	-0.0107	-0.0564**	0.0364	0.0279	0.0383	0.0390	0.0180
	(1.425)	(-0.272)	(-1.970)	(1.202)	(0.939)	(1.358)	(1.367)	(0.622)
Institution HHI$_{i,t-1}$	-0.0369	-0.1198**	-0.0334	-0.0569	-0.0516	-0.0716*	-0.0828*	-0.0031
	(-0.873)	(-2.420)	(-0.919)	(-1.293)	(-1.186)	(-1.687)	(-1.915)	(-0.071)
N	117,938	117,938	117,938	117,938	117,938	117,938	117,938	117,938
R^2	0.154	0.048	0.00801	0.157	0.157	0.0938	0.107	0.111
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results from regressing the firm-level climate risk measure on disaster dummies and a set of firm attributes. In Panel A, our main climate risk measure, firm-level total climate risk $ClimateRisk_{i,t}$, is the dependent variable. In Panel B, the dependent variables are the eight disaggregated climate risk measures. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 6: Decomposition of Climate Risk

Controls	R^2 None	R^2 Natural Disasters	R^2 Natural Disasters + Firm Attributes	Improvement in R^2
No FE	0	0.004	0.049	
YQ	0.0828	0.085	0.129	0.080
YQ + Sector	0.133	0.135	0.147	0.098
YQ + State	0.110	0.111	0.140	0.091
YQ + Sector + State	0.146	0.148	0.158	0.109
Sector × YQ + State	0.192	0.186	0.195	0.037
Sector + State × YQ	0.186	0.204	0.218	0.060
Sector × YQ + State × YQ	0.235	0.235	0.249	0.091
Firm-Level Variation	0.765	0.765	0.751	
Firm + YQ		0.275	0.281	0.032
Firm + Sector × YQ			0.350	0.101
Firm + State × YQ			0.365	0.116
Firm + Sector × YQ + State × YQ			0.395	-0.644
Residual			0.605	
Number of States		53		
Number of Sectors		64		
Number of Firms		4,483		

The table reports the results on the R^2 from a projection of $ClimateRisk_{i,t}$ on various sets of fixed effects. Column 1 corresponds to regressions with no other control variables but fixed effects. Column 2 adds $Disaster_{c,t}$, an indicator variable equals to 1 if natural disaster events occur in county c during time t, as control variable. Column 3 further controls for a set of firm attributes as specified in Table 5. The last column reports the maximal change in R^2.

Table 7: Validation: Implied Volatility

Panel A: Implied Vol

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var			Implied $\text{Vol}_{i,t}$			
Indep Var	Climate Risk		Expected Climate Risk		Unexpected Climate Risk	
Climate $\text{Risk}_{i,t}$	-0.0285***	-0.0029	0.5201***	0.0952**	-0.0120**	-0.0034
	(-6.257)	(-1.276)	(6.388)	(2.066)	(-2.465)	(-1.476)
N	87,274	87,125	87,274	87,125	87,274	87,125
R^2	0.403	0.792	0.403	0.800	0.402	0.800
YQ FE	No	Yes	No	Yes	No	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: Controlling for Other Risks

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var			Implied $\text{Vol}_{i,t}$			
Indep Var	Climate Risk		Expected Climate Risk		Unexpected Climate Risk	
Climate $\text{Risk}_{i,t}$	-0.0037	-0.0036	0.1037**	0.0950**	-0.0042*	-0.0040*
	(-1.549)	(-1.491)	(2.142)	(2.061)	(-1.750)	(-1.692)
Total $\text{Risk}_{i,t}$	0.0148***		0.0147***		0.0148***	
	(4.858)		(4.805)		(4.863)	
Political $\text{Risk}_{i,t}$		0.0082***		0.0081***		0.0082***
		(3.470)		(3.428)		(3.474)
Non-Political $\text{Risk}_{i,t}$		0.0071***		0.0070***		0.0071***
		(3.102)		(3.081)		(3.103)
N	79,558	79,558	79,558	87,125	79,558	79,558
R^2	0.802	0.802	0.802	0.800	0.802	0.794
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel A reports the results of validation test specified in Equation (3). Panel B reports the results when we control for total risk, political risk, and non-political risk. The dependent variable is the implied stock price volatility, which is measured using 90-day at-the-money options. For both panels, column (1) and column (2) present results using the overall climate risk, $ClimateRisk_{i,t}$, as the main explanatory variable. In column (3) and column (4), the main explanatory variable is the expected climate risk, the fitted value from the first-stage regression as specified in column (5) of Panel A in Table 5. In column (5) and (6), the main explanatory variable is the unexpected climate risk, the residual from the same first stage regression. We control for the same set of firm attributes as specified in Table 5. These control variables are not presented in this table but included in each regression specification. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 8: Corporate Response: Investment

Panel A: Total Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Climate Risk		Expected Climate Risk		Unexpected Climate Risk	
Climate Risk$_{i,t}$	0.5410***	0.1682***	-0.6179	-1.5796**	0.2587***	0.1701***
	(10.597)	(4.065)	(-0.649)	(-2.026)	(4.910)	(4.099)
N	117,313	117,144	117,313	117,144	117,313	117,144
R^2	0.061	0.393	0.0593	0.371	0.0596	0.393
YQ FE	No	Yes	No	Yes	No	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: Severe and Non-Severe Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Severe Climate Risk			Non-Severe Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.1556***	-1.6940**	0.1600***	0.0406	7.4966***	0.0397
	(3.786)	(-2.182)	(3.883)	(0.999)	(2.741)	(0.978)
N	117,144	117,144	117,144	117,144	117,144	117,144
R^2	0.393	0.371	0.371	0.371	0.393	0.371
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Long-Run and Short-Run Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Long-Run Climate Risk			Short-Run Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.0620*	24.4450***	0.0616*	0.1628***	-1.5766**	0.1670***
	(1.873)	(2.882)	(1.861)	(3.930)	(-2.034)	(4.019)
N	117,144	117,144	117,144	117,144	117,144	117,144
R^2	0.371	0.371	0.393	0.393	0.393	0.393
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Backward-Looking and Forward-Looking Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Backward-Looking Climate Risk			Forward-Looking Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.1460***	-1.5918**	0.1501***	0.1554***	-2.1243**	0.1582***
	(3.556)	(-2.054)	(3.645)	(4.181)	(-2.043)	(4.249)
N	117,144	117,144	117,144	117,144	117,144	117,144
R^2	0.393	0.371	0.393	0.393	0.393	0.371
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Q&A and Non-Q&A Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Q&A Climate Risk			Non-Q&A Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.1185***	-1.5154*	0.1211***	0.0934**	-3.4317***	0.0963**
	(3.054)	(-1.686)	(3.114)	(2.293)	(-2.629)	(2.362)
N	117,144	117,144	117,144	117,144	117,144	117,144
R^2	0.393	0.393	0.393	0.371	0.393	0.393
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results from regressions using Cap Ex scaled by capital stock as the dependent variable. We control for the same set of firm attributes as in Table 5. These control variables are not presented in this table but included in each regression specification. Panel A presents the estimates where the main explanatory variable is the overall climate risk, $ClimateRisk_{i,t}$, in column (1) and (2), expected overall climate risk in column (3) and (4), unexpected overall climate risk in column (5) and (6). Expected climate risk is the predicted value from the first-stage regression as specified in column (5) of Panel A in Table 5. Unexpected climate risk is the estimated residual from the same regression. We replace the overall climate risk, $ClimateRisk_{i,t}$, by the eight disaggregated climate risk measures in the remaining panels. Each disaggregated climate risk measure is further decomposed into expected and unexpected using the same methodology as in Panel A. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table 9: Corporate Response: Employment

Panel A: Total Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ $\times$ 100					
Indep Var	Overall		Expected		Unexpected	
Climate Risk$_{i,t}$	0.0308	-0.3997**	-53.2851***	-52.3170***	-0.1222	-0.3031
	(0.195)	(-2.117)	(-4.227)	(-3.852)	(-0.716)	(-1.585)
N	28,887	28,435	28,885	28,434	28,885	28,434
R^2	0.084	0.279	0.085	0.280	0.0840	0.181
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: Severe and Non-Severe Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ $\times$ 100					
Indep Var	Severe Climate Risk			Non-Severe Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	-0.4167**	-58.0007***	-0.3120*	0.1237	-37.2907*	0.1115
	(-2.240)	(-4.053)	(-1.650)	(0.613)	(-1.916)	(0.565)
N	28,435	28,434	28,434	28,435	28,434	28,434
R^2	0.279	0.280	0.279	0.279	0.279	0.181
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Long-Run and Short-Run Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ $\times$ 100					
Indep Var	Long-Run Climate Risk			Short-Run Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	-0.1466	-4.4845	-0.1593	-0.3860**	-51.5703***	-0.2888
	(-0.613)	(-0.130)	(-0.682)	(-2.047)	(-3.841)	(-1.510)
N	28,435	28,434	28,434	28,435	28,434	28,434
R^2	0.279	0.279	0.279	0.181	0.280	0.181
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Backward-Looking and Forward-Looking Climate Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ × 100					
Indep Var	Backward-Looking Climate Risk			Forward-Looking Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	-0.4195**	-53.1962***	-0.3133	-0.2785	-69.6240***	-0.2320
	(-2.187)	(-3.900)	(-1.609)	(-1.528)	(-3.804)	(-1.262)
N	28,435	28,434	28,434	28,435	28,434	28,434
R^2	0.181	0.182	0.181	0.279	0.182	0.279
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel E: Q&A and Non-Q&A Climate Risk

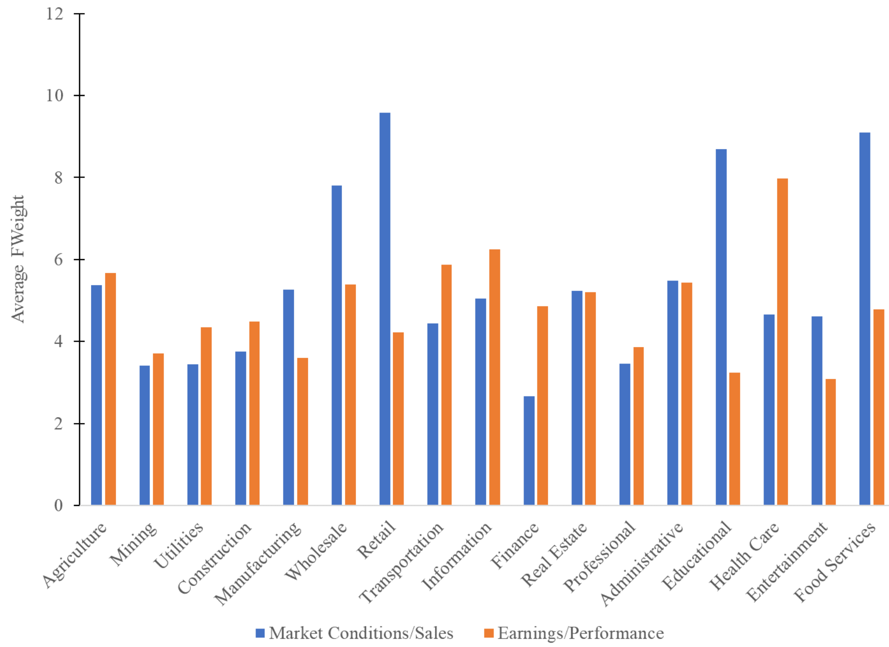
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ × 100					
Indep Var	Q&A Climate Risk			Non-Q&A Climate Risk		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	-0.0676	-64.4830***	-0.0070	-0.6530***	-58.7443***	-0.5292***
	(-0.346)	(-3.468)	(-0.036)	(-3.608)	(-3.972)	(-2.938)
N	28,435	28,434	28,434	28,435	28,434	28,434
R^2	0.279	0.182	0.181	0.181	0.182	0.279
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results from regressions using change in employment as dependent variable. We control for the same set of firm attributes as in Table 5. These control variables are not presented in this table but included in each regression specification. Panel A presents the estimates where the main explanatory variable is the overall climate risk, $ClimateRisk_{i,t}$, in column (1) and (2), expected overall climate risk in column (3) and (4), unexpected overall climate risk in column (5) and (6). Expected climate risk is the fitted value from the first-stage regression as specified in column (5) of Panel A in Table 5. Unexpected climate risk is the estimated residual from the same regression. We replace the overall climate risk, $ClimateRisk_{i,t}$, by the eight disaggregated climate risk measures in the remaining panels. Each disaggregated climate risk measure is further decomposed into expected and unexpected using the same methodology as in Panel A. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

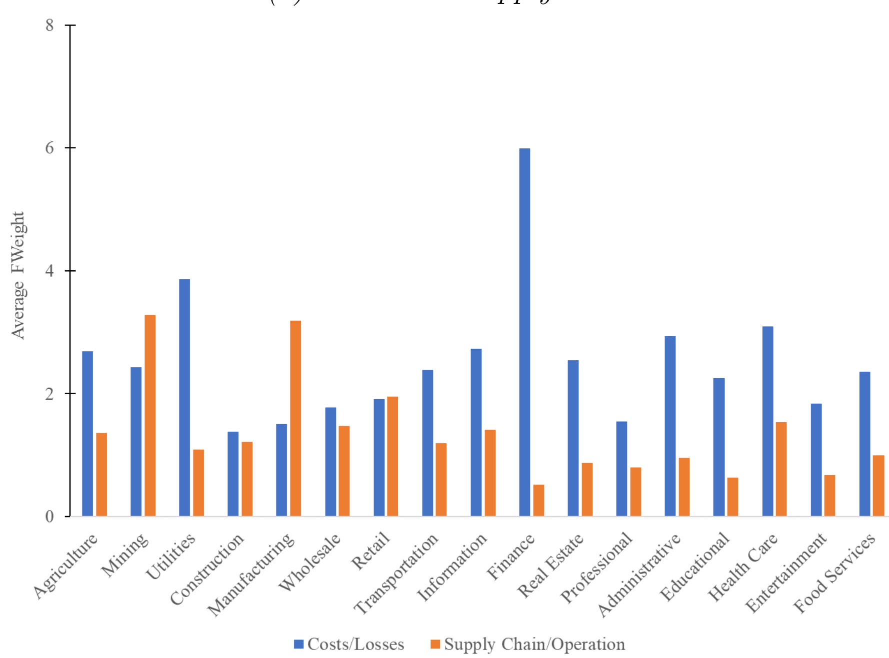
Appendix

Figure A1. Affected Corporate Functions by Industry

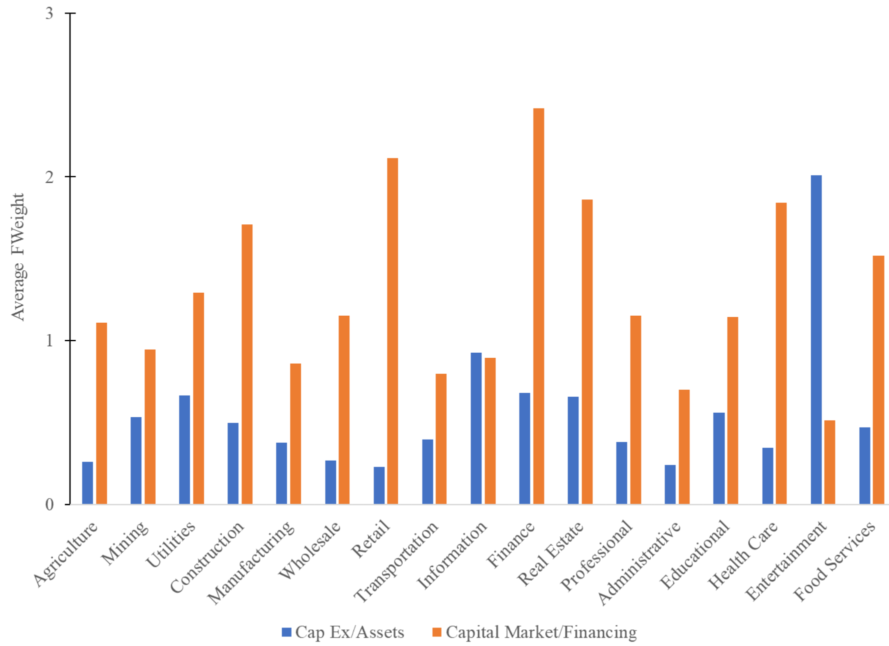
(a) Market Conditions and Financial Performance



(b) Costs and Supply Chain

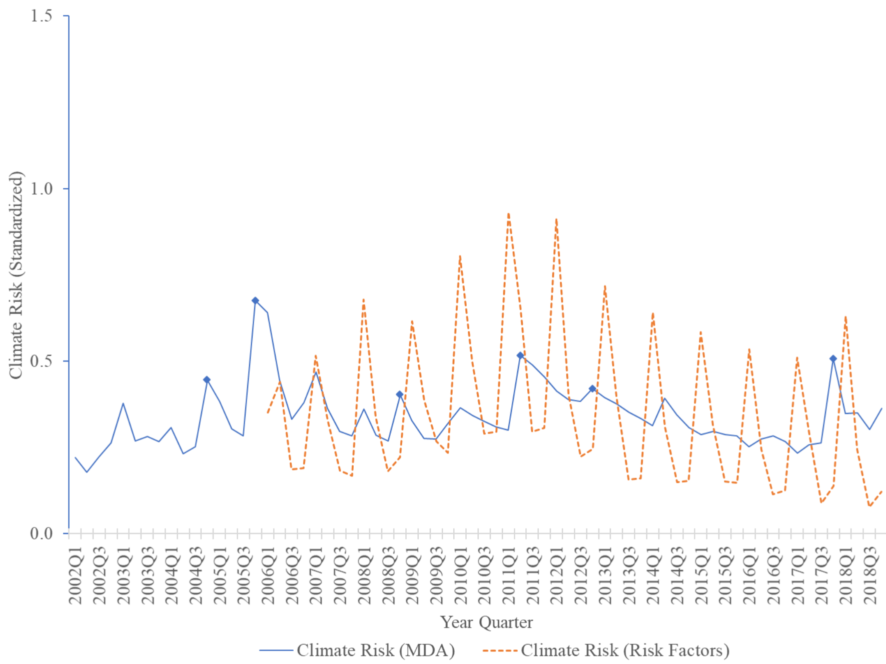


(c) Physical Assets and Capital Market



The figure plots the sector average of frequency weight of corporation functions affected by climate risk. We manually review the top 2,000 bigrams before and after climate keywords in the earnings call transcripts and classify them, based on their similarity, into four broad corporate functions that might be affected by climate risk. The four series of corporate functions by industry are presented in two separate panels for a neat view. Panel (a) plots the average of market conditions and costs/losses across industries. Panel (b) plots the average of supply chain and CAPEX across industries.

Figure A2. Climate Risk Summarized from 10K Data



This figure plots the average of the two alternative climate risk measures constructed from the 10-K data over time. The blue solid line plots the climate risk measure constructed from MDA section. The orange dashed line plots the measure constructed from Risk Factors section.

Table A1: Top Bigrams near Climate Risk

Market Conditions/Sales		Costs/Losses		CapEx/Assets		Supply Chain/Operation	
Bigram	Freq	Bigram	Freq	Bigram	Freq	Bigram	Freq
store sales	1153	loss ratio	941	capital expenditures	378	supply chain	707
revenue growth	887	catastrophe losses	888	asset management	267	raw material	597
sales growth	790	operating expenses	648	property damage	244	business interruption	503
market conditions	738	costs associated	515	charge offs	185	raw materials	363
economic conditions	689	tax rate	479	capital spending	177	continuing operations	342
gas prices	644	related costs	381	construction activity	118	inventory levels	298
net sales	612	costs related	302	physical damage	116	material costs	292
market share	560	pre tax	289	restoration efforts	111	power outages	232
commodity prices	450	related expenses	273	asset sales	103	new products	227
insurance proceeds	417	operating costs	272	property losses	96	new product	217
organic growth	411	related losses	264	capital projects	93	business model	210
growth rate	400	expense ratio	237	maintenance expense	83	gas production	204
sales increased	335	losses related	213	net investment	72	product line	180
volume growth	323	energy costs	210	construction projects	70	product lines	174
crude oil	302	expenses related	197	write down	61	product sales	150
consumer spending	296	effective tax	195	capital investment	60	production volumes	147
new business	283	fuel costs	187			business segments	133
strong demand	274	cost increases	186			energy services	131
sales volumes	268	cost savings	156			product demand	130
revpar growth	268	higher costs	144			transportation costs	124
customer base	251	expenses associated	131			oil production	121
new stores	248	cost structure	124			supply disruptions	111
fuel prices	241	repair costs	120			production levels	109
strong growth	238	cost recovery	116			production growth	104
oil prices	234	restoration costs	116			construction delays	100
revenue increased	228	labor costs	115			lower production	89
retail sales	210	loss estimate	114			power generation	89
total revenue	210	cost reduction	113			business segment	89
revenues increased	187	maintenance costs	111			business unit	89
growth rates	185	loss ratios	106			building materials	85

This table reports the top bigrams that are discussed surrounding the climate words in our library and their corresponding frequency counts. These bigrams are classified into four broad corporate functions that may be affected by climate risk: 1) Market conditions/Sales; 2) Costs/Losses; 3) Fixed assets/Capex; and 4) Supply chain/Production/Operation.

Table A2: Corporate Responses / Strategies

Industry	Climate Risk	Passive Responses	Proactive Responses
Agriculture	hurricane	recapture lost sales; strengthen customer relations; improve operational effectiveness	transfer production to other facilities to reduce exposure to future hurricanes
	drought		develop drought tolerant corps
Mining	hurricane	inspection; repair work; extend timetable; revise production guidance; evacuation; implement emergency plans	accelerate idle well abandonment
Utilities	hurricane	repair	hedge by put options and swap contracts
	wildfire	help customers recover and rebuild; conduct patrols	investigate the potential origins and causes; advocate legislative reforms to mitigate wildfire risk; improve safety culture; Community Wildfire Safety Program; proactively shut off power for safety; enhance situational awareness; upgrade system; vegetation management
	drought	water contingency shortage plans; provision on wasteful practices; reducing leaks	customer analysis; quantitative analysis of drought responses ; improve the efficiency standards ; educate community; long-term strategic water use efficiency program
Construction	hurricane	repair work; restoration of electrical, power, and cleanup efforts; provide support, financial support, and temporary housing to employees; restore power and put up new infrastructure; deploy people across the organization and away from the storm	preplan with customers before hurricanes make landfall; position the majority of resources in or near impacted areas well in advance of the storms
Manufacturing	hurricane, flood	evacuate employees; submit insurance claim; rebuild business	launch hurricane-resistant product; make investments
Retail Trade	hurricane	evacuations; redirect products; hire back employees; increase down payments of generator and air-conditioning units during the storm	build inventory to support the hurricane-driven sales increases
Transportation	hurricane	clear down trees and debris; restore the railroad to normal operations; filed an insurance claim	inspect tracks and bridges;
Information	hurricane	repair cable plant; help restore service to customers; extend the discounted pricing; rebuild or replace damaged plant and equipment	
Real Estate	hurricane	temporarily suspend collection activities; replace damage products in customers' homes	board up the stores, prepare for the storms
Health Care	hurricane	evacuate residents; arrange generators, refuel, set up communications with the families of residents; clean up the damage;	monitor the Weather Channel, work with local emergency officials, prepare for evacuation before storm; preassemble drinking water, ice, additional electrical generators; board up windows and prepare doors and roofs; secure additional supply chain
Accommodation	hurricane	submit insurance claim; recovery efforts; reopen stores; financial aid to employees; work closely with contractors and insurers to put rooms back into service	close restaurants in affected areas before hurricane arrives

The table summarizes by industry the main response keywords based on the top 50 transcripts sorted by $ClimateRisk_{i,t}$. The responses are classified into passive responses (repair or recover work after the climate events) and proactive responses (prevention activities to reduce climate effects).

Table A3: Corporate Response using Alternative Investment Measures

Panel A: Cap Ex Scaled by Assets

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Assets$_{i,t-1}$ $\times$ 100					
Indep Var	Climate Risk		Expected Climate Risk		Unexpected Climate Risk	
Climate Risk$_{i,t}$	0.0725***	0.0621***	0.4429**	0.2031	0.0348***	0.0621***
	(6.073)	(6.108)	(2.498)	(1.197)	(2.787)	(6.110)
N	117,652	117,476	117,652	117,476	117,652	117,476
R^2	0.511	0.654	0.511	0.666	0.511	0.666
Adj R^2	0.511	0.666	0.511	0.654	0.511	0.654
YQ FE	No	Yes	No	Yes	No	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: R&D

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	R&D$_{i,t}$ / Assets$_{i,t-1}$ $\times$ 100					
Indep Var	Climate Risk		Expected Climate Risk		Unexpected Climate Risk	
Climate Risk$_{i,t}$	-0.0014***	0.0000	0.0030	-0.0001	-0.0008***	0.0000
	(-8.510)	(0.708)	(0.882)	(-0.072)	(-4.591)	(0.796)
N	63,975	63,829	63,975	63,829	63,975	63,829
R^2	0.412	0.830	0.411	0.830	0.411	0.830
YQ FE	No	Yes	No	Yes	No	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

This table presents the results from regressions using alternative investment measures as the dependent variable. The dependent variable in Panel A is Cap Ex scaled by firm assets. The dependent variable in Panel B is R&D scaled by firm assets. We control for the same set of firm attributes as in Table 5. These control variables are not presented in this table but included in each regression specification. The main explanatory variable is the overall climate risk, $ClimateRisk_{i,t}$, in column (1) and (2), expected overall climate risk in column (3) and (4), unexpected overall climate risk in column (5) and (6). Expected climate risk is the fitted value from the first-stage regression as specified in column (5) of Panel A in Table 5. Unexpected climate risk is the estimated residual from the same regression. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table A4: Corporate Responses using Alternative Climate Risk Measures

Panel A: Investment

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ $\times$ 100					
Indep Var	Climate Risk from MDA			Climate Risk from Risk Factors		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.3113***	4.9749*	0.3105***	-0.8202***	-1.5926	-0.8200***
	(5.383)	(1.662)	(5.370)	(-12.909)	(-0.564)	(-12.908)
N	95,402	95,402	95,402	77,947	77,947	77,947
R^2	0.442	0.441	0.442	0.437	0.434	0.463
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Employment

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Employment$_{i,t+1}$ $\times$ 100					
Indep Var	Climate Risk from MDA			Climate Risk from Risk Factors		
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Risk$_{i,t}$	0.1058	-26.6457**	0.1536	0.1781	16.3712	0.2468
	(0.568)	(-2.163)	(0.818)	(0.745)	(1.623)	(1.025)
N	26,862	26,766	26,766	20,668	20,616	20,616
R^2	0.284	0.187	0.285	0.193	0.305	0.305
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results of regressions using climate risk measures constructed from MD&A and Risk Factors of the 10-Ks as the main explanatory variables. The two alternative climate risk measures are further decomposed into expected and unexpected climate risk following the same method specified in section 4.6. The dependent variable in Panel A and Panel B is Cap Ex scaled by capital stock and change in employment, respectively. We control for the same set of firm attributes as specified in Table 5. These control variables are not presented in this table but included in each regression specification. Time and firm fixed effects are controlled in all the specifications. Standard errors are clustered at the firm level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level, respectively.

Table A5: Corporate Responses using Climate Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Investment$_{i,t}$ / Capital$_{i,t-1}$ × 100			Change in Employment$_{i,t+1}$ × 100		
Indep Var	Climate Sentiment					
	Overall	Expected	Unexpected	Overall	Expected	Unexpected
Climate Sent_t	-0.0214	0.7295	-0.0214	0.2155	1.8312	0.2148
	(-0.674)	(0.437)	(-0.677)	(1.181)	(0.167)	(1.178)
Observations	117,156	117,156	117,156	30,240	30,240	30,240
R^2	0.391	0.391	0.369	0.275	0.275	0.275
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the corporate response results from regressions using the net climate sentiment as the main explanatory variable. This climate sentiment measure is decomposed into expected and unexpected climate risk following the same method specified in section 4.6. We control for the same set of firm attributes as specified in Table 5. These control variables are not presented in this table but included in each regression specification. Time and firm fixed effects are controlled in all the specifications. Standard errors are clustered at the firm level.